

# The SWOT Mission and Its Capabilities for Land Hydrology

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The SWOT mission and capabilities for land hydrology

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Abstract

Surface water storage and fluxes in rivers, lakes, reservoirs and wetlands are currently poorly observed at the global scale, even though they represent major components of the water cycle and deeply impact human societies. *In situ* networks are heterogeneously distributed in space, and many river basins and most lakes – especially in the developing world and in sparsely populated regions – remain unmonitored. Satellite remote sensing has provided useful complementary observations, but no past or current satellite mission has yet been specifically designed to observe, at the global scale, surface water storage change and fluxes. This is the purpose of the planned Surface Water and Ocean Topography (SWOT) satellite mission. SWOT is a collaboration among the (U.S.) National Aeronautics and Space Administration (NASA), Centre National d’Études Spatiales (CNES, the French Spatial Agency), the Canadian Space Agency (CSA), and the United-Kingdom Space Agency (UKSA), with launch planned in late 2020. SWOT is both a continental hydrology and oceanography mission. However, only the hydrology capabilities of SWOT are discussed here. After a description of the SWOT mission requirements and measurement capabilities, we review the SWOT-related studies concerning land hydrology published to date. Beginning in 2007, studies demonstrated the benefits of SWOT data for river hydrology, both through discharge estimation directly from SWOT measurements and through assimilation of SWOT data into hydrodynamic and hydrology models. A smaller number of studies have also addressed methods for computation of lake and reservoir storage change or have quantified improvements expected from SWOT compared to current knowledge of lake water storage variability. We also briefly review other land hydrology capabilities of SWOT, including those related to transboundary river basins, human water withdrawals, and wetland environments. Finally, we discuss additional studies needed before and after the launch of the mission, along with perspectives on a potential successor to SWOT.

Keywords: Surface Water and Ocean Topography (SWOT) satellite mission; continental surface waters; lakes; reservoirs; rivers

## 55 1. SWOT mission overview

### 56 57 1.1. The needs for a global water surface mission and its requirements

58  
59 In the late 1990s and early 2000s, the crucial need for more quantitative data on spatiotemporal  
60 dynamics of surface waters at a global scale became clear in context of a declining *in situ* gage  
61 network and increasing need to observe and model the global water cycle (Alsdorf et al. 2003). To  
62 address this challenge, Alsdorf and Lettenmaier (2003) advocated development of a “topographic  
63 imager” satellite mission with ~100 m spatial resolution (to observe main channels, floodplains and  
64 lakes), temporal resolution on the order of a few days (to sample flood waves and river dynamic at  
65 basin scale), and capability to measure height changes that characterize variations in river discharge  
66 and lake water storage. Alsdorf et al. (2007) provided a more in-depth study showing that “spatial  
67 and temporal dynamics of surface freshwater discharge and changes in storage globally” are poorly  
68 known because:

- 69 - *in situ* networks are very heterogeneous (some countries have dense networks, whereas others
- 70 have a few measurements points),
- 71 - these data are not always shared at the international level,
- 72 - current satellite missions do not provide measurements adequate to observe global spatio-temporal
- 73 dynamics of continental water surface.

74 For that reason, Alsdorf et al. (2007) proposed a new satellite mission based on synthetic aperture  
75 radar (SAR) interferometry, called Water and Terrestrial Elevation Recovery (WATER). The  
76 concept of this satellite mission is built on the legacy of the Shuttle Radar Topography Mission  
77 (SRTM) and the Wide Swath Ocean Altimeter (WSOA). SRTM (Farr et al. 2007) was a SAR  
78 interferometer in C- and X-bands that flew in February 2000 on the NASA Space Shuttle  
79 Endeavour. SRTM provided a near-global Digital Elevation Model (DEM) at 90 m spatial  
80 resolution between 60°S and 60°N, but because of the specular returns characteristic of its oblique  
81 look angles (between 30° and 60°) it provided poor measurements of surface water. Because the  
82 two interferometric antennas were separated by a 60 m mast, construction of an SRTM-like system  
83 on a satellite platform would be problematic. A similar concept, WSOA, was envisioned as an  
84 additional payload to the altimetry Jason-2 satellite mission with the aim of imaging ocean  
85 topography. The distance between the two Ku-band antennas was set to 6.4 m to facilitate inclusion  
86 on a satellite platform (resulting in kilometric pixel resolution), and a near-nadir look angle was  
87 chosen to better observe the ocean surface (Fu and Rodríguez 2004). WSOA was definitely  
88 withdrawn in 2004 and never flown. To adapt this concept to the needs of continental water surface  
89 observation, Alsdorf et al. (2007) proposed to use Ka-band instead of Ku-band, allowing better

spatial resolution (see section 1.2). In 2007, in its Decadal Survey (NRC 2007), the National Research Council recommended to NASA this new satellite mission, under the name Surface Water and Ocean Topography (SWOT, <https://swot.jpl.nasa.gov/>), to measure both the ocean and land water surface topography. Since then, SWOT has been collaboratively developed by NASA, the Centre National d'Etudes Spatiales (CNES, the French space agency) and more recently the Canadian Space Agency (CSA/ASC) and the United-Kingdom Space Agency (UKSA). Currently, SWOT is planned for launch in late 2020. It will observe the whole continental waters-estuaries-ocean continuum and therefore link the ocean and hydrology scientific communities. However, in this paper, the ocean component of the mission will not be addressed.

Figure 1 gives an overview of the main spatiotemporal physical processes related to the land hydrological cycle and the SWOT observation window. SWOT is designed to observe a large fraction of rivers and lakes globally and will provide robust observations of their seasonal cycles. However, at least by itself, it is not conceived to observe climate-scale variability (and especially climate change) and will not be able (except on rare occasions) to monitor flash floods. As stated by Rodríguez (2015), SWOT aims to address the following hydrologic science questions:

- What are the temporal and spatial scales of the hydrologic processes controlling surface water storage and transport across the world's continents?
- What are the spatially distributed impacts of humans on surface water, for example through water impoundment behind dams, withdrawals and releases to rivers and lakes, trans-boundary water sharing agreements, diversions, levees, and other structures?
- What are the regional- to global-scale sensitivities of surface water storages and transport to climate, antecedent floodplain conditions, land cover, extreme droughts, and the cryosphere?
- Can regional and global extents of floodable land be quantified through combining remotely sensed river surface heights, widths, slopes, and inundation edge with coordinated flood modeling?
- What are the hydraulic geometries and three-dimensional spatial structures of rivers globally, knowledge of which will improve our understanding of water flow?

The scientific rationales for these questions and the measurement needs are presented in the SWOT Mission Science Document (Fu et al. 2012). Based on these needs, the SWOT Science Requirements (Rodríguez 2015, summed up in Table 1) have been derived to design the SWOT mission, which is presented in subsections 1.2 to 1.4 (sections 1.2 for the main payload, section 1.3 concerning SWOT products over land and section 1.4 for its spatiotemporal sampling). Then, sections 2 and 3 present the benefits of SWOT for measurement of rivers and other water bodies, respectively.

## 1.2. Characteristics of the KaRIn instrument

126 To meet the SWOT science requirements (Table 1), a Ka-band Radar Interferometer (KaRIn) has  
127 been designed as the mission main payload. KaRIn will be a SAR interferometer in Ka-band (35.75  
128 GHz frequency or 8.6 mm wavelength), with near nadir incidence angles (between  $0.6^\circ$  and  $3.9^\circ$ ,  
129 Fjørtoft et al. 2014). Figure 2 shows a conceptual view of the KaRIn operating system and ground  
130 coverage. It will provide images of water elevations within two swaths, one on each side of the  
131 satellite. These two swaths (each 50 km wide) will be separated by a 20 km gap at the satellite nadir  
132 (Figure 2). KaRIn will operate in bistatic mode: one antenna emits the electromagnetic signal  
133 towards the closest swath and the two antennas (10 m apart) receive the backscattered signal in their  
134 respective directions. Interferometry effectively involves a triangulation: each point in the swath  
135 will be observed from two different positions (the antennas positions), which will allow precise  
136 estimation of the location of each point. More precisely, the phase difference between the  
137 backscattered signals received by the two antennas (the so-called interferogram) will be used to  
138 invert water elevations. More details of SAR interferometry and the KaRIn measurements are  
139 provided in chapters 6 and 7 in Fu et al. (2012) and by Fjørtoft et al. (2014). Table 2 summarizes the  
140 main characteristics of the KaRIn instrument.

141 KaRIn will provide images of water surface elevation with pixel sizes  $\sim 6$  m in the azimuth  
142 direction (direction of the satellite orbit) and from 60 m (near range, see Fig. 2) to 10 m (far range)  
143 in the range direction (perpendicular to the azimuth), as also indicated in Table 2 (Fu et al., 2012,  
144 Fjørtoft et al. 2014, Biancamaria et al. 2010). However, it should be clearly understood that this  
145 image is obtained in “radar projection” and not in a geolocated projection. Indeed, the radar  
146 instrument measures the distance between the observed point and the antenna. Therefore, in radar  
147 images, two consecutive pixels in the range direction correspond to points on the ground that have a  
148 similar distance from the satellite. For that reason, when pixels are geolocated they are more  
149 scattered, they do not correspond to a regular grid, and their shape becomes distorted. For example,  
150 a hill, which is few km away from a river, could have a distance to the satellite similar to that of the  
151 center of the river and therefore could be located close to the river center in a SAR image. However,  
152 in this example, the river banks will have a different distance from the satellite and could be several  
153 pixels distant from the river center pixel. Therefore, the top of the hill will be closer to the river  
154 center than the river banks. This effect, hereafter referred to as “layover”, occurs when surrounding  
155 topography or vegetation is at the same distance from the satellite as the water surface (land over  
156 water layover). Furthermore, pixels with large vertical errors will also have high geolocation error  
157 (vertical and horizontal accuracies are functions of the phase interferogram accuracy). For that  
158 reason, the most basic geolocated SWOT products will likely be delivered as point cloud products  
159 that can more accurately take into account these geolocation inversion effects (Rodríguez 2015).

160 The 10 m to 60 m x 6 m intrinsic pixel size also can be somewhat misleading, as a SWOT  
161 measurement requirement (Table 2) is not given for this spatial resolution. While these pixels  
162 represent the basic unit of SWOT measurement, in fact, water elevations measured by the KaRIn  
163 instrument at this native pixel size will be metric if not decametric in accuracy. Achieving the  
164 decimetric accuracy that is a stated requirement in Rodríguez (2015) and Table 2 will require  
165 averaging over many such pixels. This issue is discussed in more detail in the section 1.3.

166 In Ka-band, water is more or less specular, whereas land is rougher. KaRIn near-nadir incidence  
167 angles are particularly suited to monitor water bodies, as water will backscatter most of the emitted  
168 energy toward the satellite nadir (because of its specular behavior and the near-nadir look angle),  
169 whereas land will backscatter energy in all directions and therefore less in the antenna direction.  
170 Because of this different energy scattering between water and land, the difference in amplitude of  
171 the received electromagnetic wave between water and non-water pixels should be quite high and  
172 will be used to compute the water mask. However, because SWOT look angles are close to the  
173 nadir, but not exactly at the nadir, some water surface roughness is still needed to get sufficient  
174 energy. Thus, when the water surface becomes extremely flat, typically for wind speed  $\ll 1 \text{ m.s}^{-1}$ ,  
175 there could be some loss of data in the far-swath where look angle are close to  $3.9^\circ$  (Enjolras and  
176 Rodríguez 2009, Moller and Esteban-Fernandez 2015). This issue is currently under investigation  
177 using measurements from the AirSWOT platform, an airborne SWOT analogue (Rodriguez et al.  
178 2010), obtained during campaigns conducted in 2014 and 2015. It will allow better quantification of  
179 the frequency and magnitude of layover effects.

180 Very few satellite missions have used Ka-band, which is therefore not as well understood as  
181 lower frequency bands. For example, most current nadir altimeters use Ku- or C-bands, whereas  
182 SAR imaging missions are in L-, C- or X-bands. Additionally, these current sensors have lower  
183 (nadir altimeters) or higher (SAR imagery missions) observation incidence angles than SWOT.  
184 However, using Ka-band instead of higher wavelength bands has several advantages: first, it allows  
185 a finer spatial resolution (which is dependent on the electromagnetic wavelength) from the SAR  
186 processing and second, it facilitates a shorter baseline (distance between the two antennas) for a  
187 given targeted instrumental vertical accuracy, for the interferometry processing (a shorter baseline  
188 corresponds to a shorter mast between the two antennas, which is easier to construct). Shorter  
189 wavelengths also result in less penetration into soil, snow and vegetation (Fjørtoft et al. 2014),  
190 which should allow better estimation of wetland and saturated soil surface elevation and snow  
191 volume variations, if interferograms can be computed.

192 A drawback of Ka-band is its sensitivity to rain rates above about 3 mm/hour (Rodríguez 2015).  
193 The only altimetry satellite mission in Ka-band preceding SWOT is the Satellite with Argos and  
194 ALtiKa (SARAL) mission with the ALtiKa nadir altimeter, launched only recently (February 2013).

Measurements obtained from this new instrument will help to better understand backscattering in Ka-band over different surfaces (water, bare soil, vegetation, snow, etc). However, AltiKa, as a nadir altimeter, does not have exactly SWOT look angles; its measurements integrate all the energy backscattered in a cone covering angles between  $-0.3^\circ$  and  $0.3^\circ$  to the nadir (AltiKa half antenna aperture is  $0.3^\circ$ , Steunou et al. 2015). The Global Precipitation Measurement (GPM) Mission Core Observatory, launched in February 2014, carries the Dual-Frequency Precipitation Radar (DPR) in Ku and Ka bands (<http://pmm.nasa.gov/GPM/flight-project/DPR>). In Ka-band, DPR scans across a 125 km swath ( $\pm 8.5^\circ$  across track) with a 5 km footprint. Analyzing DPR measurements will provide useful information on backscatter properties in Ka-band, however the GPM observation angle covers a wider range than SWOT with a much coarser spatial resolution. For those reasons, airborne and field campaigns have been organized by the Jet Propulsion Laboratory (JPL) (Moller and Esteban-Fernandez 2015) and CNES (Fjørtoft et al. 2014) to better understand Ka-band backscattering at SWOT-like incidence angles. These campaigns have confirmed the decrease of the backscatter coefficient with the incidence angle and a water/land backscatter coefficient contrast of around 10 dB, except when the water surface is very flat (low wind speed and hence extremely low surface roughness). Moller and Esteban-Fernandez (2015) have also reported the impact of decorrelation time (and therefore wind speed and water surface turbulence) on pixel azimuth size, which could become higher than expected based on the instrument characteristics (Table 2). In addition to KaRIn, SWOT will carry additional scientific payload (Table 2), including a dual frequency (Ku and C-band) nadir altimeter, similar to the Poseidon-3 instrument on-board Jason-2 (Desjonquères et al. 2010). It will provide water elevation measurements in the middle of the 20 km gap between the two KaRIn swaths. A radiometer will also facilitate, over the oceans, corrections to path delay due to wet tropospheric effects. However, it will not be used over land because land emissivity dominates the radiometric signal (Fu et al. 2012). Wet troposphere corrections over land will be computed using an atmospheric model, one effect of which will be that the residual tropospheric error will likely be larger over land than over the ocean and should be on the order of 4 cm (Fu et al. 2012).

### 1.3 SWOT measurements over terrestrial surface waters

SWOT will provide measurements of surface water elevation, slope and water mask. **In this paper, water elevation ( $H$ ) corresponds to the distance between the top of the water surface and a given reference surface (geoid or ellipsoid), whereas water depth ( $d$ ) corresponds to the distance between the water surface and the water body (e.g. river) bottom.** It is important to note that SWOT will not measure water depth. SWOT level-2 data products (i.e. the highest level of



processed data delivered by NASA and CNES to end-users) are currently being defined. There remains, therefore, some uncertainty as to their specific nature. However, some characteristics of SWOT level-2 data product over land are provided in the science requirements document (Rodríguez 2015), which is the basis for the discussion in this section. As outlined in Rodríguez (2015) these products will likely include:

- For each pass, a water mask consisting of a geolocated point cloud product with all KaRIn pixels that are identified as water, with the finest spatial resolution to meet appropriate geolocation accuracy (i.e. 10% of the pixel size in any direction). Surface water elevation corresponding to the provided pixel size (with an estimation of the surface water elevation uncertainty) will be associated with each point within the water mask.
- At least once every repeat cycle, a global water mask following the shorelines of all observed water bodies will be provided in vector format, with one water elevation for each individual water body, along with other information (such as area within the water body and its slope). Water storage within each such water body will be easily derived from this product.
- A global one-dimensional vector product that will include estimated discharge along river reaches at each observation time, for all river reaches wider than 50 m.
- A cross-section map of all observed water bodies will be derived from time-varying water elevations along the shores of each water body. This map will be updated yearly.

As SWOT will observe almost all continental surfaces every 21 days, it will provide a tremendous amount of data in the point cloud product, which includes the KaRIn pixels resolution stated in Table 2 (as a reminder, vertical accuracy at such spatial resolution is very low). It will therefore be very difficult for end-users to use so much data in a non-gridded format at global, regional or even basin scales. For that reason, vector products providing height integrated measurements for entire lakes and for discrete river reaches have been defined.

The SWOT mission is designed to observe all rivers wider than 100 m and water bodies (lakes, reservoirs, ponds, continuous wetlands) with an area greater than 250 m x 250 m (i.e. 62 500 m<sup>2</sup>) that lie within the swath coverage. Moreover, NASA and CNES teams will strive to design an instrument and processing methods that will be able to observe rivers wider than 50 m and water bodies with an area above 100 m x 100 m. If SWOT is able to observe smaller rivers or water bodies, the measured data will be provided. Besides, lower level product (SAR amplitude and phase images, interferograms) will be provided on-demand and could be used to reprocess data a posteriori, which might help to improve products resolution if feasible. The main sources of errors that will affect KaRIn measurements are instrument thermal noise (white noise), differences in the return signal speckle, error in the interferometric baseline roll angle, wet and dry tropospheric effects, ionospheric effects, topographic layover and vegetation layover and attenuation (see chapter

6 in Fu et al. 2012). Thermal noise and speckle dominates the error budget at the KaRIn pixel level (10 m to 60 m x 6 m, Table 2), leading to multi-meter vertical errors. These errors are random for one pixel, but their standard deviations tend to increase in the far range of the measurement swath (Enjolras and Rodríguez 2009). Fortunately, these random errors can be reduced by averaging over water pixels by the square root of the number of pixels averaged. For this reason, the science requirements (Table 1) are provided for water areas much larger than a single pixel. However, the other sources of error will not be reduced by the averaging process. Over 1 km<sup>2</sup> (e.g. a 10 km reach for a river of 100 m width), SWOT water elevation will have a 10 cm (1  $\sigma$ ) accuracy. For this averaging area, random errors and wet tropospheric effects are the main error sources. Locally, especially near the water bodies margins, topographic and vegetation layover can be a source of large errors, especially given the near nadir incidence angles used by KaRIn. Therefore, the received energy by the antenna will be a mixture of the energy backscattered by water and topography or vegetation, leading to potentially large errors in retrieved water elevation, geolocation and water extent. SWOT performance will be evaluated for water bodies meeting the observation requirement (lakes, reservoirs, and wetlands with area greater than 250 m x 250 m and rivers wider than 100 m), in order to validate that the instrument meets the accuracies provided in Table 1. Furthermore, SWOT performance will be characterized for the observational goals (100 m x 100 m to 250 m x 250 m water bodies and 50 m to 100 m wide rivers). Estimates of measurement accuracy will be provided with SWOT data products.

There is currently no near-real time consideration for provision of SWOT data products, consistent with the scientific rather than operational nature of the mission. However, derived products are expected to be provided within 60 days of their collection (requirement). There is also a goal to provide water elevations for a select number of reservoirs (less than 1000) within 30 days of collection. Finally, it is worth noting that an on-board averaged ocean water elevation product computed over a regular grid will also be provided over continents (all observed pixels will be available, not just the ones that are entirely covered by water). This ocean product will have a spatial resolution between 250 m and 1 km (the grid size has not yet been finalized). However, while the elevation accuracy over oceans will be centimetric, the accuracy of this product over continents is not defined and has not yet been evaluated, in part because SAR interferometry processing over land is much more complex than over oceans.

#### 1.4. SWOT spatiotemporal coverage

There will be an initial calibration phase for the SWOT mission with a fast sampling orbit (1-day repeat period), but reduced spatial coverage relative to the subsequent orbit. The objective of this

300 fast sampling phase of the mission is to obtain frequent overpasses of the satellite over specific  
301 ocean/land hydrology targets that will allow calibration of radar system parameters. For open  
302 oceans, it will also help to characterize water elevation temporal decorrelation times. This initial  
303 calibration phase will last three months, which is expected to be sufficient to obtain a fully  
304 calibrated system for the nominal phase (Rodríguez 2015). The nominal phase of the mission (also  
305 termed the science phase), will have a non-sun synchronous, 890.5 km altitude, 20.86 day repeat  
306 period and 77.6° inclination orbit (Table 2) and will last at least 3 years. The remainder of this  
307 section is applicable only to this nominal orbit.

308 SWOT spatial coverage and revisit times per orbit repeat period (i.e. ~21 days) depend on orbit  
309 characteristics, instrument swath width (2x50 km), nadir gap width (20 km) and is a function of  
310 latitude as well. Figure 3 shows a map of the number of SWOT revisits per orbit repeat period (~21  
311 days) over the continents between 78°S and 78°N (a.). To improve figure readability and given the  
312 scope of this paper, oceans have been masked in blue. However, oceans and continents will have the  
313 same sampling pattern. Figure 3.b shows the Lower Amazon basin, which illustrates the extent of  
314 locations that will never be sampled by SWOT (white diamonds). Tropical regions will be sampled  
315 less frequently than higher latitudes; the number of revisits per repeat period ranges from a  
316 maximum of two at the equator to more than ten above 70°N/S. Few regions will never be observed  
317 (white in Figures 3.a and 3.b); however much of the equatorial regions will be seen only once per  
318 repeat period.

319 Figure 3 also shows that the mission will observe almost all continental surfaces from 78°S to  
320 78°N, which will be a tremendous improvement compared to nadir altimeters, which miss many  
321 water bodies. Regions not observed by SWOT are the results of the 20 km nadir gap between the  
322 two swaths (white diamonds without magenta boundaries on Figure 3.b) and the orbit intertrack  
323 distance, which does not always allow for adjacent swaths to overlap at the lowest latitudes (white  
324 diamonds with magenta boundaries on Figure 3.b). Gaps due to orbit intertrack distance are only  
325 present in the 25°S-25°N latitude band, with their largest extent between 10°S and 10°N. Coverage  
326 gaps resulting from the nadir gap cover a much broader latitude band (60°S-60°N) and are the main  
327 source of observation gaps. The total gap area over all latitudes between 78°S and 78°N is about  
328 3.55% of the whole land area (or  $4.90 \times 10^6 \text{ km}^2$ ). This is consistent with the SWOT science  
329 requirement (Rodríguez 2015), which states: “SWOT shall collect data over a minimum of 90% of  
330 all ocean and land areas covered by the orbit inclination for 90% of the operation time” (Table 2).  
331 The coverage gap can, however, be locally higher than 10% between 10°S and 10°N. On average  
332 over this band of latitudes, 7% of land is unobserved and the maximum coverage gap is 14% over a  
333 1° latitude band centered on 4.5°N.

334 Satellite nadir altimeters measure water elevation along the satellite tracks, and therefore, most

335 sampled river reaches are observed only once per repeat period (except for the few locations where  
336 ascending and descending tracks cross). Thus, temporal sampling of rivers by nadir altimeters is  
337 essentially equal to the orbit repeat period. Large lakes may be sampled more than once during a  
338 repeat cycle by altimeters, but uncertainties in the geoid when different parts of a lake are sampled  
339 must be corrected for (Crétaux et al., 2011). These difficulties will be overcome for SWOT, as for  
340 most locations in both rivers and lakes there will be more than one observation per repeat period for  
341 the reasons indicated above. The number of revisits is, however, unevenly distributed in time during  
342 the repeat period. This is illustrated in Figure 4, which shows the SWOT observation mask (black  
343 bars correspond to observation dates) for all latitudes along the 30°E meridian versus days during a  
344 repeat period. For example, at the equator and at 30°E, there will be two observations: one at day 15  
345 and one at day 20, but no observations for 16 consecutive days. The distribution of revisit times  
346 during a repeat period does not monotonically controlled by latitude, which makes it difficult to  
347 infer directly how errors from temporal sampling vary as a function of latitude. SWOT products that  
348 will be used for seasonal studies may require computing monthly time series. The uneven SWOT  
349 temporal sampling will be a source of error in the computation of monthly means. Computing  
350 cycle-based averaged (i.e. 21-days average) might be a viable alternative for SWOT, but this option  
351 requires additional study. The impacts of these variations in temporal sampling depend on the nature  
352 of the water body sampled. For example, the water surface elevation of some lakes may not vary  
353 significantly except on monthly or longer timescales, while many rivers exhibit changes in  
354 discharge on daily or even hourly timescales. In rivers, errors associated with gaps in temporal  
355 sampling result from missed local maximum/minimum flows (Biancamaria et al. 2010, Papa et al.  
356 2012), the importance of which depends on the flashiness of the river. To estimate error in monthly  
357 averages due only to the SWOT uneven temporal sampling, Biancamaria et al. (2010) proposed a  
358 method that used daily *in situ* discharge time series from 216 gages for a previously proposed  
359 SWOT orbit (970 km, 22 day repeat period and 78° inclination orbit with two 60 km swaths). For  
360 simplicity and solely for the purpose of estimating the impact of temporal sampling error, the  
361 Biancamaria et al. (2010) method assumed that SWOT measurements have already been converted  
362 to discharge. Furthermore, errors due to instantaneous estimation of discharge were not considered,  
363 though in reality they may be a significant component of the error budget. *In situ* discharge time  
364 series were used because they are much more readily available than water height. Since the errors in  
365 monthly discharge are expressed as percentages, the results should be somewhat similar to those for  
366 water height. Updated for the current orbit, the method of Biancamaria et al. (2010) gives a mean  
367 temporal sampling error for all 216 gages of 8.1%. On average, monthly mean temporal sampling  
368 errors decreased with increasing latitude, ranging from 10.0% around the equator to 6.1% above  
369 60°N. For 11 large rivers distributed from the equator to the high latitudes, Papa et al. (2012)

370 showed that insufficiently frequent temporal sampling around the seasonal peak discharge can lead  
371 to substantial errors in mean river discharge computed over a satellite repeat period. For boreal  
372 rivers, nadir altimetry sampling with a repeat period longer than 20 days leads to errors  $\gg 20\%$  due  
373 to the relatively large fraction of the annual discharge of boreal rivers that occurs over relatively  
374 short periods following ice breakup. Errors are much smaller using SWOT temporal sampling.  
375 Furthermore, considering the 11 rivers, SWOT temporal sampling errors are correlated to the  
376 discharge temporal variance contained in all frequencies above  $1/(20 \text{ days})$  ( $R^2=0.87$ ) rather than  
377 drainage area ( $R^2=0.18$ ), at least for the few number of tested large rivers.

378 Unlike for rivers, there are not yet comprehensive studies estimating the impact of SWOT  
379 temporal sampling on measurement of variations in lake storage. However, given the fact that  
380 storage change in the large majority of global lakes remain entirely unobserved and that storage  
381 change in many observed lakes varies on seasonal or annual timescales (Crétaux et al., 2015), it is  
382 expected that the impacts of limited temporal sampling will be smaller than in the case of rivers.

383 In summary, despite the uneven time sampling and the limited regions that will not be sampled,  
384 SWOT will provide unprecedented observations of continental surface waters at global scale. The  
385 next sections review in more detail published studies that have explored, for different science  
386 questions, the benefits of the SWOT mission for land hydrology (section 2 for rivers, section 3.1 for  
387 lakes and reservoirs, and section 3.2 for other water bodies and specific applications).

388

## 389 2. River studies

390

### 391 2.1. Rivers seen by SWOT

392

393 SWOT will monitor the spatial and temporal dynamics of surface water globally, especially  
394 rivers. At a specific location, river stage, width, and velocity variations and therefore discharge  
395 depend on many local factors such as soil characteristics, bedrock characteristics, topographic  
396 variability, channel density, vegetation characteristics, and the space-time variability of  
397 precipitation, and drainage area, among other characteristics. SWOT will provide the first globally  
398 consistent and coherent images of river storage and discharge variations. Over the last two decades,  
399 optical imagery and digital elevation data have helped to map medium to large rivers, whereas  
400 airborne and local measurements have provided valuable information for smaller rivers (Lehner et  
401 al. 2008, Allen and Pavelsky 2015). SWOT will provide consistent and coherent information about  
402 the spatial distribution of river storage and discharge, which will especially improve the availability  
403 of information about rivers that are not well monitored because *in situ* observations are not  
404 collected or because they are not shared across political boundaries. In addition, SWOT will provide

critical information about the impact of river discharge characteristics and variations on human societies. This includes the nature of floods and droughts in poorly monitored river basins and the characteristics of discharge in rivers that cross international boundaries (transboundary basins).

Notwithstanding the profound improvement that SWOT will provide in the availability of information about rivers globally, SWOT does not have the objective of and cannot be an *in situ* gage network replacement. In most circumstances, *in situ* gages will be, by far, more precise than any remote sensing discharge estimates. This is especially important for applications such as water management, where highly accurate and precise information is required for legally significant purposes. For example, data from the gauge on the Colorado River at Lees Ferry, AZ is used to determine the allocation of water to surrounding states. SWOT will likely not be sufficiently accurate for this purpose. On the other hand, stream gage information is by its nature local and does not provide a full view of the spatial variations of streamflow. Moreover, some types of rivers such as highly braided channels and rivers with poorly defined banks are not well-suited to *in situ* gauge measurements. The main benefit of SWOT in this respect will be to provide new and complementary 2D observations for a wide range of different river planforms. Clearly, SWOT will not observe full river networks because it will be limited to measuring rivers 50-100 m in width. Therefore, a key question is: what portions of the global river network SWOT will observe and what improvement will it represent compared to current capabilities? Pavelsky et al. (2014a) have addressed these questions. Using river networks from Hydro1k (Verdin and Greenlee 1998) and HydroSHEDS (Lehner et al. 2008), the global *in-situ* gage discharge time series database from the Global Runoff Data center (GRDC, [http://www.bafg.de/GRDC/EN/Home/homepage\\_node.html](http://www.bafg.de/GRDC/EN/Home/homepage_node.html)) and downstream hydraulic geometry (power law relationships between drainage area, mean annual discharge and river width at sub-basin scales), they have quantified the fraction of global river basins that SWOT would observe given river observability thresholds of 100 m and 50 m. They found that SWOT would observe more than 60% of the global sub-basins with an area of 50,000 km<sup>2</sup> given the ability to observe rivers wider than 100 m. If SWOT can meet the goal of observing 50 m wide rivers, more than 60% of sub-basins with an area of 10,000 km<sup>2</sup> would be observed. For the smallest river basins observed, only the mainstem river will likely be measured by SWOT.

For SWOT-observable rivers, a number of studies have investigated the potential to produce river discharge estimates directly from SWOT water level, surface slope, and inundation extent observations. We review these studies in section 2.2. In section 2.3, we review studies that have pursued an alternate pathway of combining SWOT observations with hydrologic and river hydrodynamic modeling to produce river discharge estimates.

## 2.2. Instantaneous direct river discharge estimations

Space-based observations of discharge began nearly two decades ago with the observation that variations in river width, observable from satellites, can be used along with limited *in situ* discharge data to develop rating curves (Smith et al. 1995, 1996, Smith 1997, Smith and Pavelsky 2008). A few years later, the first attempts were made to use nadir altimetry in conjunction with *in situ* observations to derive river discharge from altimetry-based water elevation data using rating curves (e.g. Kouraev et al. 2004). An alternative strategy of estimating discharge using water elevation, width, slope and velocity observed by or derived from spaceborne sensors was pursued in studies by Bjerklie et al. (2003) and Bjerklie et al. (2005) at about the same time. These attempts were specific to individual study reaches, were highly parametrized, and required ancillary *in situ* data in addition to altimetry-based variables. It was recognized that the next logical step was to develop discharge algorithms that could take advantage of all the information provided by SWOT (water elevations, slopes and inundation extent) so as to produce river discharge estimates at the scale of large river basins or even globally. Following the analysis by Pavelsky and Durand (2012) that new discharge algorithms specifically tuned for SWOT data need to be developed, four different discharge algorithms have been proposed to derive river discharge from SWOT. Characteristics of these algorithms are summarized in Table 3 and are briefly presented in the next paragraph. Gleason and Smith (2014) and Gleason et al. (2014) have pursued an approach that they termed At-Many-stations Hydraulic Geometry (AMHG hereafter). Bjerklie (2007) describes an approach (B2007 hereafter) that is based on an equation similar to the Manning equation with tuned power law coefficients. Garambois and Monnier (2015), hereafter GM2015, propose a method based on physical and numerical approximations of the Saint-Venant equations to invert the unobserved equivalent bathymetry and friction coefficient and then derive discharge. Durand et al. (2014) also use physical and numerical approximations (different than GM2015) of the Saint-Venant equations. This algorithm is referred to hereafter as ‘MetroMan’, because it uses the Manning equation along with the continuity equation and a Metropolis algorithm to invert bathymetry, friction and discharge. We discuss each of these algorithms, including hypotheses and limitations, briefly below. Additionally, these algorithms are summarized in Table 3.

The AMHG algorithm will use the intensive SWOT observations of river width to derive discharge using the well-known geomorphologic relationship between river width ( $w$ ) and discharge ( $Q$ ) at a specific location:  $w=aQ^b$ . The  $a$  and  $b$  coefficients are considered constant in time but vary along a given river. The innovation of the AMHG algorithm is based on the important fact (reported for the first time in Gleason and Smith 2014) that  $a$  and  $b$  at cross-sections within the same river reach commonly exhibit a well-defined log-linear relationship. Therefore, by considering width

475 variations at many cross-sections along a river in combination, the number of unknowns is  
476 decreased, allowing  $a$ ,  $b$ , and  $Q$  to be estimated using a genetic algorithm requiring only  
477 multitemporal width observations at many river reaches (Gleason et al. 2014). A global  
478 parametrization is proposed by Gleason et al. (2014) when no a priori information is available. In  
479 this paper, the authors highlight a series of cases for which the algorithm will not work  
480 (corresponding to rivers that do not verify the conditions listed in column ‘Tested river types’ for  
481 this algorithm in Table 3). When these cases (types of rivers) are excluded, the relative Root Mean  
482 Square Error (RMSE) between AMHG and *in situ* discharge ranges from 26% to 41% for  
483 instantaneous discharge.

484 Bjerklie’s algorithm (Bjerklie 2007) is based on a tuned Manning equation, using a constant river  
485 slope and parameterized Manning coefficient ( $n$ ) varying in time and taking into account idealized  
486 channel shape. It requires as ancillary parameters the mean annual discharge (required because  
487 SWOT will provide surface water elevation and not river water depth). This method is robust if  
488 there are no floods and if the mean annual discharge is accurately known.

489 The GM2015 algorithm is a forward and inverse model based on the 1D Saint-Venant’s  
490 equations applied to river reaches and rewritten to take into account SWOT measurements of water  
491 surface elevation, width and slope. It assumes no lateral inflows, steady-state flows at observation  
492 times, low Froude Number ( $<0.5$ , corresponding to neglecting the inertia term in the Momentum  
493 Equation), trapezoidal cross-section, and constant friction coefficient in time. The inverse model  
494 allows retrieval of discharge and an effective friction coefficient (Strickler or Manning coefficient)  
495 and cross sectional geometry for the lowest observed level (i.e. the low flow bathymetry), for a  
496 given set of observations. The identified coefficients (friction and cross section geometry) can then  
497 be used to compute discharge for other SWOT observations using the forward model. Garambois  
498 and Monnier (2015) tested the GM2015 algorithm on more than 90 synthetic rivers covering a wide  
499 range of conditions (width, depth, discharge) that will be observed by SWOT. They reported RMSE  
500 of discharge below 15% for first guess error exceeding 50% and a very robust estimation of  
501 discharge, as measurements errors and errors due to physical approximation are included in the  
502 estimated bathymetry and friction coefficient errors. Even if some equifinality (Beven 2006) exists  
503 between friction coefficients and bathymetry, the GM2015 algorithm seems to provide accurate  
504 estimates of equivalent bathymetry and friction in the range of tested discharge.

505 The MetroMan algorithm, like GM2015, uses an approximation (the diffusive wave  
506 approximation) of the 1D Saint-Venant equations. However, the mathematical implementation of  
507 the forward and inverse models are different, and it also takes into account unknown lateral inflows.  
508 It has been evaluated using a 22.4 km river reach of the Severn River (river width ~60 m) in the  
509 United Kingdom and one of its tributary for an in-bank flow event (duration 5 days) and an out-of-



510 bank flood event (duration 15 days). For the in-bank event, when lateral inflows from tributaries  
511 were known, discharge was retrieved with 10% RMSE, whereas when lateral inflows were  
512 unknown, the discharge RMSE went up to 36%. For the out-of-bank flood event with unknown  
513 lateral inflows, the RMSE was 19%. Both the GM2015 and MetroMan algorithms required multiple  
514 observations (at different times) of water surface height, width and slope (average over 1-10 km  
515 river reaches) and require substantial variability in water elevation and discharge across the  
516 observations. Bathymetry and friction affect river flows at different spatial scales. It worth noting  
517 that MetroMan and GM2015 retrieve these river parameters at the kilometer river reach scale and  
518 might therefore be slightly different from the ones estimated at the local scale.

519 Results from these investigations are encouraging and demonstrate the feasibility of retrieving  
520 river discharge from SWOT observations alone. Although these four algorithms were developed by  
521 different teams, their development was not independent as all author groups are members of the  
522 SWOT Science Definition Team (SDT) Discharge Algorithms Working Group. Intercomparison  
523 studies are currently being performed over different types of rivers and the relative strengths and  
524 weaknesses of each algorithm are being evaluated. Pending the results of these ongoing  
525 comparisons, the potential for implementation and performance of the algorithms at global scales is  
526 still an open question. Furthermore, at this point they have only been tested over non-braided rivers,  
527 whereas many large rivers (e.g. the Amazon, Ganges/Brahmaputra, and Ob') and many smaller  
528 rivers are at least partially braided. The precise river reaches to which the algorithms can be applied  
529 globally remain undefined but most likely will have lengths ranging from a few km to a few 10s of  
530 km. For those algorithms that require ancillary information and/or a first guess (see '1<sup>st</sup>  
531 guess/ancillary data' column in Table 3) this information will be defined and provided globally  
532 before launch. Finally, testing of algorithms with real SWOT data and realistic errors will be crucial  
533 for fully assessing the suitability of these algorithms.

534

### 535 2.3. Data assimilation and optimal interpolation

536

537 An alternate strategy for estimation of discharge and other water surface variables is the use of  
538 indirect and/or statistical methods. Work in this area falls into two categories: optimal interpolation  
539 (OI) to improve spatial/temporal coverage of SWOT water elevation and discharge estimates (Yoon  
540 et al. 2013 and Paiva et al. 2015) and data assimilation (DA), which uses SWOT data to correct  
541 hydraulic/hydrologic model parameters or state vectors (Andreadis et al. 2007, Durand et al. 2008,  
542 Biancamaria et al. 2011, Yoon et al. 2012, Andreadis and Schumann 2014, Pedinotti et al. 2014,  
543 Munier et al. 2015). Table 4 summarizes all these studies. All of the nine studies summarized were  
544 designed in the context of Observing System Simulation Experiments (OSSE), a methodology

545 designed to assess the potential of a new type of measurements before it is built or deployed. Figure  
546 5 shows the conceptual framework of an OSSE in the context of SWOT studies using optimal  
547 interpolation (a.) and data assimilation (b.). Among these nine studies, the OSSE consisted of first  
548 computing time series of realistic states (water elevations and discharges) over a specified study  
549 domain with a hydraulic or hydrologic model. This simulation is considered to be the “truth” in the  
550 context of the OSSE (Figure 5). Then, a SWOT simulator is run to provide what the algorithm treats  
551 as SWOT measurements. These so-called “virtual” or “synthetic” SWOT observations are then used  
552 with OI or DA methods to improve the SWOT estimate of river discharge and/or related variables.  
553 Comparison of these derived values to the “truth” allows quantification of the benefits of SWOT  
554 data coupled with the dynamic model. In all studies included here, synthetic SWOT data have been  
555 simulated with simple methods: SWOT spatio-temporal sampling is computed using SWOT orbit  
556 and swath extents to sample “true” water elevations (or discharge for Paiva et al. 2015), to which  
557 white noise (corresponding to instrument noise only) has been added. As the SWOT mission has  
558 evolved through different design stages between 2007 and 2015, different orbits and swath extents  
559 (e.g. no nadir gap) have been considered (see Table 4). Only Munier et al 2015 is recent enough to  
560 consider the final SWOT nominal orbit presented in section 1.4. Furthermore, all of the studies have  
561 been performed as twin experiments in which the same model has been used for computing the  
562 “true” states and the “corrupted” ones (Figure 5).

563 Among the OI studies, Yoon et al. (2013) used local space-time ordinary kriging to estimate  
564 water height between SWOT observation times over the Tennessee River. Their method used  
565 hydrodynamic model outputs to compute the true heights. They obtained mean spatial and temporal  
566 RMSE of 11 cm and 12 cm, respectively. However, when they used *in situ* gage time series as the  
567 truth, the temporal RMSE increased to 32 cm. This difference is apparently due in part to effects of  
568 water management, which are not taken into account in the hydrodynamic model. Paiva et al.  
569 (2015) also used spatio-temporal OI but applied it to estimate discharge rather than water height.  
570 They developed an innovative method termed River Kriging (RK), which analytically derives  
571 space-time discharge covariance using the diffusive wave approximation to the Saint-Venant  
572 equations. They showed, using the Ganges-Brahmaputra-Meghna Rivers system in Bangladesh, that  
573 the RK method out-performed linear interpolation, simple kriging and ordinary kriging.  
574 Furthermore, RK-interpolated daily discharge had accuracy similar to that of the initial SWOT  
575 discharge time series. However, the method did not perform well when tidal forcing dominated the  
576 discharge signal. Taken together, the Yoon et al. (2013) and Paiva et al. (2015) studies show the  
577 potential to interpolate SWOT observations at daily time scales. However, they have been applied to  
578 a very limited set of rivers to date.

579 DA techniques are increasingly being used in the framework of real time operations to forecast

580 water levels in the context of flooding (Bates et al. 2014), for real-time reservoir operations (Munier  
581 et al. 2015), for model calibration and parameter estimation (Bates et al. 2014) or for the purpose of  
582 reconstructing the history of some components of the continental water cycle (Reichle et al. 2014).  
583 All of these themes have been addressed by one or more of the SWOT DA studies referenced in  
584 Table 4. Andreadis et al. (2007) and Biancamaria et al. (2011) used virtual SWOT water depth  
585 measurements to correct water depth from river hydrodynamics models applied to the Ohio and Ob'  
586 Rivers, respectively. Assumptions included well-known bathymetry and no bias in water elevation  
587 measurements. They showed that in these two applications, model errors dominated and therefore  
588 assimilating SWOT (synthetic) data helped to decrease water depth error and consequently  
589 discharge estimates. These studies demonstrated the potential of SWOT data to improve forecasting  
590 of streamflow. Keeping in mind that the SWOT mission will likely not produce near real time  
591 products, these approaches nonetheless can be applied to producing discharge and water level  
592 products retrospectively once the SWOT data become available, especially with the use of a DA  
593 smoother (Biancamaria et al. 2011) that tends to smooth discontinuities before and after the  
594 assimilation time of an observation with a DA filter.

595 Flood forecasting is an area of hydrology particularly suited to the use of DA techniques. In  
596 these applications, model initial conditions are critical to producing accurate forecast. This was the  
597 motivation for the work of Andreadis and Schumann (2014) who developed methods of using  
598 satellite water elevation and water area (from nadir altimetry, Lidar, SAR imagery and SWOT) to  
599 correct initial conditions in an application of a hydrodynamic model to the Ohio River. They  
600 showed that using satellite observations improved water elevation and flood extent forecasts with  
601 lead times up to 10 days. For some flood events, however, model errors exceeded errors due to  
602 initial conditions after a few days, and the benefits of the assimilation dissipated. Additionally, it has  
603 recently been shown that assimilating flood water level derived from SAR images combined with  
604 floodplain topography into a hydrodynamic modeling helps to improve flood forecasts (García-  
605 Pintado et al. 2013, García-Pintado et al. 2015).

606 Other studies have demonstrated the capability of using SWOT data to correct hydraulic model  
607 parameters (especially bathymetry, elevation, and slope; see Durand et al. 2008 and Yoon et al.  
608 2012) or hydrologic model parameters (friction coefficients; see Pedinotti et al. 2014). Errors in the  
609 corrected parameters have decreased in some cases by more than 50% via DA. Of course, these  
610 results have to be interpreted carefully, as they are dependent on the model/observation errors used  
611 and the fact that they have been done in the context of model twin experiments, which often result  
612 in a benefit to DA-based methods in comparison with “real” applications. Nonetheless, these studies  
613 are promising and clearly show the potential benefits of SWOT data in conjunction with river  
614 hydrodynamic modeling even if the SWOT data are not delivered in near real time.

615 Finally, Munier et al. (2015), using DA in conjunction with an automatic control algorithm,  
616 showed the potential of SWOT to improve management of the Selingue Reservoir in the upper  
617 Niger River basin by optimizing reservoir releases to meet a minimum low flow requirement  
618 upstream of the Niger Inner Delta. Their algorithm made use of SWOT data both for estimation of  
619 reservoir storage and for discharge computation using a simplified river hydrodynamics model  
620 applied to the reach downstream of the reservoir.

621 It should be highlighted that all the teams involved in the studies reported here are collaborating  
622 at different levels. Members of the author groups that produced the papers reviewed in this section  
623 met during the “Hydrologic Data Assimilation for the SWOT Mission” meeting, held on 12-13  
624 November 2013 (Biancamaria et al. 2014) and further DA work in the next few years leading up to  
625 launch of the SWOT mission is promising.

626  
627 The studies reviewed in sections 2.1-2.3 show the benefits that can be expected from SWOT  
628 measurements for better understanding river flow dynamics, from the river reach scale to the river  
629 basin scale. New and innovative techniques have already been developed that can exploit SWOT  
630 data, and these methods will be available from the beginning of the mission to ensure quick use and  
631 science return of SWOT data. However, more work is still needed, especially to explore the  
632 implications of SWOT errors, which have been represented to date using highly simplifying  
633 assumptions. SWOT errors will be much more complex than white noise. In particular, the impacts  
634 of layover, water classification errors, wet troposphere effects, and correlated instrument error along  
635 the swath are topics of immediate relevance that currently are being investigated.

636  
637 3. Lake/reservoir studies and other land hydrology applications

638  
639 Section 2 summarized SWOT river-related studies with a focus on river discharge estimation  
640 (both directly and through data assimilation). Lakes and reservoirs have been somewhat less studied  
641 as shown in Table 5, which summarizes SWOT-related lake and reservoir studies. Compared to the  
642 five SWOT discharge algorithms papers and nine DA/OI papers, there are only three papers that  
643 consider lakes and/or reservoirs in the context of SWOT. This is in part due to the fact that the main  
644 SWOT lake/reservoir product, storage change estimation of all observed lakes and reservoirs, is  
645 more easily derived from SWOT direct measurements (maps of water elevations and water surface  
646 extent), than is river discharge. Nonetheless, SWOT has important implications for understanding  
647 the dynamics of individual lakes and reservoirs and their part in the land surface water budget. The  
648 mission is expected to lead to a major leap in our understanding of these water bodies. For instance,  
649 storage variations in reservoirs globally, which have been estimated to have produced a “drag” on

650 sea level rise of about 0.5 mm/yr or around 1/6 of observed sea level rise, are so poorly estimated  
651 that the sign of this term is no longer known due to slowing of global reservoir construction and  
652 filling of existing reservoirs with sediment (Lettenmaier and Milly, 2009).

653 Furthermore, SWOT will not only observe rivers and lakes/reservoirs, but also all other water  
654 bodies on the continents and at their interfaces with the oceans: wetlands, stream-aquifer interfaces,  
655 estuaries and ice sheets. In particular, it will be a tremendous source of information for  
656 transboundary river basins, which are a challenge for water managing between upstream and  
657 downstream countries. More generally, SWOT will observe the direct human impact on the  
658 continental water cycle and therefore will have scientific but also societal and political implications.

659

660 3.1. Lakes and reservoirs

661

662 There is currently large uncertainty concerning the global distribution of lakes (Downing et al.  
663 2006, Verpoorter et al. 2014) and the variations of water stored in them. The locations of largest  
664 lakes are, of course, well known and monitored. It is also well known that the majority of lakes are  
665 located at high latitudes (above 50°N; Lehner and Döll 2004). However there is still considerable  
666 uncertainty concerning the number of medium and small lakes, even aside from their spatial and  
667 temporal dynamics. For example, according to Downing et al. (2006), based on multiple databases  
668 and extrapolation for smaller lakes, there are slightly more than 300 million lakes globally with  
669 surface area exceeding 0.001 km<sup>2</sup>, most of which (99.87% in number and 43% in area) have surface  
670 areas less than 1 km<sup>2</sup>. However, the numbers of small lakes in Downing et al. (2006) are inferred  
671 from the distribution of larger lakes rather than being directly observed, so this estimate is highly  
672 uncertain. In contrast, Verpoorter et al. (2014) report, using Landsat imagery, about 117 million  
673 lakes with surface areas that exceed 0.002 km<sup>2</sup>, a predominance of which have areas between 0.1  
674 and 1 km<sup>2</sup>. However, the use of Landsat imagery (which has a pixel size of 30 m) tends to  
675 underestimate small water bodies, especially those that cover less than about 10 Landsat pixels, or  
676 about 0.01 km<sup>2</sup>. Furthermore, it is difficult to classify water surfaces at the global scale  
677 automatically because of clouds, cloud shadow, the use of images acquired at different dates,  
678 differences in lake turbidity, and other factors, all of which add uncertainty to current estimates of  
679 the global distribution of lakes by area. In addition, it is very difficult to automatically differentiate  
680 the smallest lakes observable in Landsat imagery from segments of partially detected rivers. Finally,  
681 all of the current global lakes databases (e.g. Lehner and Döll 2004, Verpoorter et al. 2014) are  
682 static and do not provide any information about spatio-temporal dynamics, notwithstanding well-  
683 known studies of long-term variations in the surface areas of both large (e.g. Gao et al. 2012) and  
684 small (e.g. Smith et al. 2005) lakes. SWOT will provide revolutionary information concerning lake

685 extent and water storage, which will be beneficial not just for a better understanding of the  
686 continental hydrological cycle but also for the carbon (Cole et al. 1994) and methane (Walter et al.  
687 2007) cycles at continental and global scales.

688 If the global distribution of lakes is subject to large uncertainties, their water elevation changes  
689 are even less well known. Therefore, estimating total water storage change of all lakes remains a  
690 challenge. Biancamaria et al. (2010) have provided early estimates. Using, annual water level  
691 amplitudes from 224 lakes worldwide, they found no clear correlation between annual water level  
692 variations and lake area or lake drainage area. Rather, it seemed that inter-annual water surface  
693 amplitudes followed a log-normal distribution, which they used to estimate water level variations  
694 for all lakes globally. They used a power-law relationship between the number of lakes and lake  
695 area derived by Downing et al. (2006) to compute the number of all lakes and their size. By  
696 performing a very rough approximation of cylindrical lake bathymetry, using the previously  
697 mentioned lake log-normal water level distribution, the Downing et al. (2006) lake numbers versus  
698 lake areas relationship, they were able to compute cumulative lake storage change as a function of  
699 lake area and, ultimately, the total annual lake storage change (about 9,000 km<sup>3</sup>). Their computation  
700 was based on just one realization of the log-normal water level distribution for each lake area bin  
701 and did not consider uncertainty due to the random distribution. In order to take this uncertainty into  
702 account, 100 realizations of the log-normal water level distribution have been generated for each  
703 lake area bin. For each realization the same methodology of Biancamaria et al. (2010), previously  
704 described, has been applied. Figure 6 shows the updated results with the ensemble of 100  
705 realizations (grey curves). The mean of this ensemble, which is likely a better approximation of the  
706 cumulative annual lake storage change than a single realization of the log-normal distribution, is  
707 represented by the green curve on Figure 6. The ensemble mean is close to the cumulative storage  
708 change published by Biancamaria et al. (2010), while the ensemble spread clearly shows the  
709 uncertainty associated with the log-normal water level distribution approximation. Of course, there  
710 are also errors from the number of lakes versus lake area power law and the cylindrical bathymetry  
711 approximation, which add (unrepresented) errors to the annual storage change estimates at global  
712 scale. It should be noted that these errors are extremely difficult to estimate and have yet to be  
713 modeled.

714 Currently, storage change can be computed for the small number of lakes for which *in situ* data  
715 are freely available. The alternative is to use satellite data to derive water elevation (from nadir  
716 altimeters or Lidar) and surface extent (from optical or SAR sensors) (Gao et al. 2012, Zhang et al.  
717 2014, Arsen et al. 2014, Baup et al. 2014, Crétaux et al. 2015). However, these approaches require  
718 data from at least two different satellites, nearly always at different observation times, with different  
719 space-time resolutions. As such, they require significant manual editing of the time series

(especially for water elevation) and are challenging to apply automatically at large scales. The resolution of current nadir altimeters also limits the application of these methods. Satellite capability to monitor specific lakes depends on not just the radar footprint on the ground but also the lake shape. Current results (for example, from the Hydroweb database, <http://www.legos.obs-mip.fr/en/soa/hydrologie/hydroweb/>) show that 10 km<sup>2</sup> lake area (dashed red line on Figure 6) is, on average, a good guess for the minimum lake extent that nadir altimeters can observe, though some results can be obtained for smaller lakes (Baup et al. 2014). Considering the constellation of satellites that are the most likely to fly in the near future (AltiKa, Jason-3, Sentinel-3A and -3B), based on the distribution shown in Figure 6 (green curve) and assuming that these satellites will sample all lakes above 10 km<sup>2</sup> area that are intersected by their nadir ground tracks (which is a very optimistic hypothesis), then only 36% of the total annual storage change can be measured (as not all lakes above 10 km<sup>2</sup> will be observed). In contrast, SWOT, should be able to monitor about 65% of total annual storage change (Biancamaria et al. 2010). On Figure 6, all lakes above 250m x 250m or about 0.06 km<sup>2</sup> (blue dashed line) account for 68% of the total annual storage change, but SWOT will miss a small fraction of these lakes. This is due to measurement errors that could be higher than the annual water level amplitude for some lakes in between 0.06 km<sup>2</sup> and 1 km<sup>2</sup>. However, SWOT should overcome most of the uncertainty in the lake spatial distribution (grey curves on Figure 6), at least for lakes with an area above 0.06 km<sup>2</sup>. To assess the accuracy that could be expected from SWOT-derived lake storage changes, Lee et al. (2010) performed an OSSE for Arctic lakes, using a methodology similar to the one presented in section 2.3 for optimal interpolation and shown on Figure 5a. Based on daily interpolated lake level variations from altimetry, satellite optical images and parametrizations, daily water level variations for several thousands of lakes in the Peace-Athabasca Delta (Canada), Northern Alaska (US) and West Siberia (Russia) were derived and used as the “truth”. With this data set, they estimated that at high latitudes, SWOT lake storage change measurements will likely have errors lower than 5% for lakes larger than 1 km<sup>2</sup>, whereas errors for lakes with areas of 0.01 km<sup>2</sup> should be around 20%, confirming the relatively high accuracy that is expected from SWOT data. However, this study did not consider measurements errors due to layover, water classification, wet troposphere... (see section 1.3). Work on a more limited number of lakes in the Peace-Athabasca Delta suggests that errors in water surface elevation will dominate the calculation of storage change measurements in comparatively large lakes, while errors in inundated area will play a more important role for storage change calculations in small lakes (Smith and Pavelsky, 2009).

Reservoirs also play an important role in the continental water cycle. Zhou et al. (in review) showed, using a large scale water management model, that 166 of the world’s largest reservoirs, which have a total storage capacity of 3900 km<sup>3</sup> (~60% of all reservoirs storage), could have almost

755 700 km<sup>3</sup> seasonal storage variation (~10% of the total reservoirs storage). Despite this significant  
756 variability, there is only the study of Munier et al. (2015) that has investigating the potential of  
757 SWOT for reservoirs monitoring (see section 2.3). This study showed the potential use of SWOT  
758 reservoir measurements to optimize reservoir operations. Gao et al. (2012) and Crétaux et al. (2015)  
759 have shown the feasibility of computing storage change for large reservoirs using nadir altimetry,  
760 which is very promising for SWOT. The lack of knowledge of the distribution of small lakes is also  
761 true for reservoirs. Even with global datasets for reservoirs, like the one compiled by the  
762 International Commission on Large Dams (ICOLD) or the Global Reservoir and Dam (GRanD)  
763 database (Lehner et al. 2011), there is little information for intermediate and small reservoirs. Given  
764 gaps in current understanding of the number and area distribution of lakes and reservoirs, SWOT  
765 will provide a major improvement in the ability to observe the dynamics of these water bodies  
766 directly. In particular, it will help to better characterize the role of small lakes and reservoirs at  
767 global scales, which are mostly ignored in current estimates of the dynamics of land water storage  
768 (Zhou et al. in review).

### 769 770 3.2. Other Land hydrology applications and synergistic land sciences

771  
772 To date, published studies concerning SWOT have been mostly focused on understanding and  
773 assessing benefits of the new type of measurements that will be produced for river and lakes  
774 dynamics. This focus was essential as the mission was in an early stage of definition. Nonetheless, a  
775 number of other applications of SWOT data are expected in the land hydrology arena (Durand et al.  
776 2010, Fu et al. 2012, Rodríguez 2015). One of these is the management of water in transboundary  
777 river basins. These basins cross one or more international boundaries and imply sharing of water,  
778 which in many cases can lead to tensions between upstream and downstream countries.  
779 Transboundary river basins are important globally, as they cover around 45% of the global land  
780 area, involve 145 countries and 40% of the total human population (Wolf et al. 1999). Clark et al.  
781 (2015, accepted) have reviewed studies using nadir altimetry for three transboundary basins (the  
782 Brahmaputra-Ganges-Meghna, the Indus and the Niger basins) and highlighted the importance of  
783 upcoming SWOT data for providing freely available observations of storage change, water level  
784 and discharge over the entire basin areas (not including the minor observations gaps discussed in  
785 section 1.4) repetitively and independently from national networks.

786 Another field that will greatly benefit from SWOT data will be the study of the direct impact of  
787 human activities (like water management infrastructures and water withdrawals) on the land  
788 hydrological cycle. For example, reservoirs (Shiklomanov and Lammers 2009) and soil changes and  
789 erosion (Descroix et al. 2012) can have important impacts on downstream river discharge, and these



790 impacts will be observed and may be quantifiable by SWOT. SWOT will also provide valuable  
791 information to model development and validation, especially for land surface models used in  
792 numerical weather prediction and climate models. Most such models at present only represent  
793 natural rivers. SWOT observations may also have application to studies of stream-aquifer  
794 exchanges at basin and continental scales, filling a current observation gap (Flipo et al. 2014).

795 SWOT will also provide useful data in wetland environments, although the range of observable  
796 wetlands remains uncertain. In wetlands with sparse vegetation and large extents of open water it is  
797 likely that SWOT will provide useful measures of water surface elevation and inundation extent.  
798 Where vegetation is denser, it remains unclear to what extent SWOT will be affected by scattering  
799 and layover caused by the vegetation. However, given difficulties in measuring the hydrology of  
800 large wetlands *in situ* and their importance in the global carbon and methane cycles, SWOT  
801 measurements may provide substantial benefits even if sampling under dense vegetation proves  
802 limited. Experiments to better define the opportunities and constraints of SWOT wetland  
803 measurements are, as of this writing, in the final planning stages. They will use measurements from  
804 AirSWOT (Rodriguez et al. 2010), to better understand SWOT returns from inundated vegetation.

805 Complementary to land hydrology, some additional science objectives for SWOT, referred to as  
806 synergistic sciences (Fu et al. 2012, Rodríguez 2015), have been identified, including:

807 - Freshwater/marine interfaces, especially in estuaries. This issue bridges ocean and continental  
808 hydrology and, while it is a key component of the hydrological cycle, it is just beginning to be  
809 addressed in the context of SWOT.

810 - Antarctic and Greenland ice sheet topographic variability. As shown on Figure 3, most of  
811 Greenland (which extends up to 82°N) and a substantial portion of Antarctica (and all its coastal  
812 regions) will be sampled at the highest time sampling frequency. However, it should be noted that  
813 SWOT performance over ice and snow is not yet well characterized (Fjørtoft et al. 2014). In  
814 addition, it is likely that SWOT data for many portions of these ice sheets will be available only at  
815 the lower resolution used for SWOT ocean products.

816 - Helping to characterize snow cover variability and, perhaps, help to characterize land cover  
817 variability.

818 - Estimation of vertical deflection due to gravity changes over large lakes.

819 These are just some of the anticipated SWOT scientific applications that have yet to be investigated  
820 in any substantial detail. Because most of these applications are synergistic to SWOT's principal  
821 scientific goals and because SWOT observing technology is not optimized for them, more  
822 investigations are needed to determine how useful SWOT data will be. For example, better  
823 characterization of Ka-band backscatter over snow and ice is needed (this also has implications for  
824 observations of high latitude rivers during ice breakup). In addition, for most new satellite

825 technologies like SWOT, applications not yet anticipated will emerge once the data becomes  
826 available.

827

828

#### 829 4. Conclusions and perspectives

830

831 We have described the characteristics of the upcoming wide swath altimetry satellite mission,  
832 SWOT, and have reviewed recent published papers that have evaluated key scientific hydrology  
833 uses of SWOT data. We argue that SWOT will be transformational for land hydrology in providing  
834 fundamental information about rivers, lakes, and wetlands that has never before been available  
835 directly from observations. The SWOT mission will provide, for instance, maps of surface water  
836 elevation and their temporal evolution, therefore providing for the first time estimates of surface  
837 water storage and fluxes at global scale for rivers wider than 50-100.

838 It will also characterize spatio-temporal variability of lakes and reservoirs with areas larger than  
839  $\sim 0.06 \text{ km}^2$ , implying direct estimates of about 2/3 of global lake and reservoir storage variations  
840 (current nadir altimeters provide estimates in both cases that represent less than 20 percent of the  
841 total). Some of the types of studies for which SWOT data will be especially well suited are:

- 842 - global water balance studies,
- 843 - flood dynamics for medium to large rivers, especially those that persist for multiple SWOT  
844 revisits,
- 845 - studies of surface water in the global carbon and methane cycles,
- 846 - documentation and quantification, of direct human impacts on the hydrological cycle.

847 With respect to Earth system modeling, it will provide constraints and diagnostics that will allow  
848 better representation of processes such as flood dynamics and human influence on the water cycle,  
849 which at present are poorly quantified in global coupled land-atmosphere-ocean models. For  
850 example, most such models do not represent the storage of water in man-made reservoirs, or its  
851 effect on river discharge (Wood et al. 2011). SWOT will also have important societal impacts on  
852 understanding of transboundary river basins; in many such cases, data about river discharge and  
853 reservoir storage are not shared among upstream and downstream countries, and in this respect the  
854 SWOT data, which will be freely available, will be transformational.

855 However, there is still much to be learned before the planned launch of the mission some five  
856 years from the time of this writing. One priority must be to strengthen the results of studies  
857 performed to date, especially by taking into account more realistic quantifications of the magnitudes  
858 and types of SWOT measurement errors (e.g., spatially-correlated instrumental noise, error due to  
859 the roll of the satellite, wet troposphere errors, water classification errors, topography and

860 vegetation errors, among others). These errors will be chiefly explored using two complementary  
861 tools: an increasingly sophisticated high-resolution SWOT simulator and AirSWOT airborne  
862 campaigns, which will provide SWOT-like measurements that can be compared to simultaneous  
863 ground validation data. To compute river discharge, four algorithms have been proposed, and they  
864 need to be investigated on diverse real cases, especially braided rivers. They also require a priori  
865 information such as river bathymetry and friction coefficients. The sensitivity of discharge estimates  
866 to the accuracy of these a priori parameters should be estimated, and they should be computed at a  
867 global scale prior to launch.

868 Furthermore, synergies with other satellite missions observing different component of the water  
869 cycle that are likely to collect data simultaneously with SWOT should be investigated, to improve  
870 understanding of the water cycle as a whole. Results from discussion of the SWOT Science  
871 Definition Team to date suggest that data assimilation approaches are not yet mature enough for  
872 global application. For this reason, studies like those reviewed in section 2.2 are based on the need  
873 for simple algorithms, which can be applied more or less directly to SWOT observations of river  
874 water levels, slopes, and widths to estimate discharge. However, some recent studies (Yamazaki et  
875 al. 2011, Neal et al. 2012, Schumann et al. 2013, Bates et al. 2014) suggest that application of river  
876 hydrodynamics models have advanced to the point that applications of these models (which would  
877 be the physics core for data assimilation algorithms) may now be feasible at continental and global  
878 scales (Wood et al. 2011, Schumann et al. 2014, Bierkens et al. 2015). Thus, the role of data  
879 assimilation in SWOT river discharge and related variables may need to be revisited.

880 Finally, some thinking about the successor of SWOT is now appropriate. If SWOT is successful,  
881 it almost certainly will motivate demand for continuing observations, in the same way that the first  
882 ocean altimeter, TOPEX/Poseidon, did for ocean sciences. With the launch date of SWOT  
883 approaching quickly, it is not too early to think about how a future mission might extend and  
884 improve on results from SWOT.

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886

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899 References

900

901 Allen GF, Pavelsky TM (2015) Patterns of river width and surface area revealed by satellite-derived  
902 North American River Width data set. *Geophys Res Lett* 42(2):295-402.  
903 doi:10.1002/2014GL062764

904

905 Alsdorf DE, Lettenmaier DP, Vörösmarty C (2003) The need for global, satellite-based observations  
906 of terrestrial surface waters. *EOS Trans Am Geophys Union* 84(29):269-276.  
907 doi:10.1029/2003EO290001

908

909 Alsdorf DE, Lettenmaier DP (2003) Tracking fresh water from space. *Science* 301:1485-1488

910

911 Alsdorf DE, Rodríguez E, Lettenmaier DP (2007) Measuring surface water from space. *Rev*  
912 *Geophys* 45(2):RG2002. doi:10.1029/2006RG000197

913

914 Andreadis KM, Clark EA, Lettenmaier DP, Alsdorf DE (2007) Prospects for river discharge and  
915 depth estimation through assimilation of swath-altimetry into a raster-based hydrodynamics model.  
916 *Geophys Res Lett* 34:L10403

917

918 Andreadis KM, Schumann GJP (2014) Estimating the impact of satellite observations on the  
919 predictability of large-scale hydraulic models. *Adv Water Resour* 73:44-54.  
920 doi:10.1016/j.advwatres.2014.06.006

921

922 Arsen A, Crétaux JF, Berge-Nguyen M (2014) Remote sensing-derived bathymetry of lake Poopo.  
923 *Remote Sens* 6(1):407-420. doi:10.3390/rs6010407

924

925 Bates PD, Neal JC, Alsdorf DE, Schumann GJP (2014) Observing global surface water flood  
926 dynamics. *Surv Geophys* 35(3):839-852. doi:10.1007/s10712-013-9269-4

927

928 Baup F, Frappart F, Maubant J (2014) Combining high-resolution satellite images and altimetry to  
929 estimate the volume of small lakes. *Hydrol Earth Syst Sci* 18:2007-2020. doi:10.5194/hess-18-  
930 2007-2014

931

932 Beven K (2006) A manifesto for the equifinality thesis. *J Hydrol* 320(1-2):18-36.  
933 doi:10.1016/j.jhydrol.2005.07.007

934

935 Biancamaria S, Andreadis, KM, Durand MT, Clark EA, Rodriguez E, Mognard NM, Alsdorf DE,  
936 Lettenmaier DP, Oudin Y (2010) Preliminary characterization of SWOT hydrology error budget and  
937 global capabilities. *IEEE J Sel Top Appl Earth Obs Remote Sens* 3(1):6-19.  
938 doi:10.1109/JSTARS.2009.2034614

939

940 Biancamaria S, Durand MT, Andreadis K, Bates PD, Boone A, Mognard NM, Rodriguez E, Alsdorf  
941 DE, Lettenmaier DP, Clark EA (2011) Assimilation of virtual wide swath altimetry to improve  
942 Arctic river modelling. *Remote Sens Environ* 115(2):373-381. doi:10.1016/j.rse.2010.09.008

943

944 Biancamaria S, Andreadis K, Ricci S (2014) Using images of continental water surface  
945 Elevations from upcoming satellite mission. *EOS Trans Am Geophys Union* 95(12):105.

doi:10.1002/2014EO120004

Bierkens MFP, Bell VA, Burek P, Chaney N, Condon LE, David CH, de Roo A, Döll P, Drost N, Famiglietti JS, Flörke M, Gochis DJ, Houser P, Hut R, Keune J, Kollet S, Maxwell RM, Reager JT, Samaniego L, Sudicky E, Sutanudjaja EH, van de Giesen N, Winsemius H, Wood EF (2015) Hyper-resolution global hydrological modelling: what is next? Everywhere and locally relevant. *Hydrol Process* 29(2):310-320. doi:10.1002/hyp.10391

Bjerklie DM, Dingman SL, Vörosmary CJ, Bolster CH, Congalton R (2003) Evaluating the potential for measuring river discharge from space. *J Hydrol* 278(1):17-38. doi:10.1016/S0022-1694(03)00129-X

Bjerklie DM, Moller D, Smith LC, Dingman SL (2005) Estimating discharge in rivers using remotely sensed hydraulic information. *J Hydrol* 309(1-4):191-209. doi:10.1016/j.jhydrol.2004.11.022

Bjerklie DM (2007) Estimating the bankfull velocity and discharge for rivers using remotely sensed river morphology information. *J Hydrol* 341(3-4):144-155. doi:10.1016/j.jhydrol.2007.04.011

Blöschl G, Sivapalan M (1995) Scale issues in hydrological modelling: A review. *Hydrol Process* 9(3-4):251-290. doi:10.1002/hyp.3360090305

Clark EA, Biancamaria S, Hossain F, Crétaux JF, Lettenmaier DP (accepted) Current and future application for altimetry in trans-boundary river management. In: Benveniste J, Vignudelli S, Kostianov AG (ed) *Inland Water Altimetry*, Springer, ISBN 978-3-642-22678-6 (should be published in 2015)

Crétaux JF, Biancamaria S, Arsen A, Bergé-Nguyen M, Becker M (2015) Global surveys of reservoirs and lakes from satellites and regional application to the Syrdarya river basin. *Environ Res Lett* 10(1):015002. doi :10.1088/1748-9326/10/1/015002

Crétaux JF, Jelinski W, Calmant S, Kouraev A, Vuglinski V, Berge-Nguyen M, Gennero M-C, Abarca Del Rio R, Cazenave A, Maisongrande P (2011) SOLS: A lake database to monitor in the Near Real Time water level and storage variations from remote sensing data. *Advances in Space Research* 47(9): 1497-1507. doi:10.1016/j.asr.2011.01.004

Cole JJ, Caraco NF, Kling GW, Kratz TK (1994) Carbon-dioxide supersaturation in the surface waters of lakes. *Science* 265(5178):1568-1570. doi:10.1126/science.265.5178.1568

Descroix L, Genthon P, Amogu O, Rajot JL, Sighomnou D, Vauclin M (2012) Change in Sahelian Rivers hydrograph: the case of the recent red floods of the Niger River in the Niamey region. *Glob Planet Change* 98-99:18-30. doi:10.1016/j.gloplacha.2012.07.009

Desjonquères JD, Carayon G, Steunou N, Lambin J (2010) Poseidon-3 Radar Altimeter: new modes and in-flight performances. *Marine Geodesy* 33(S1):53-79. doi:10.1080/01490419.2010.488970

Downing JA, Prairie YT, Cole JJ, Duarte CM, Tranvik LJ, Striegl RG, McDowell WH, Kortelainen P, Caraco NF, Melack JM, Middelburg JJ (2006) The global abundance and size distribution of lakes, ponds, and impoundments. *Limnol Oceanogr*, 51(5):2388-2397. doi:10.4319/lo.2006.51.5.2388

Durand MT, Andreadis KM, Alsdorf DE, Lettenmaier DP, Moller D, Wilson M (2008) Estimation

of bathymetric depth and slope from data assimilation of swath altimetry into a hydrodynamic model. *Geophys Res Lett* 35:L20401. doi:10.1029/2008GL034150

Durand MT, Fu LL, Lettenmaier DP, Alsdorf DE, Rodríguez E, Esteban-Fernandez D (2010) The Surface Water and Ocean Topography mission: Observing terrestrial surface water and oceanic submesoscale eddies. *Proc IEEE* 98(5): 766-779. doi:10.1109/JPROC.2010.2043031

Durand MT, Neal J, Rodríguez E, Andreadis K, Smith L, Yoon Y (2014) Estimating reach-averaged discharge for the River Severn from measurements of river water surface elevation and slope. *J Hydrol* 511:92-104. doi:10.1016/j.jhydrol.2013.12.050

Enjolras VM, Rodríguez E (2009) An assessment of a Ka-band radar interferometer mission accuracy over Eurasian Rivers. *IEEE Trans Geosci Remote Sens* 47(6):1752-1765. doi:10.1109/TGRS.2008.2006370

Farr TG, Rosen PA, Caro E, Crippen R, Duren R, Hensley S, Kobrick M, Paller M, Rodríguez E, Roth L, Seal D, Shaffer S, Shimada J, Umland J, Werner M, Oskin M, Burbank D, Alsdorf D (2007) The shuttle radar topography mission. *Rev Geophys* 45(2):R2004. doi:10.1029/2005RG000183

Flipo N, Mouhri A, Labarthe B, Biancamaria S, Rivière A, Weill P (2014) Continental hydrosystem modelling: the concept of nested stream-aquifer interfaces. *Hydrol Earth Syst Sci* 18(8):3121-3149. doi:10.5194/hess18-3121-2014

Fjørtoft R, Gaudin JM, Pourthié N, Lalaurie JC, Mallet A, Nouvel JF, Martinot-Lagarde J, Oriot H, Borderies P, Ruiz C, Daniel D (2014) KaRIn on SWOT: characteristics of near-nadir Ka-band interferometric SAR imagery. *IEEE Trans Geosci Remote Sens* 52(4):2172-2185. doi:10.1109/TGRS.2013.2258402

Fu LL, Rodríguez E (2004) High-resolution measurement of ocean surface topography by radar interferometry for oceanographic and geophysical applications. In: Sparks RSJ, Hawkesworth CJ (ed) *The State of the Planet: Frontiers and Challenges in Geophysics*. Geophysical Monograph 150, AGU, Washington DC, pp. 209-224

Fu LL, Alsdorf DE, Morrow R, Rodríguez E, Mognard NM (2012) SWOT: the Surface Water and Ocean Topography Mission. JPL Publication 12-05. [http://swot.jpl.nasa.gov/files/swot/SWOT\\_MSD\\_1202012.pdf](http://swot.jpl.nasa.gov/files/swot/SWOT_MSD_1202012.pdf). Accessed 20 February 2015

Gao H, Bohn TJ, Podest E, McDonald KC, Lettenmaier DP (2011) On the causes of the shrinking of Lake Chad. *Environ Res Lett* 6(3):034021. doi:10.1088/1748-9326/6/3/034021

Gao H, Birkett C, Lettenmaier DP (2012) Global monitoring of large reservoir storage from satellite remote sensing. *Water Resour Res* 48(9):W09504. doi:10.1029/2012WR012063

Garambois PA, Monnier J (2015) Inference of effective river properties from remotely sensed observations of water surface. *Adv Water Resour* 79:103-120. doi:10.1016/j.advwatres.2015.02.007

García-Pintado J, Neal JC, Mason DC, Dance S, Bates PD (2013) Scheduling satellite-based SAR acquisition for sequential assimilation of water level observations into flood modelling. *J Hydrol*, 495, 252-266. doi:10.1016/j.jhydrol.2013.03.050

García-Pintado J, Mason DC, Dance SL, Cloke HL, Neal JC, Freer J, Bates PD (2015) Satellite-

supported flood forecasting in river networks: A real case study. *J Hydrol*, 523, 706-724.  
doi:10.1016/j.jhydrol.2015.01.084

Gleason CJ, Smith LC (2014) Toward global mapping of river discharge using satellite images and at-many-stations hydraulic geometry. *PNAS* 111(13):4788-4791

Gleason CJ, Smith LC, Lee J (2014) Retrieval of river discharge solely from satellite imagery and at-many-stations hydraulic geometry: sensitivity to river form and optimization parameters. *Water Resour Res* 50(12):9604-9619. doi:10.1002/2014WR016109

Kouraev AV, Zakharova EA, Samain O, Mognard NM, Cazenave A (2004) Ob' river discharge from TOPEX/Poseidon satellite altimetry (1992–2002). *Remote Sens Environ* 93(1–2):238–245.  
doi:10.1016/j.rse.2004.07.007

Lee H, Durand MT, Jung HC, Alsdorf D, Shum CK, Sheng Y (2010) Characterization of surface water storage changes in Arctic lakes using simulated SWOT measurements. *Int J Remote Sens* 31(14):3931-3953. doi:10.1080/01431161.2010.483494

Lehner B, Döll, P (2004) Development and validation of a global database of lakes, reservoirs and wetlands. *J Hydrol* 296:1-22. doi:10.1016/j.jhydrol.2004.03.028

Lehner B, Verdin K, Jarvis A (2008) New global hydrography derived from spaceborne elevation data. *EOS Trans Am Geophys Union* 89(10):93-94. doi:10.1029/2008EO100001

Lehner B, Reidy Liermann C, Revenga C, Vörösmarty C, Fekete B, Crouzet P, Döll P, Endejan M, Frenken K, Magome J, Nilsson C, Robertson JC, Rödel R, Sindorf N, Wisser D (2011) High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Front Ecol Environ* 9(9):494-502. doi:10.1890/100125

Lettenmaier DP, Milly PCD (2009) Land waters and sea level. *Nat Geosci* 2(7):452-454.  
doi:10.1038/ngeo567

Mersel MK, Smith LC, Andreadis KM, Durand MT (2013) Estimation of river depth from remotely sensed hydraulic relationships. *Water Resour Res* 49(6):3165-3179. doi:10.1002/wrcr.20176

Moller D, Esteban-Fernandez D (2015) Near-nadir Ka-band field observations of fresh water bodies. In: Lakshmi V, Alsdorf D, Anderson M, Biancamaria S, Cosh M, Entin J, Huffman G, Kustas W, van Oevelen P, Painter T, Parajka J, Rodell M, Rüdiger C (ed) *Remote Sensing of the Water Cycle*. AGU Geophysical Monograph, 206, Wiley, New York, pp 143-155

Munier S, Polebistki A, Brown C, Belaud G, Lettenmaier DP (2015) SWOT data assimilation for operational reservoir management on the upper Niger River Basin. *Water Resour Res* 51.  
doi:10.1002/2014WR016157

National Research Council (2007) *Earth Science and Applications From Space: National Imperatives for the Next Decade and Beyond*. National Academies Press, Washington DC

Neal JC, Schumann GJP, Bates PD (2012) A subgrid channel model for simulating river hydraulics and floodplain inundation over large and data sparse areas. *Water Resour Res* 48:W11506.  
doi:10.1029/2012WR012514

Paiva RCD, Durand MT, Hossain F (2015) Spatiotemporal interpolation of discharge across a river

1102 network by using synthetic SWOT satellite data. *Water Resour Res* 51.  
 1103 doi:10.1002/2014WR015618  
 1104  
 1105 Papa F, Biancamaria S, Lion C, Rossow WB (2012) Uncertainties in mean river discharge estimates  
 1106 associated with satellite altimeters temporal sampling intervals: a case study for the annual peak  
 1107 flow in the context of the future SWOT hydrology mission. *IEEE Geosc Rem Sens Lett* 9(4):569-  
 1108 573. doi:10.1109/LGRS.2011.2174958  
 1109  
 1110 Pavelsky T M, Durand MT (2012) Developing new algorithms for estimating river discharge from  
 1111 space. *EOS Trans Am Geophys Union* 93(45):457. doi:10.1029/2012EO450006  
 1112  
 1113 Pavelsky, TM, Durand MT, Andreadis KM, Beighley RE, Paiva RCD, Allen GH, Miller ZF (2014a)  
 1114 Assessing the potential global extent of SWOT river discharge observations. *J Hydrol* 519:1516-  
 1115 1525. doi:10.1016/j.jhydrol.2014.08.044  
 1116  
 1117 Pavelsky TM (2014b) Using width-based rating curves from spatially discontinuous satellite  
 1118 imagery to monitor river discharge. *Hydrol Process* 28(6):3035-3040. doi:10.1002/hyp.10157  
 1119  
 1120 Pedinotti V, Boone A, Ricci S, Biancamaria S, Mognard NM (2014) Assimilation of satellite data to  
 1121 optimize large-scale hydrological model parameters : a case study for the SWOT mission. *Hydrol*  
 1122 *Earth Syst Sci* 118(11):4485-4507. doi:10.5194/hess-18-4485-2014  
 1123  
 1124 Reichle RH, De Lannoy GJM, Forman BA, Drapper CS, Liu Q (2014) Connecting satellite  
 1125 observations with water cycle variables through land data assimilation: examples using the NASA  
 1126 GEOS-5 LDAS. *Surv Geophys* 35:577-606. doi:10.1007/s10712-013-9220-8.  
 1127  
 1128 Rodríguez E (2015) Surface Water and Ocean Topography Mission (SWOT),  
 1129 Science Requirements Document. JPL document D-61923.  
 1130 [https://swot.jpl.nasa.gov/files/swot/SRD\\_021215.pdf](https://swot.jpl.nasa.gov/files/swot/SRD_021215.pdf). Accessed 20 February 2015  
 1131  
 1132 Rodriguez E, Moller D, Smith LC, Pavelsky TM, Alsdorf DE (2010) AirSWOT: an airborne  
 1133 monitoring platform for surface water monitoring. AGU Fall Meeting Abstract #H32D-06.  
 1134  
 1135 Schumann GJP, Neal JC, Voisin N, Andreadis KM, Pappenberger F, Phanthuwongpakdee N, Hall  
 1136 AC, Bates PD (2013) A first large-scale flood inundation forecasting model. *Water Resour Res*  
 1137 49(10):6248-6257. doi:10.1002/wrcr.20521  
 1138  
 1139 Schumann GJP, Bates PD, Neal JC, Andreadis KM (2014) Fight floods on a global scale. *Nature*  
 1140 507(7491):169  
 1141  
 1142 Shiklomanov AI, Lammers RB (2009) Record Russian river discharge in 2007 and the limits of  
 1143 analysis. *Environ Res Lett* 4(4):045015. doi:10.1088/1748-9326/4/4/045015  
 1144  
 1145 Skøien JO, Blöschl G, Western AW (2003) Characteristic space scales and timescales in hydrology.  
 1146 *Water Resour Res* 39(10):1304. doi:10.1029/2002WR001736  
 1147  
 1148 Smith LC (1997) Satellite remote sensing of river inundated area, stage, and discharge: a review.  
 1149 *Hydrol Process* 11: 1427-1439.  
 1150  
 1151 Smith LC, Pavelsky TM (2008) Estimation of river discharge, propagation speed, and hydraulic  
 1152 geometry from space: Lena River, Siberia. *Water Resour Res* 44: W03427.  
 1153 doi:10.1029/2008GL033268



1154  
1155 Smith LC, Pavelsky TM (2009) Remote sensing of volumetric storage change in lakes. *Earth Surf*  
1156 *Process Landf* 34:1353-1358.  
1157  
1158 Smith LC, Isacks BL, Forster RR, Bloom AL, Preuss I (1995) Estimation of discharge from braided  
1159 glacial rivers using ERS-1 SAR: First results. *Water Resour Res* 31(5): 1325-1329.  
1160  
1161 Smith LC, Isacks BL, Bloom AL, Murray AB (1996) Estimation of discharge from three braided  
1162 rivers using synthetic aperture radar (SAR) satellite imagery: Potential application to ungaged  
1163 basins. *Water Resour Res* 32(7): 2021-2034.  
1164  
1165 Smith LC, Sheng Y, MacDonald GM, Hinzman LD (2005) Disappearing Arctic lakes. *Science*  
1166 308(5727):1429. doi:10.1126/science.1108142  
1167  
1168 Steunou N, Desjonquères JD, Picot N, Sengenès P, Noubel J, Poisson JC (2015) AltiKa altimeter:  
1169 instrument description and in flight performance. *Marine Geodesy* (in press)  
1170  
1171 Verdin KL, Greenlee SK (1998) HYDRO1k documentation, US Geological Survey.  
1172 <https://lta.cr.usgs.gov/HYDRO1KReadMe>. Accessed 24 February 2015.  
1173  
1174 Verpoorter C, Kutser T, Seekell DA, Tranvik LJ (2014) A global inventory of lakes based on high  
1175 resolution satellite imagery. *Geophys Res Lett* 41(18):6396-6402. doi:10.1002/2014GL060641  
1176  
1177 Walter KM, Smith LC, Chapin FS (2007) Methane bubbling from northern lakes: present and future  
1178 contributions to the global methane budget. *Philos Trans Royal Soc A-Math Phys Eng Sci*  
1179 365(1856):1657-1676. doi:10.1098/rsta.2007.2036  
1180  
1181 Wolf AT, Natharius JA, Danielson JJ, Ward BS, Pender JK (1999) International river basins of the  
1182 world. *Int J Water Resour Dev* 15(4):387-427  
1183  
1184 Wood EF, Roundy JK, Troy TJ, van Beek LPH, Bierkens MFP, Blyth E, de Roo A, Döll P, Ek M,  
1185 Famiglietti J, Gochis D, van de Giesen N, Houser P, Jaffé PR, Kollet S, Lehner B, Lettenmaier DP,  
1186 Peters-Lidard C, Sivapalan M, Sheffield J, Wade A, Whitehead P (2011) Hyperresolution global  
1187 land surface modeling: Meeting a grand challenge for monitoring Earth's terrestrial water. *Water*  
1188 *Resour Res* 47(5):W05301. doi:10.1029/2010WR010090  
1189  
1190 Yamazaki D, Kanae S., Kim H, Oki T (2011) A physically based description of floodplain  
1191 inundation dynamics in a global river routing model. *Water Resour Res*, 47(4): W04501.  
1192 doi:10.1029/2010WR009726  
1193  
1194 Yoon Y, Durand MT, Merry CJ, Clark EA, Andreadis KM, Alsdorf DE (2012) Estimating river  
1195 bathymetry from data assimilation of synthetic SWOT measurements. *J Hydrol* 464:363–375.  
1196 doi:10.1016/j.jhydrol.2012.07.028  
1197  
1198 Yoon Y., Durand, MT, Merry CJ, Rodríguez E (2013) Improving Temporal Coverage of the SWOT  
1199 Mission Using Spatiotemporal Kriging. *IEEE IEEE J Sel Top Appl Earth Obs Remote Sens*  
1200 6(3):1719-1729. doi:10.1109/JSTARS.2013.2257697  
1201  
1202 Zhang S, Gao H, Naz BS (2014) Monitoring storage in South Asia from multisatellite remote  
1203 sensing. *Water Resour Res* 50(11):8927-8943. doi:10.1002/2014WR015829  
1204  
1205 Zhou T, Nijssen B, Gao H, Lettenmaier DP (in review) The contribution of reservoirs to global land



1207 **Table 1** SWOT mission science requirements and goals (Rodríguez 2015)

Observed areas	- All observed water area will be provided - Errors are <i>evaluated</i> for $(250\text{ m})^2$ ( $= 62\,500\text{ m}^2$ ) water bodies and 100 m (width) x 10 km (long) river reaches - Error are <i>characterized</i> for $(100\text{ m})^2$ to $(250\text{ m})^2$ water bodies and 50 m to 100 m (width) x 10 km (long) river reaches
Height accuracy	< 10 cm when averaging over water area > 1 km <sup>2</sup> < 25 cm when averaging over $(250\text{ m})^2$ < water area < 1 km <sup>2</sup>
Slope accuracy	1.7 cm/km for evaluated river reaches when averaging over water area > 1 km <sup>2</sup>
Relative error on water areas	<15% for evaluated water body and river reaches < 25% of total characterized water body and river reaches
Mission lifetime	3 months of fast sampling calibration orbit + 3 years of nominal orbit
Rain/Layover/Frozen water flag	68%
Data collection	> 90% of all ocean/continents within the orbit during 90% of operational time

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**Table 2** SWOT mission characteristics

Orbit	Altitude	890 km
	Inclination	77.6°
	Repeat period	20.86 days
KaRIn (core payload)	One swath extent (total swaths: 2)	50 km
	Distance between the 2 swaths outer edges	120 km
	Distance between the 2 swaths inner edges (“nadir gap”)	20 km
	Radar frequency/wavelength	35.75 GHz/8.6 mm (Ka-band)
	Distance between the 2 antennas (baseline)	10 m
	Instrument azimuth pixel size (radar projection)	6 to 7 m
	Instrument range pixel size (radar projection)	From 60 m (near range, incidence angle ~0.6°) to 10 m (far range, ~3.9°)
Additional science payload	Nadir altimeter	Similar to the dual frequency (Ku/C) Poseidon-3 nadir altimeter on Jason-2
	Precise orbit determination system	- Laser retroreflector - DORIS receiver - GPS receiver
	Radiometer (usable only over oceans)	3-frequency (18, 23, 34 GHz) radiometer, similar to Advanced Microwave Radiometer on Jason-2

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1215 **Table 3** Current discharge algorithms designed to use SWOT data ( $n$  means Manning coefficient,  $w$   
 1216 river width,  $S$  river surface slope,  $H$  river elevation,  $A_0$  unobserved cross-sectional flow area and  $Q$   
 1217 discharge)

Discharge algorithm	Algorithm Basis	Tested river types	SWOT variables used	1 <sup>st</sup> guess/ ancillary data	Output(s)
AMHG (Gleason and Smith 2014; Gleason et al. 2014)	$w/Q$ geomorphic scaling relationship along river reach	Single channel & width variability & no lateral in/outflows & no several order magnitude variation & $b>0.1$ (in $w=aQ^b$ )	$w$	-	$Q$
B2007 (Bjerklie et al. 2003, Bjerklie et al. 2005, Bjerklie 2007)	Manning-like equation with calibrated exponent and time varying Manning coefficient	Single channel	$H, w,$ constant $S$	Mean annual $n$ and $Q$	$Q$ , time varying $n$
GM2015 (Garambois and Monnier, 2015)	Shallow water equations (low Froude)	Single channel & no in/outflows	$\delta H, w, S$	$n, A_0,$ baseflow $Q$	$Q$ , corrected $n$ , corrected $A_0$
MetroMan (Durand et al. 2014)	Diffusive approximation of shallow water equations	Single channel	$\delta H, w, S$	$n, A_0,$ baseflow $Q$	$Q$ , corrected $n$ , corrected $A_0$

**Table 4** Published SWOT-related studies using data assimilation (DA) or optimal interpolation (OI) to correct/optimize different variables ( $d$  means water depth,  $H$  water elevation,  $w$  width,  $S$  water surface slope,  $Q$  discharge,  $A_i$  inundation area,  $Z$  bathymetric elevation,  $S_z$  bathymetric slope,  $n$  Manning coefficient). In this table, (L)EnKF/S stands for (Local) Ensemble Kalman Filter/Smoothing, LSTOK for Local Space-Time Ordinary Kriging, LEnTKF for Local Ensemble Transform Kalman Filter, EKF for Extended Kalman Filter, RK for River Kriging and MPC for Model Predictive Control

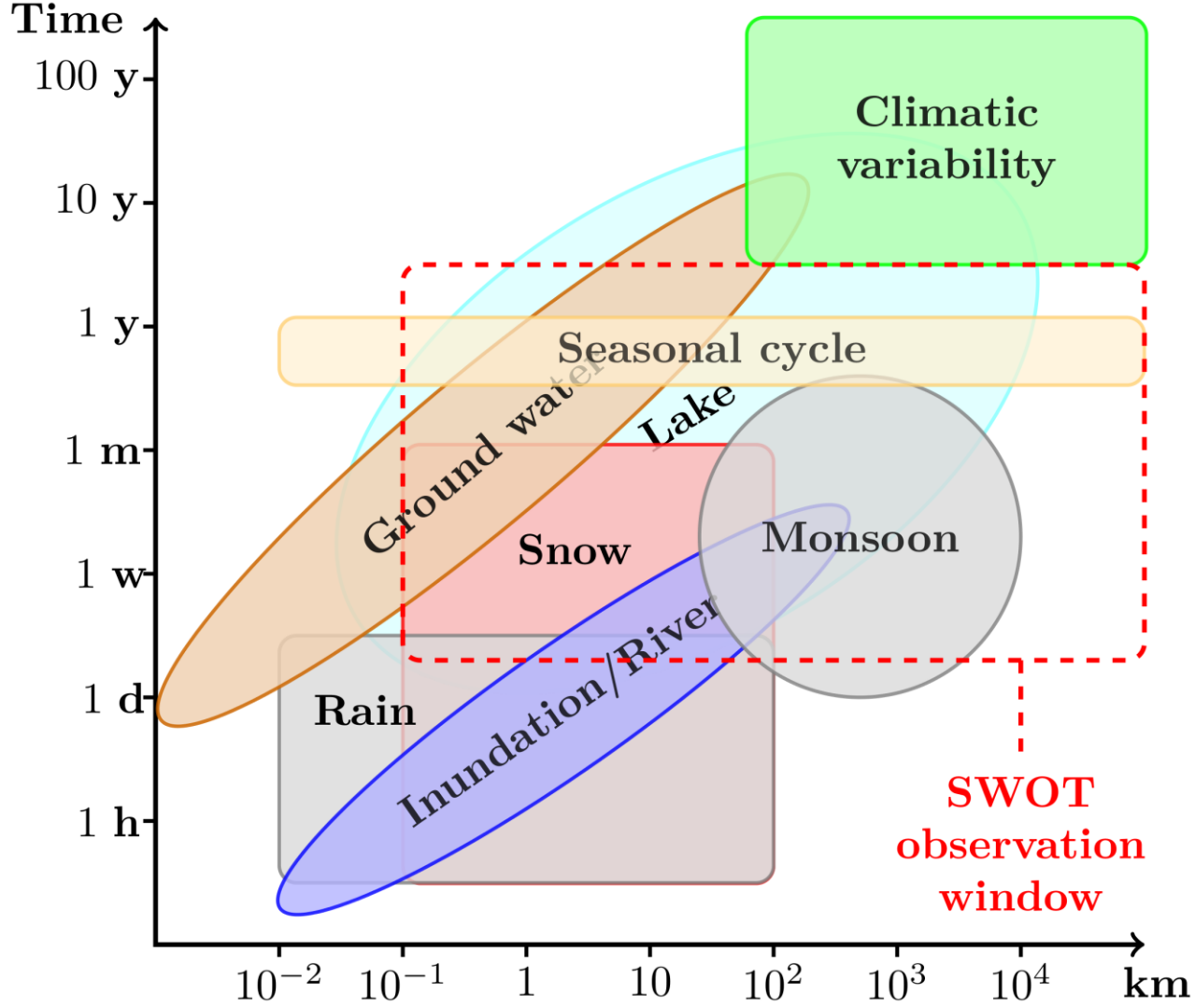
Reference	DA/OI schemes	Model(s) + error	SWOT obs used + error	Corrected/ optimized variable(s)/ parameter(s)	Study domain
Andreadis et al. (2007)	EnKF	Hydrodynamic model + inflows errors	$d$ (140km swath, 8-day/16-d/32-d orbit) + white noise	$d$	Ohio River (50km reach)
Durand et al. (2008)	EnKF	Hydrodynamic model + $S_z$ and $n$ errors	$H$ (140km swath, 16-day orbit) + white noise	$Z, S_z$	Amazon River (240km reach)
Biancamaria et al. (2011)	LEnKF+ LEnKS	Hydrodynamic model + precip errors	$d$ (140km swath, 22-day orbit) + white noise	$d$	Ob River (1120km)
Yoon et al. (2012)	EnKF+ LEnKS	Hydrodynamic model + precip errors/ $z$ errors/ $z$ spatial auto-correlation	$H, S, w$ (140km swath, 22-day orbit) + white noise	$Z, d$	Ohio basin river system
Yoon et al. (2013)	LSTOK	-	$d$ (140km swath, 22-d orbit) + white noise	$d$ at times with no SWOT obs	Tennessee River (1050km)
Andreadis and Schumann (2014)	LEnTKF	Hydrodynamic model + sampling historical simulation	$H, w, A_i$ (multi sat missions) + white noise	Initial condition to forecast model	Ohio River (500km reach)
Pedinotti et al. (2014)	EKF	Hydrologic model (0.5°×0.5° pixels) + $n$ errors	$d$ (140km swath, 22-d orbit) + white noise	$n$	Whole Niger basin
Paiva et al. (2015)	RK	Space-time $Q$ covariance from diffusive wave approx. St-Venant eq	$d, S, w, Q$ (140km swath, 22-day orbit) + white noise	$Q$ at times with no SWOT obs	Ganges-Brahmaputra-Meghna river system in Bangladesh
Munier et al. (2015)	LEnKS + MPC	Hydrodynamic model & reservoir model + precip errors	$d$ (120km swath, 21-d orbit) + white noise	$d$ + optimized reservoir release	Upper Niger basin and Selingue reservoir

1230 **Table 5** Published SWOT-related studies on lakes and reservoirs

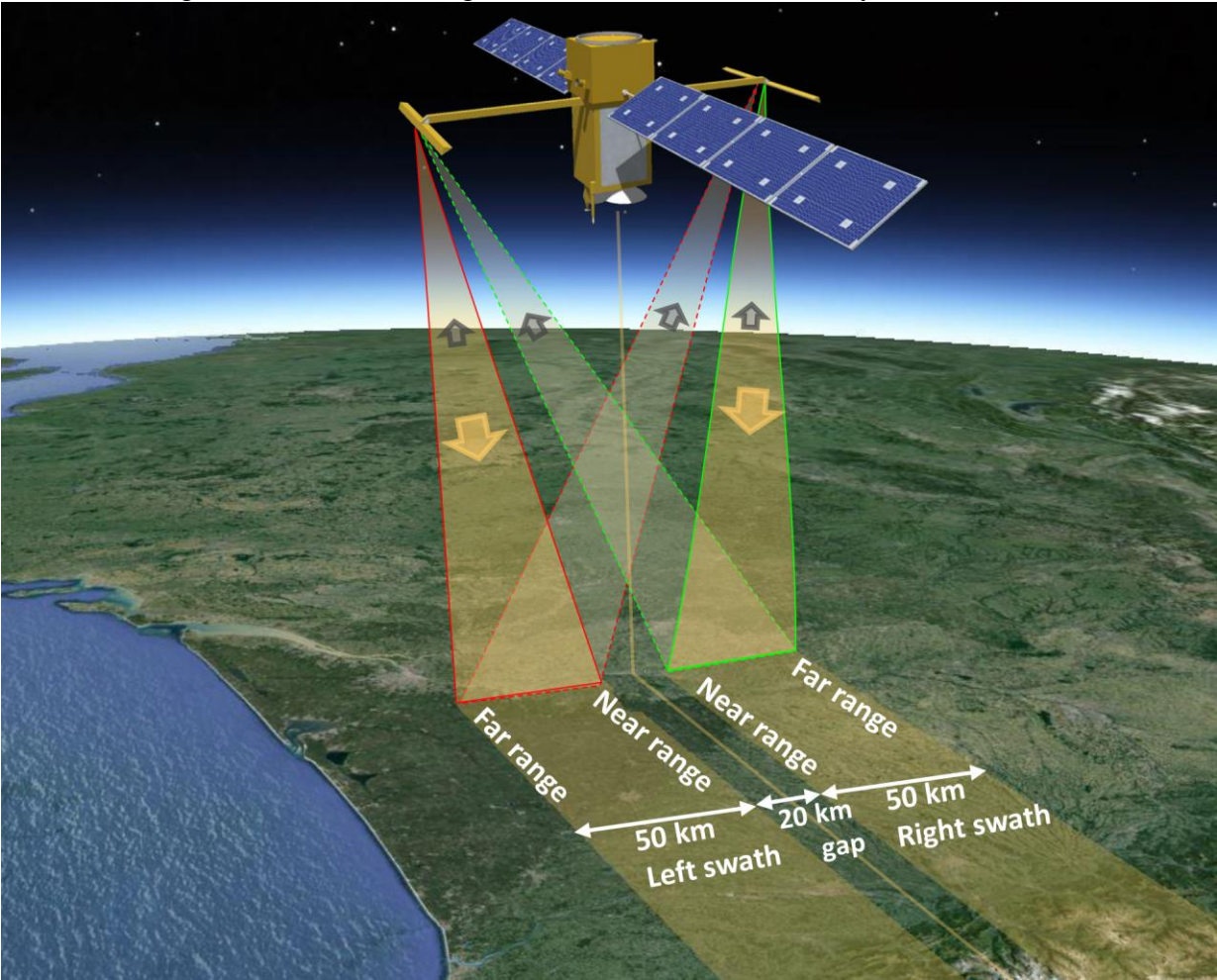
Reference	Method	SWOT obs.	Study domain
Biancamaria et al. (2010)	Parametrization of global annual storage variation	Lakes area > (250m) <sup>2</sup> and height variations> SWOT height accuracy	Extrapolation of global lakes distribution
Lee et al. (2010)	Lake storage change from optical image, satellite altimetry, <i>in situ</i> gage and parametrization	$\delta H$ with white noise function of lake area (140km swath, 3-day and 22-day orbit)	Multiple Arctic lakes
Munier et al. (2015)	Hydrologic model, hydrodynamic model + DA of SWOT obs., reservoir model + release optimization	$d$ (120km swath, 21-day orbit) + white noise	Upper Niger basin and Selingue reservoir

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1232 **Fig. 1** Time-space diagrams of continental water surface processes and SWOT observation window.  
1233 Inspired from Blöschl and Sivapalan (1995) and Skøien et al (2003)



1235 **Fig. 2** Conceptual view of the future SWOT mission with its principal payloads: the Ka-band Radar  
1236 Interferometer (KaRIn, with the observed swaths shown by the yellow polygons) and a Ku-band  
1237 nadir altimeter (yellow line). Satellite size and altitude are not to scale compared to the Google  
1238 Earth background image (South West of France), but the ground swaths are (background image:  
1239 Google earth, Landsat image, data SIO, NOAA, U.S. Navy, NGA, GEBCO)

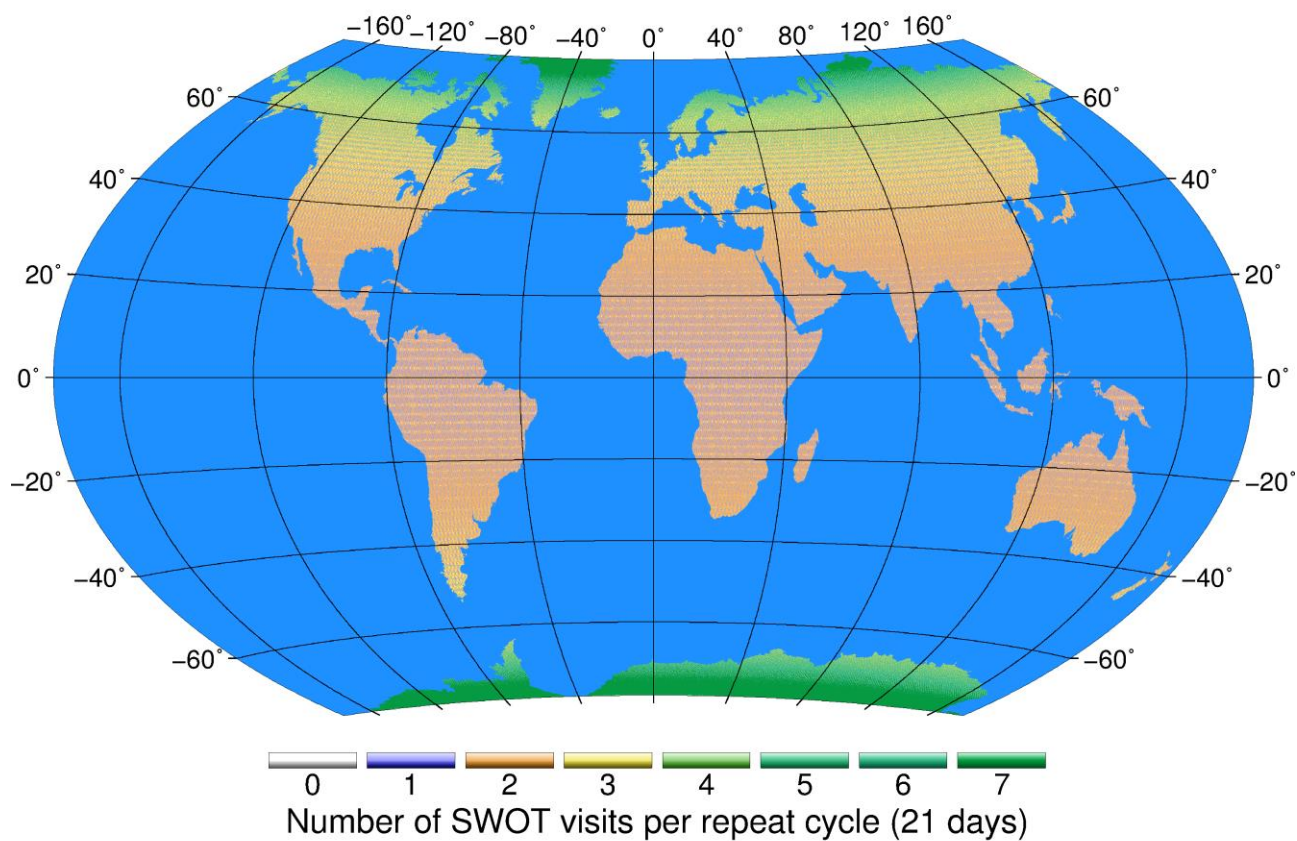


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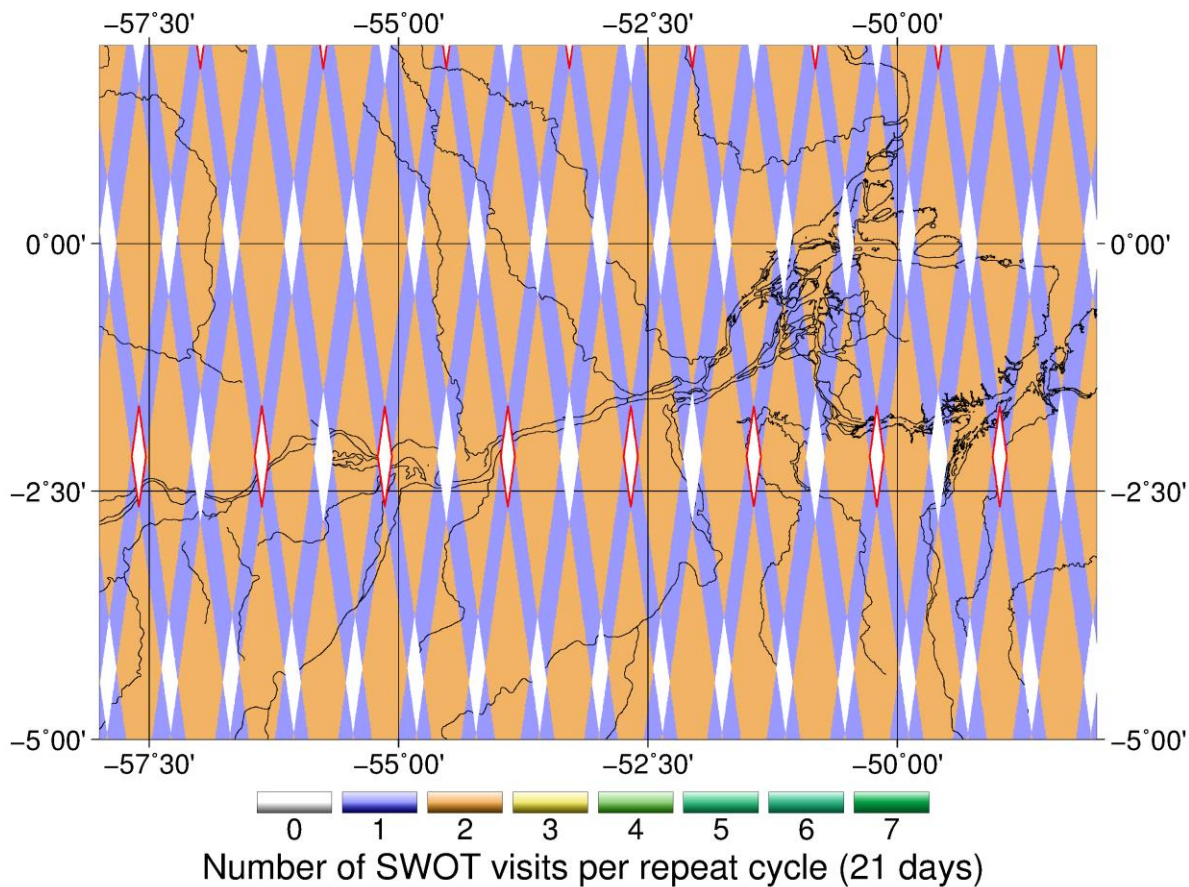


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1247 **Fig. 3** Number of SWOT revisits per orbit repeat period (21 days) over the continents (ocean have  
1248 been masked, but ocean data will also be provided) in between 78°S and 78°N (a.) and a zoom over  
1249 the Lower Amazon (b.). Over the Lower Amazon, white diamonds with magenta boundaries  
1250 corresponds to observation gaps due to the orbit intertrack distance

a. Global

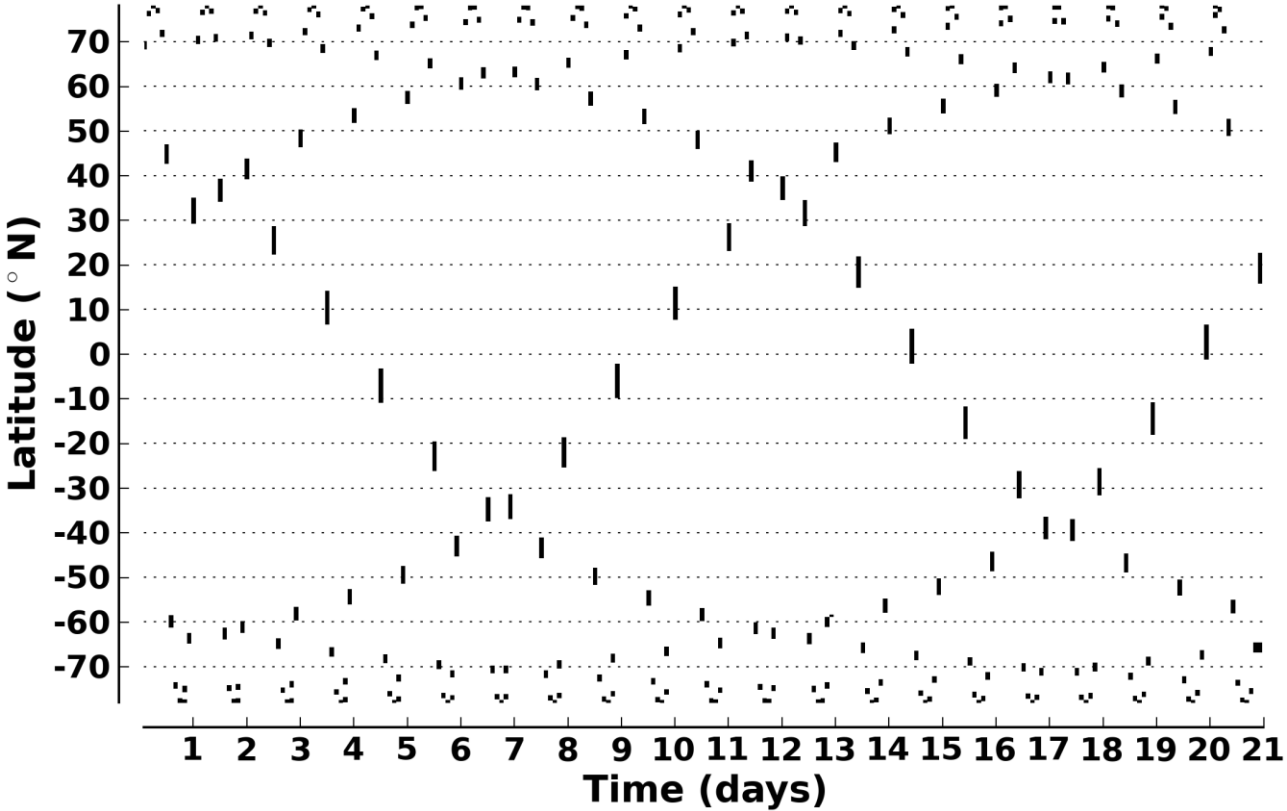


b. Lower Amazon



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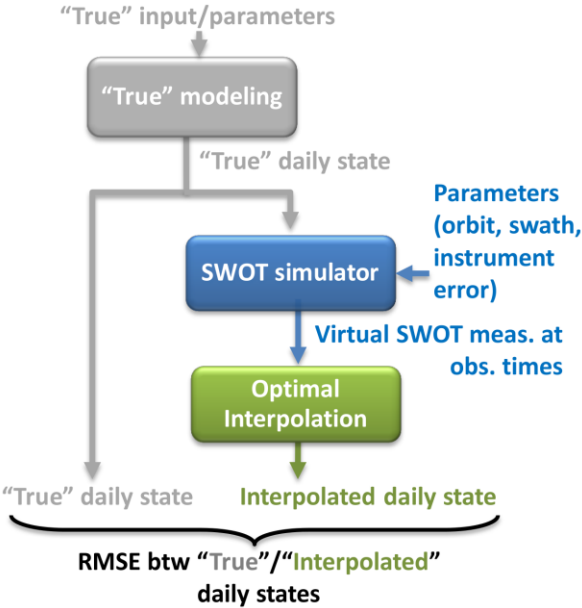
**Fig. 4** SWOT observations mask (black bars correspond to an observation) along 30°E meridian versus days (during an orbit repeat period)



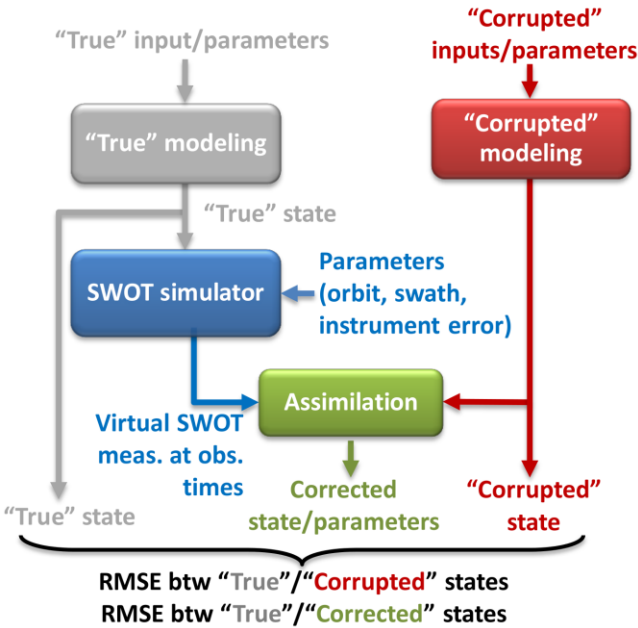
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1259 **Fig. 5** Conceptual sketches of SWOT Observing System Simulation Experiments (OSSE) using  
 1260 optimal interpolation (a.) or data assimilation (b.)

a. SWOT OSSE with optimal interpolation

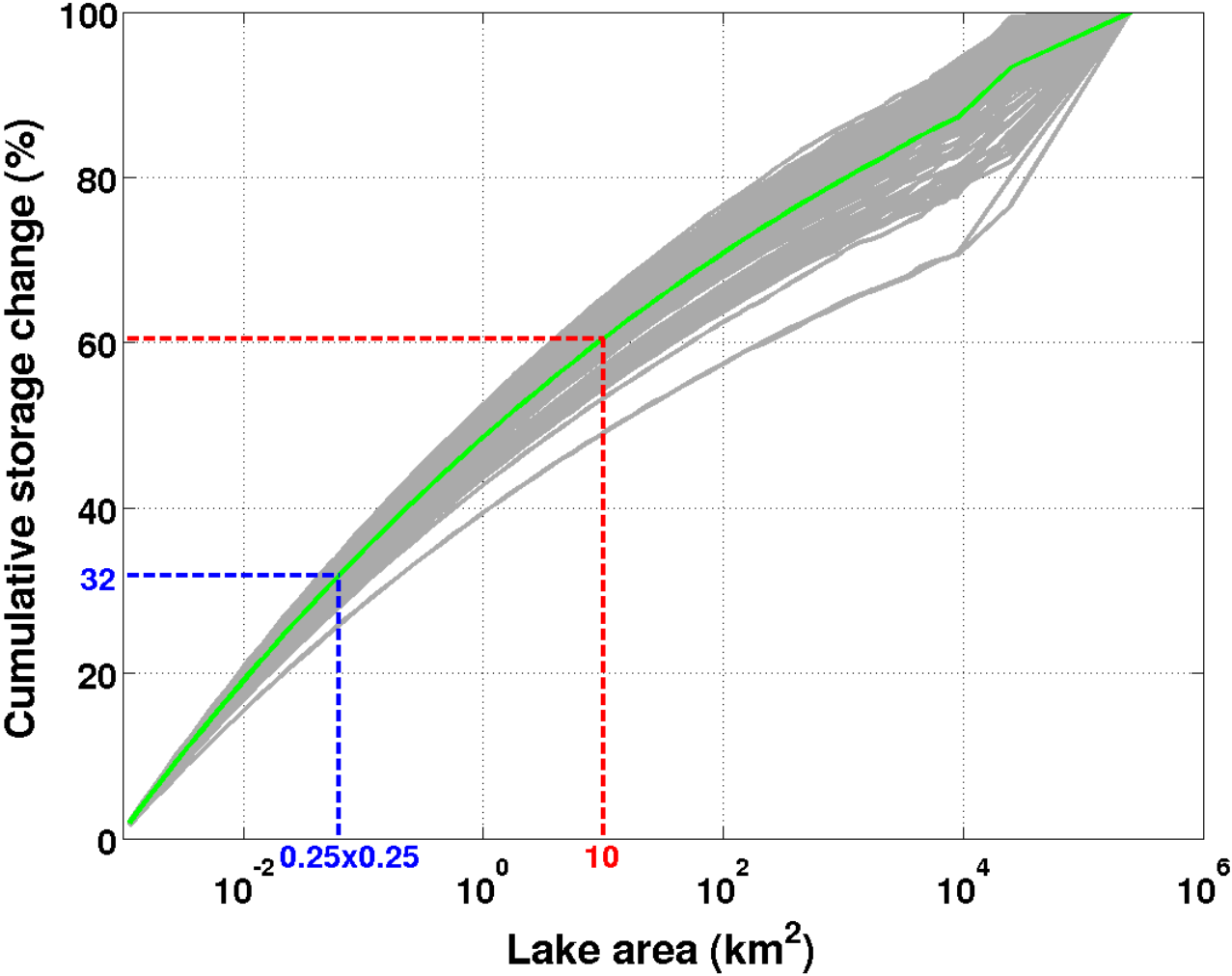


b. SWOT OSSE with data assimilation



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1262 **Fig. 6** Cumulative lake storage change (in % of the total lake storage change of the ensemble mean)  
1263 versus lake area for 100 realizations of the log-normal random distribution of the annual water level  
1264 variation estimated by Biancamaria et al. 2010. The ensemble mean corresponds to the green curve



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