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The SWOT Mission and Its Capabilities for Land Hydrology

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1 The SWOT mission and capabilities for land hydrology

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26

27 Abstract

28

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

51

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

54

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

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

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

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

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

123

124 1.2. Characteristics of the KaRIn instrument

125

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° and 3.9° ,
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 ~ 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 $\ll 1 \text{ m}\cdot\text{s}^{-1}$,
175 there could be some loss of data in the far-swath where look angle are close to 3.9° (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).

195 Measurements obtained from this new instrument will help to better understand backscattering in
196 Ka-band over different surfaces (water, bare soil, vegetation, snow, etc). However, AltiKa, as a
197 nadir altimeter, does not have exactly SWOT look angles; its measurements integrate all the energy
198 backscattered in a cone covering angles between -0.3° and 0.3° to the nadir (AltiKa half antenna
199 aperture is 0.3° , Steunou et al. 2015). The Global Precipitation Measurement (GPM) Mission Core
200 Observatory, launched in February 2014, carries the Dual-Frequency Precipitation Radar (DPR) in
201 Ku and Ka bands (<http://pmm.nasa.gov/GPM/flight-project/DPR>). In Ka-band, DPR scans across a
202 125 km swath ($\pm 8.5^\circ$ across track) with a 5 km footprint. Analyzing DPR measurements will
203 provide useful information on backscatter properties in Ka-band, however the GPM observation
204 angle covers a wider range than SWOT with a much coarser spatial resolution. For those reasons,
205 airborne and field campaigns have been organized by the Jet Propulsion Laboratory (JPL) (Moller
206 and Esteban-Fernandez 2015) and CNES (Fjørtoft et al. 2014) to better understand Ka-band
207 backscattering at SWOT-like incidence angles. These campaigns have confirmed the decrease of the
208 backscatter coefficient with the incidence angle and a water/land backscatter coefficient contrast of
209 around 10 dB, except when the water surface is very flat (low wind speed and hence extremely low
210 surface roughness). Moller and Esteban-Fernandez (2015) have also reported the impact of
211 decorrelation time (and therefore wind speed and water surface turbulence) on pixel azimuth size,
212 which could become higher than expected based on the instrument characteristics (Table 2). In
213 addition to KaRIn, SWOT will carry additional scientific payload (Table 2), including a dual
214 frequency (Ku and C-band) nadir altimeter, similar to the Poseidon-3 instrument on-board Jason-2
215 (Desjonquères et al. 2010). It will provide water elevation measurements in the middle of the 20 km
216 gap between the two KaRIn swaths. A radiometer will also facilitate, over the oceans, corrections to
217 path delay due to wet tropospheric effects. However, it will not be used over land because land
218 emissivity dominates the radiometric signal (Fu et al. 2012). Wet troposphere corrections over land
219 will be computed using an atmospheric model, one effect of which will be that the residual
220 tropospheric error will likely be larger over land than over the ocean and should be on the order of 4
221 cm (Fu et al. 2012).

222

223 1.3 SWOT measurements over terrestrial surface waters

224

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

230 processed data delivered by NASA and CNES to end-users) are currently being defined. There
231 remains, therefore, some uncertainty as to their specific nature. However, some characteristics of
232 SWOT level-2 data product over land are provided in the science requirements document
233 (Rodríguez 2015), which is the basis for the discussion in this section. As outlined in Rodríguez
234 (2015) these products will likely include:

235 - For each pass, a water mask consisting of a geolocated point cloud product with all KaRIn pixels
236 that are identified as water, with the finest spatial resolution to meet appropriate geolocation
237 accuracy (i.e. 10% of the pixel size in any direction). Surface water elevation corresponding to the
238 provided pixel size (with an estimation of the surface water elevation uncertainty) will be associated
239 with each point within the water mask.

240 - At least once every repeat cycle, a global water mask following the shorelines of all observed
241 water bodies will be provided in vector format, with one water elevation for each individual water
242 body, along with other information (such as area within the water body and its slope). Water storage
243 within each such water body will be easily derived from this product.

244 - A global one-dimensional vector product that will include estimated discharge along river reaches
245 at each observation time, for all river reaches wider than 50 m.

246 - A cross-section map of all observed water bodies will be derived from time-varying water
247 elevations along the shores of each water body. This map will be updated yearly.

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

254 The SWOT mission is designed to observe all rivers wider than 100 m and water bodies (lakes,
255 reservoirs, ponds, continuous wetlands) with an area greater than 250 m x 250 m (i.e. 62 500 m²)
256 that lie within the swath coverage. Moreover, NASA and CNES teams will strive to design an
257 instrument and processing methods that will be able to observe rivers wider than 50 m and water
258 bodies with an area above 100 m x 100 m. If SWOT is able to observe smaller rivers or water
259 bodies, the measured data will be provided. Besides, lower level product (SAR amplitude and phase
260 images, interferograms) will be provided on-demand and could be used to reprocess data a
261 posteriori, which might help to improve products resolution if feasible. The main sources of errors
262 that will affect KaRIn measurements are instrument thermal noise (white noise), differences in the
263 return signal speckle, error in the interferometric baseline roll angle, wet and dry tropospheric
264 effects, ionospheric effects, topographic layover and vegetation layover and attenuation (see chapter

265 6 in Fu et al. 2012). Thermal noise and speckle dominates the error budget at the KaRIn pixel level
266 (10 m to 60 m x 6 m, Table 2), leading to multi-meter vertical errors. These errors are random for
267 one pixel, but their standard deviations tend to increase in the far range of the measurement swath
268 (Enjolras and Rodríguez 2009). Fortunately, these random errors can be reduced by averaging over
269 water pixels by the square root of the number of pixels averaged. For this reason, the science
270 requirements (Table 1) are provided for water areas much larger than a single pixel. However, the
271 other sources of error will not be reduced by the averaging process. Over 1 km² (e.g. a 10 km reach
272 for a river of 100 m width), SWOT water elevation will have a 10 cm (1 σ) accuracy. For this
273 averaging area, random errors and wet tropospheric effects are the main error sources. Locally,
274 especially near the water bodies margins, topographic and vegetation layover can be a source of
275 large errors, especially given the near nadir incidence angles used by KaRIn. Therefore, the
276 received energy by the antenna will be a mixture of the energy backscattered by water and
277 topography or vegetation, leading to potentially large errors in retrieved water elevation,
278 geolocation and water extent. SWOT performance will be evaluated for water bodies meeting the
279 observation requirement (lakes, reservoirs, and wetlands with area greater than 250 m x 250 m and
280 rivers wider than 100 m), in order to validate that the instrument meets the accuracies provided in
281 Table 1. Furthermore, SWOT performance will be characterized for the observational goals (100 m
282 x 100 m to 250 m x 250 m water bodies and 50 m to 100 m wide rivers). Estimates of measurement
283 accuracy will be provided with SWOT data products.

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

295

296 1.4. SWOT spatiotemporal coverage

297

298 There will be an initial calibration phase for the SWOT mission with a fast sampling orbit (1-day
299 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 4.90×10^6 km²). 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

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

408 Notwithstanding the profound improvement that SWOT will provide in the availability of
409 information about rivers globally, SWOT does not have the objective of and cannot be an *in situ*
410 gage network replacement. In most circumstances, *in situ* gages will be, by far, more precise than
411 any remote sensing discharge estimates. This is especially important for applications such as water
412 management, where highly accurate and precise information is required for legally significant
413 purposes. For example, data from the gauge on the Colorado River at Lees Ferry, AZ is used to
414 determine the allocation of water to surrounding states. SWOT will likely not be sufficiently
415 accurate for this purpose. On the other hand, stream gage information is by its nature local and does
416 not provide a full view of the spatial variations of streamflow. Moreover, some types of rivers such
417 as highly braided channels and rivers with poorly defined banks are not well-suited to *in situ* gauge
418 measurements. The main benefit of SWOT in this respect will be to provide new and
419 complementary 2D observations for a wide range of different river planforms. Clearly, SWOT will
420 not observe full river networks because it will be limited to measuring rivers 50-100 m in width.
421 Therefore, a key question is: what portions of the global river network SWOT will observe and
422 what improvement will it represent compared to current capabilities? Pavelsky et al. (2014a) have
423 addressed these questions. Using river networks from Hydro1k (Verdin and Greenlee 1998) and
424 HydroSHEDS (Lehner et al. 2008), the global *in-situ* gage discharge time series database from the
425 Global Runoff Data center (GRDC, http://www.bafg.de/GRDC/EN/Home/homepage_node.html)
426 and downstream hydraulic geometry (power law relationships between drainage area, mean annual
427 discharge and river width at sub-basin scales), they have quantified the fraction of global river
428 basins that SWOT would observe given river observability thresholds of 100 m and 50 m. They
429 found that SWOT would observe more than 60% of the global sub-basins with an area of 50,000
430 km² given the ability to observe rivers wider than 100 m. If SWOT can meet the goal of observing
431 50 m wide rivers, more than 60% of sub-basins with an area of 10,000 km² would be observed. For
432 the smallest river basins observed, only the mainstem river will likely be measured by SWOT.

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

438
439

440 2.2. Instantaneous direct river discharge estimations

441

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

469 The AMHG algorithm will use the intensive SWOT observations of river width to derive
470 discharge using the well-known geomorphologic relationship between river width (w) and discharge
471 (Q) at a specific location: $w=aQ^b$. The a and b coefficients are considered constant in time but vary
472 along a given river. The innovation of the AMHG algorithm is based on the important fact (reported
473 for the first time in Gleason and Smith 2014) that a and b at cross-sections within the same river
474 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 '1st
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 km², most of which (99.87% in number and 43% in area) have surface
670 areas less than 1 km². 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 km², a predominance of which have areas between 0.1
674 and 1 km². 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 km². 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 km³). 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

720 (especially for water elevation) and are challenging to apply automatically at large scales. The
721 resolution of current nadir altimeters also limits the application of these methods. Satellite
722 capability to monitor specific lakes depends on not just the radar footprint on the ground but also
723 the lake shape. Current results (for example, from the Hydroweb database, [http://www.legos.obs-](http://www.legos.obs-mip.fr/en/soa/hydrologie/hydroweb/)
724 [mip.fr/en/soa/hydrologie/hydroweb/](http://www.legos.obs-mip.fr/en/soa/hydrologie/hydroweb/)) show that 10 km² lake area (dashed red line on Figure 6) is, on
725 average, a good guess for the minimum lake extent that nadir altimeters can observe, though some
726 results can be obtained for smaller lakes (Baup et al. 2014). Considering the constellation of
727 satellites that are the most likely to fly in the near future (AltiKa, Jason-3, Sentinel-3A and -3B),
728 based on the distribution shown in Figure 6 (green curve) and assuming that these satellites will
729 sample all lakes above 10 km² area that are intersected by their nadir ground tracks (which is a very
730 optimistic hypothesis), then only 36% of the total annual storage change can be measured (as not all
731 lakes above 10 km² will be observed). In contrast, SWOT, should be able to monitor about 65% of
732 total annual storage change (Biancamaria et al. 2010). On Figure 6, all lakes above 250m x 250m or
733 about 0.06 km² (blue dashed line) account for 68% of the total annual storage change, but SWOT
734 will miss a small fraction of these lakes. This is due to measurement errors that could be higher than
735 the annual water level amplitude for some lakes in between 0.06 km² and 1 km². However, SWOT
736 should overcome most of the uncertainty in the lake spatial distribution (grey curves on Figure 6), at
737 least for lakes with an area above 0.06 km². To assess the accuracy that could be expected from
738 SWOT-derived lake storage changes, Lee et al. (2010) performed an OSSE for Arctic lakes, using a
739 methodology similar to the one presented in section 2.3 for optimal interpolation and shown on
740 Figure 5a. Based on daily interpolated lake level variations from altimetry, satellite optical images
741 and parametrizations, daily water level variations for several thousands of lakes in the Peace-
742 Athabasca Delta (Canada), Northern Alaska (US) and West Siberia (Russia) were derived and used
743 as the “truth”. With this data set, they estimated that at high latitudes, SWOT lake storage change
744 measurements will likely have errors lower than 5% for lakes larger than 1 km², whereas errors for
745 lakes with areas of 0.01 km² should be around 20%, confirming the relatively high accuracy that is
746 expected from SWOT data. However, this study did not consider measurements errors due to
747 layover, water classification, wet troposphere... (see section 1.3). Work on a more limited number
748 of lakes in the Peace-Athabasca Delta suggests that errors in water surface elevation will dominate
749 the calculation of storage change measurements in comparatively large lakes, while errors in
750 inundated area will play a more important role for storage change calculations in small lakes (Smith
751 and Pavelsky, 2009).

752 Reservoirs also play an important role in the continental water cycle. Zhou et al. (in review)
753 showed, using a large scale water management model, that 166 of the world’s largest reservoirs,
754 which have a total storage capacity of 3900 km³ (~60% of all reservoirs storage), could have almost

755 700 km³ 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.

885

886

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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 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 ² < 25 cm when averaging over $(250\text{ m})^2$ < water area < 1 km ²
Slope accuracy	1.7 cm/km for evaluated river reaches when averaging over water area > 1 km ²
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 st 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

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1221 **Table 4** Published SWOT-related studies using data assimilation (DA) or optimal interpolation (OI)
 1222 to correct/optimize different variables (d means water depth, H water elevation, w width, S water
 1223 surface slope, Q discharge, A_i inundation area, Z bathymetric elevation, S_z bathymetric slope, n
 1224 Manning coefficient). In this table, (L)EnKF/S stands for (Local) Ensemble Kalman
 1225 Filter/Smoothing, LSTOK for Local Space-Time Ordinary Kriging, LEnTKF for Local Ensemble
 1226 Transform Kalman Filter, EKF for Extended Kalman Filter, RK for River Kriging and MPC for
 1227 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

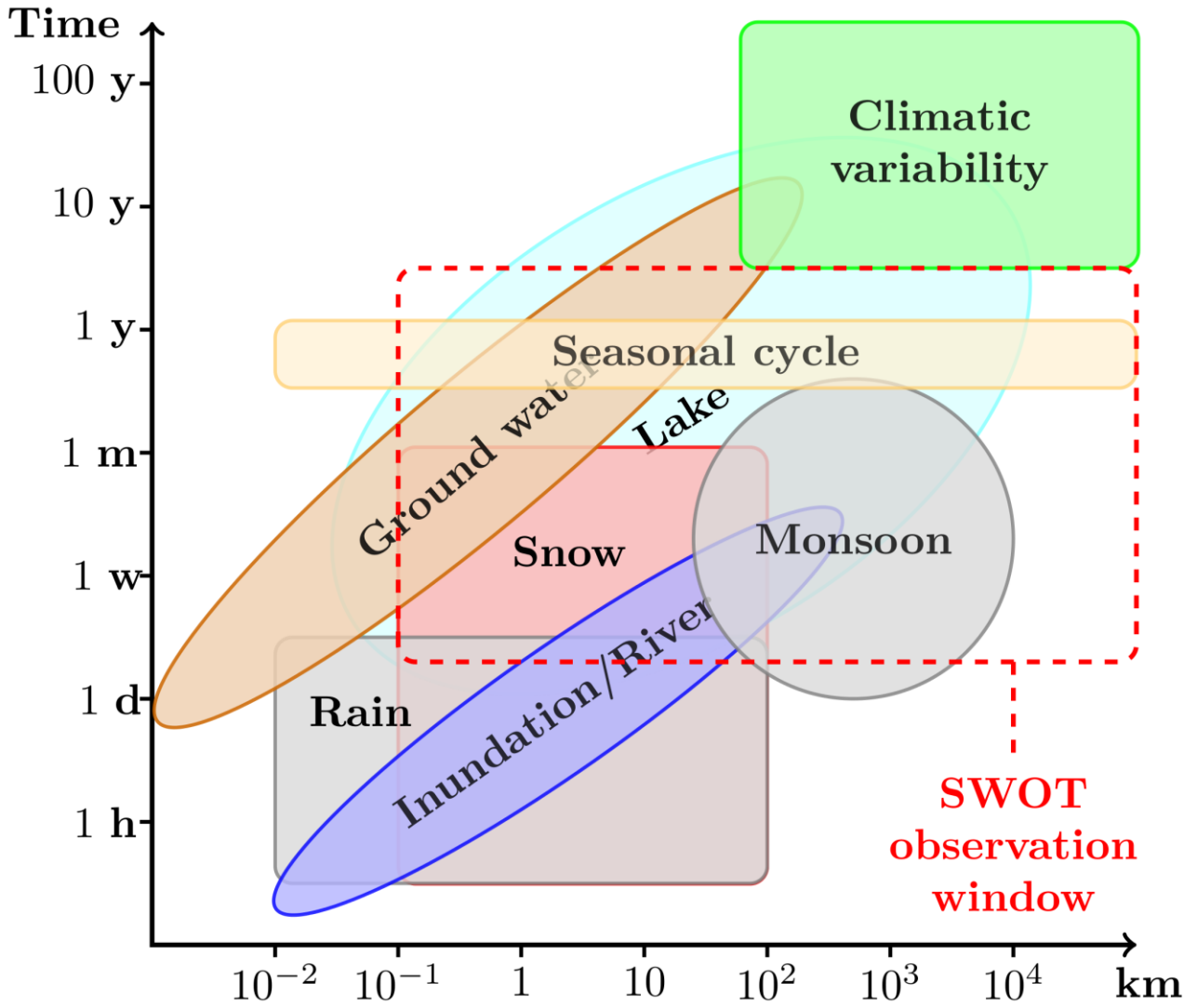
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1230 **Table 5** Published SWOT-related studies on lakes and reservoirs

Reference	Method	SWOT obs.	Study domain
Biancamaria et al. (2010)	Parametrization of global annual storage variation	Lakes area > (250m) ² 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	δH 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

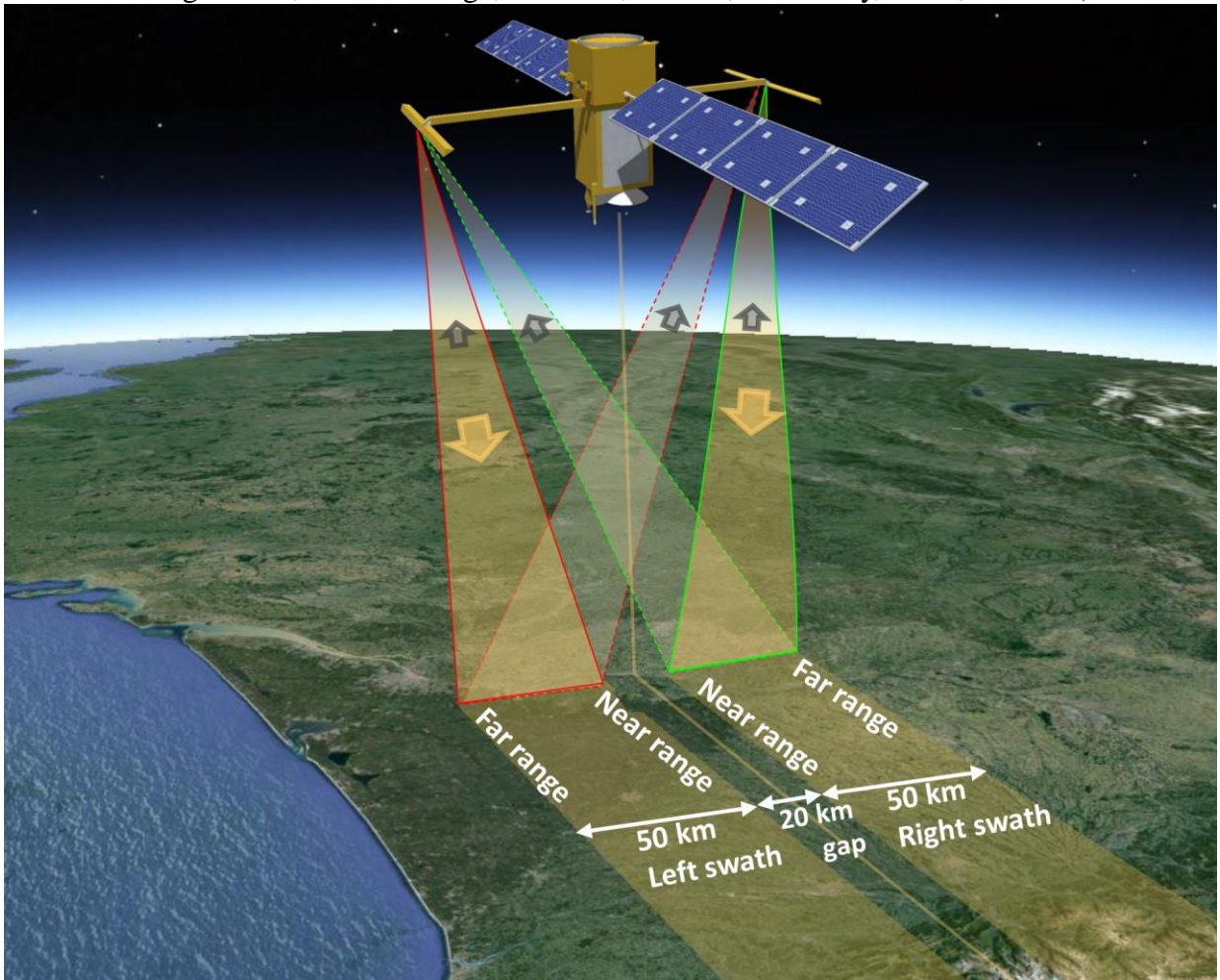
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1232 **Fig. 1** Time-space diagrams of continental water surface processes and SWOT observation window.
1233 Inspired from Blöschl and Sivapalan (1995) and Skøien et al (2003)



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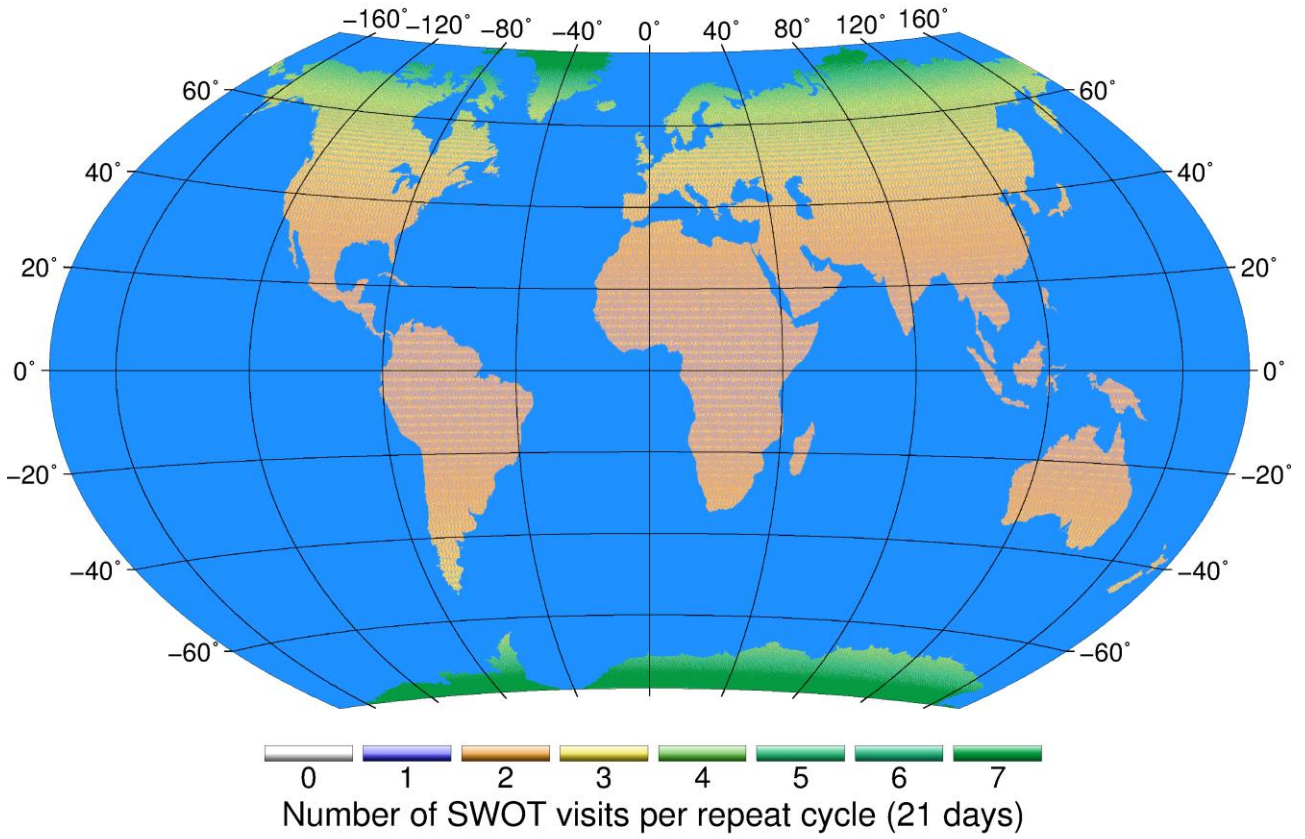
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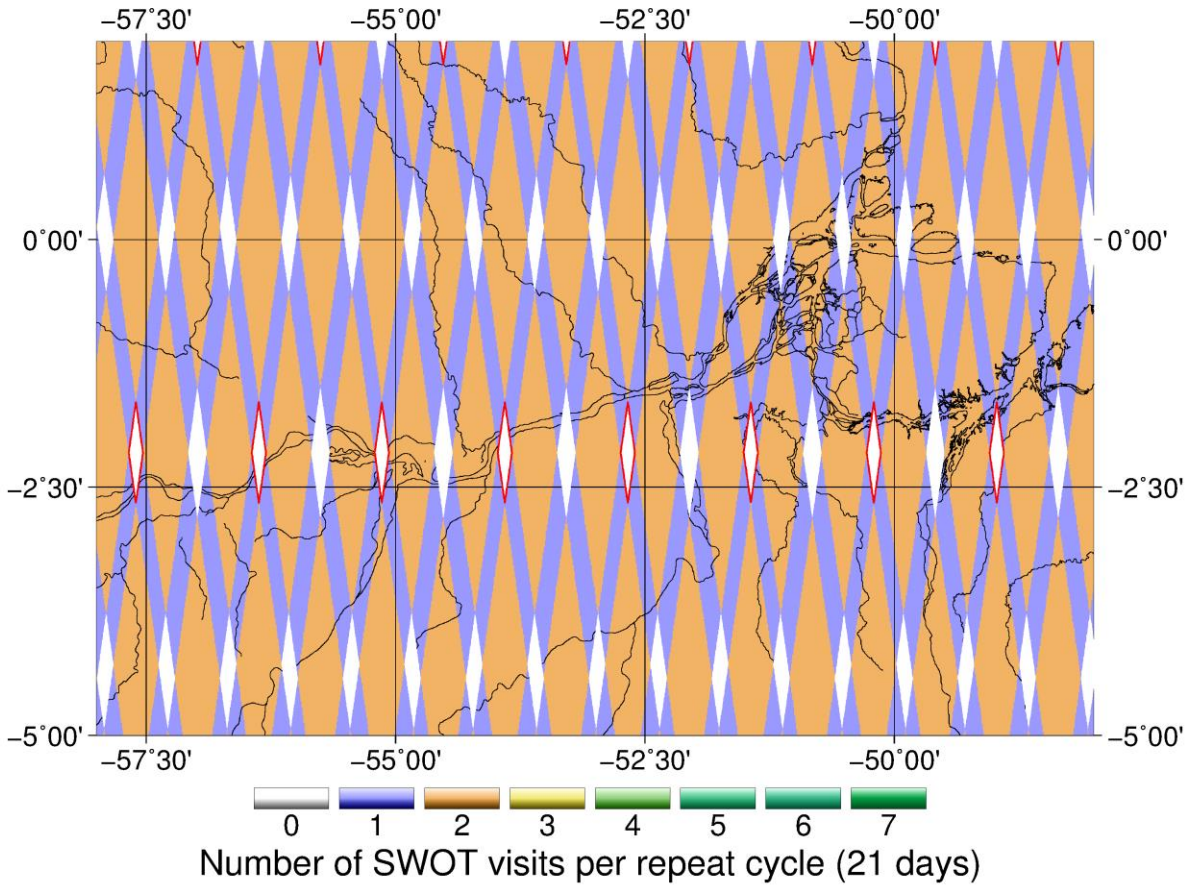
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Fig. 3 Number of SWOT revisits per orbit repeat period (21 days) over the continents (ocean have been masked, but ocean data will also be provided) in between 78°S and 78°N (a.) and a zoom over the Lower Amazon (b.). Over the Lower Amazon, white diamonds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

a. Global

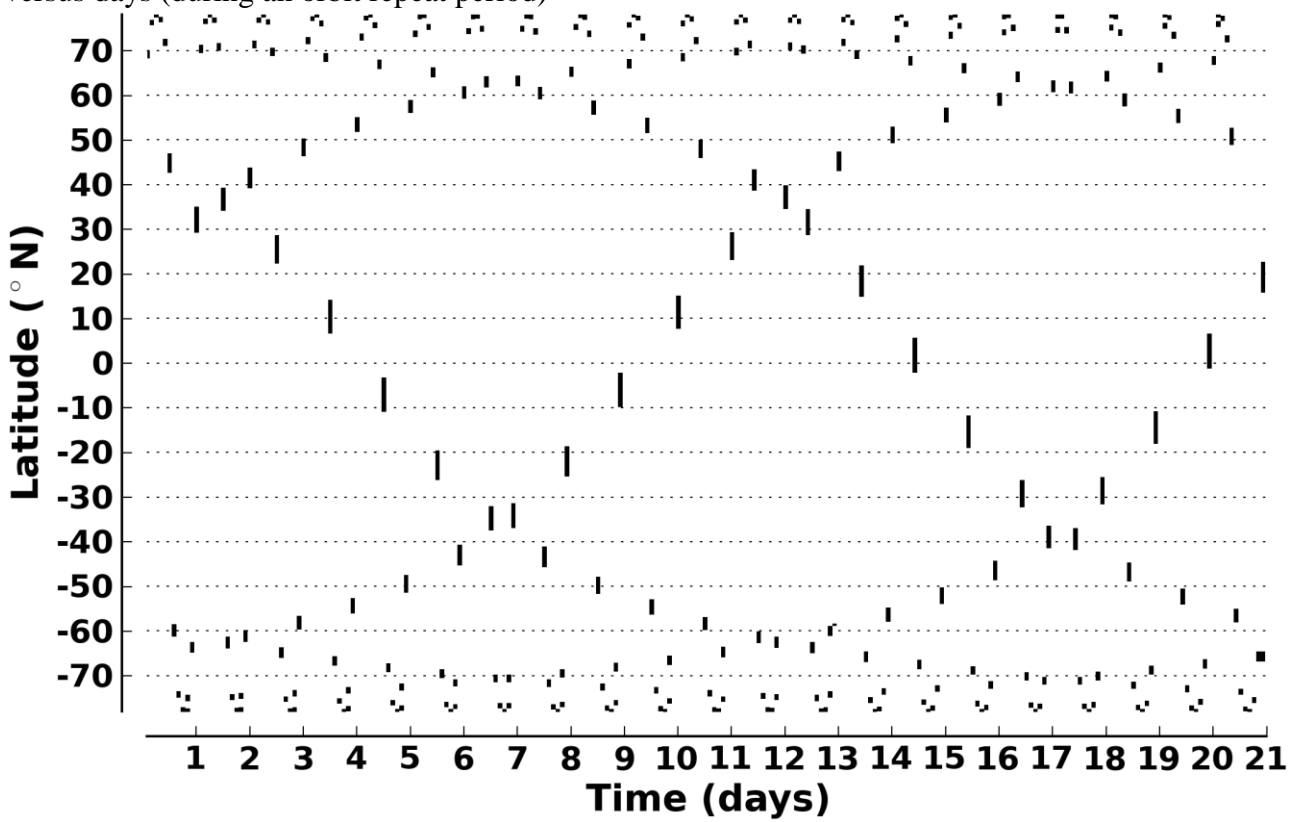


b. Lower Amazon



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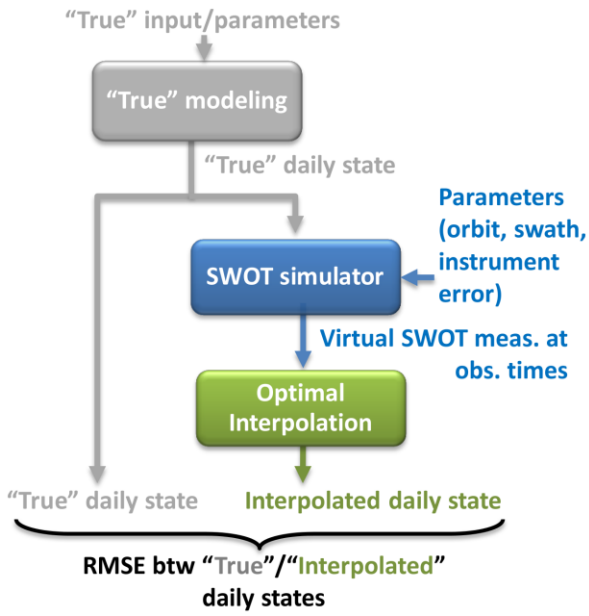
Fig. 4 SWOT observations mask (black bars correspond to an observation) along 30°E meridian versus days (during an orbit repeat period)



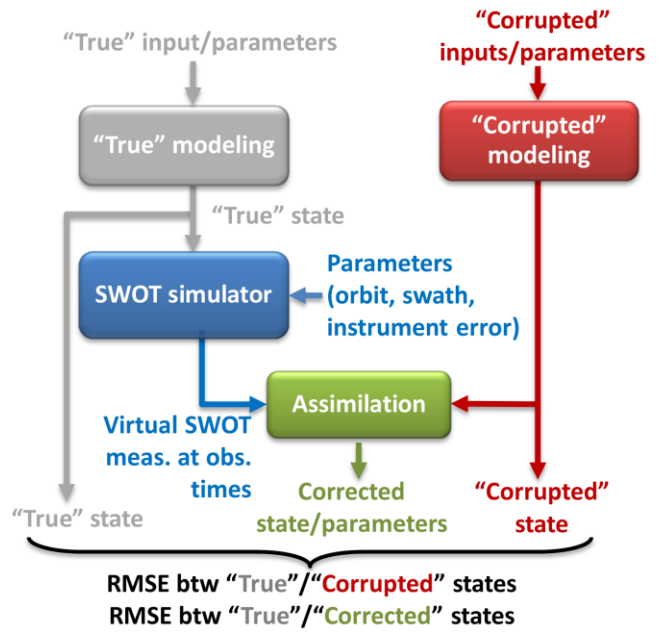
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1259 **Fig. 5** Conceptual sketches of SWOT Observing System Simulation Experiments (OSSE) using
 1260 optimal interpolation (a.) or data assimilation (b.)

a. SWOT OSSE with optimal interpolation

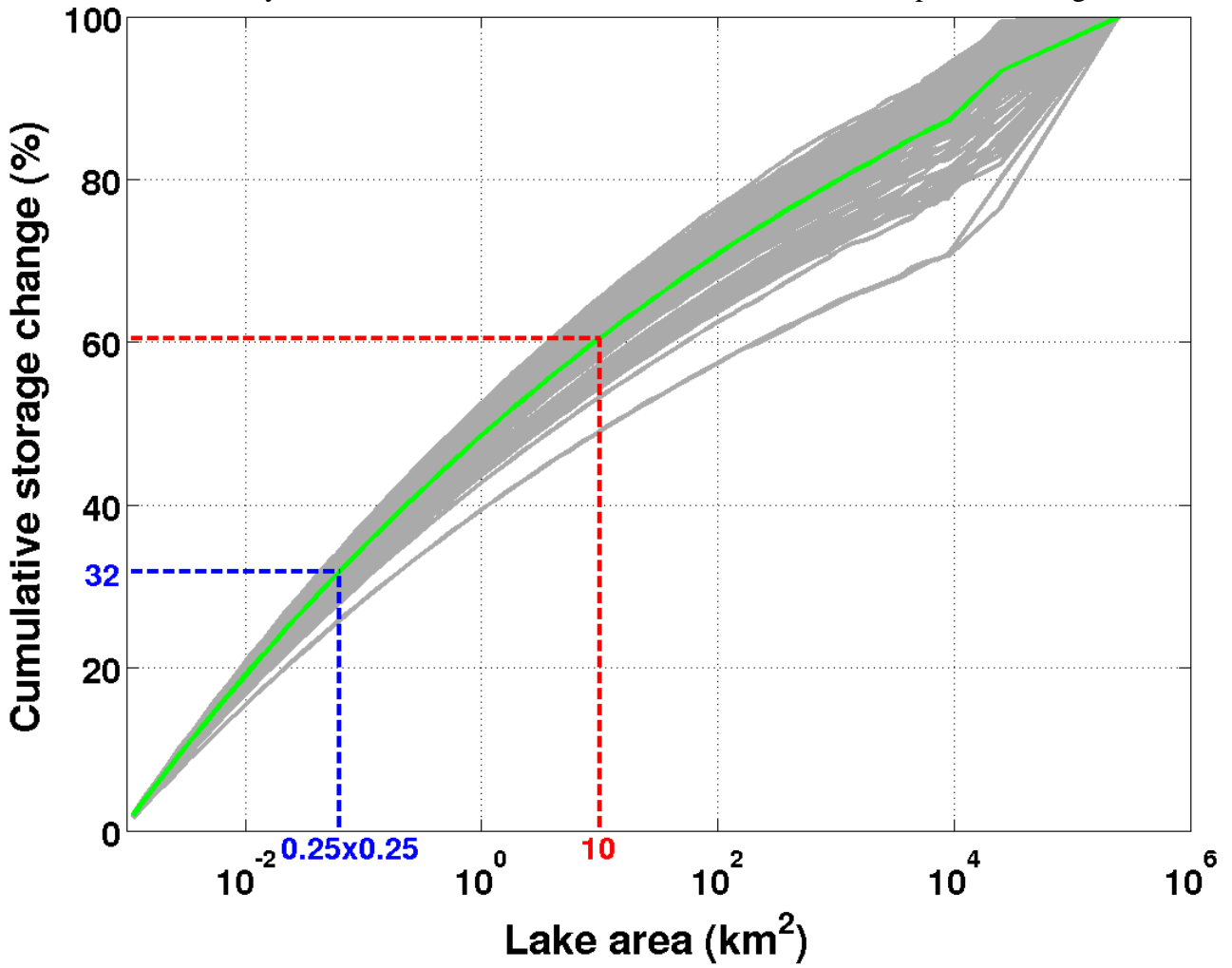


b. SWOT OSSE with data assimilation



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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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