Unmanned Aerial System (UAS) observations of water surface elevation in a small stream

Comparison of radar altimetry, LIDAR and photogrammetry techniques

Bandini, Filippo; Sunding, Tanya Pheiffer; Linde, Johannes; Smith, Ole; Jensen, Inger Klint; Köppl, Christian Josef; Butts, Michael; Bauer-Gottwein, Peter

Published in:
Remote Sensing of Environment

Link to article, DOI:
[10.1016/j.rse.2019.111487](https://doi.org/10.1016/j.rse.2019.111487)

Publication date:
2020

Document Version
Peer reviewed version

[Link back to DTU Orbit](#)

Citation (APA):
Bandini, F., Sunding, T. P., Linde, J., Smith, O., Jensen, I. K., Köppl, C. J., Butts, M., & Bauer-Gottwein, P. (2020). Unmanned Aerial System (UAS) observations of water surface elevation in a small stream: Comparison of radar altimetry, LIDAR and photogrammetry techniques. *Remote Sensing of Environment*, 237, [111487]. <https://doi.org/10.1016/j.rse.2019.111487>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Unmanned Aerial System (UAS) observations of water surface elevation in a small stream: comparison of radar altimetry, LIDAR and photogrammetry techniques.

Filippo Bandini^{1*}, Tanya Pheiffer Sunding¹, Johannes Linde², Ole Smith³, Inger Klint Jensen³, Christian Josef Köppl¹, Michael Butts⁴, Peter Bauer-Gottwein¹.

*Corresponding author at: Department of Environmental Engineering, Technical University of Denmark, Bygning 115, 2800 Kgs. Lyngby, Denmark. E-mail address: fband@env.dtu.dk

¹Department of Environmental Engineering, Technical University of Denmark, Bygning 115, 2800 Kgs. Lyngby, Denmark.

²DTU Space, National Space Institute, Elektrovej, building 328, 2800 Kgs. Lyngby, Denmark.

³Orbicon, A/S, Høje-Taastrup, Linnés Allé 2, 2630 Taastrup, Denmark.

⁴Water Resources Department, DHI, 2970 Hoersholm, Denmark

Keywords: UAS, LIDAR, radar, photogrammetry, water level, water surface elevation

Abstract

Water Surface Elevation (WSE) is an important hydrometric observation, useful to calibrate hydrological models, predict floods, and assess climate change. However, the number of in-situ gauging stations is in decline worldwide. Satellite altimetry, including the recently launched satellite missions (e.g. the radar altimetry missions Cryosat 2, Jason 3, Sentinel 3A/B and the LIDAR mission ICESat-2), can determine WSE only in rivers which are more than ca. 100 m wide. WSE measurements in small streams currently remain limited to the few existing in-situ stations or to

time-consuming in-situ surveys. Unmanned Aerial Systems (UAS) can acquire real-time WSE observations during periods of hydrological interest (but with flight limitations in extreme weather conditions), within short survey times and with automatic or semi-automatic flight operations. UAS-borne photogrammetry is a well-known technique that can estimate land elevation with an accuracy as high as a few cm, similarly UAS-borne LIDAR can estimate land elevation but without requiring Ground Control Points (GCPs). However, both techniques face limitations in estimating WSE: water transparency and lack of stable visual key points on the Water Surface (WS) complicate the UAS-borne photogrammetric estimates of WSE, while the LIDAR reflection from the water surface is generally not strong enough to be captured by most of the UAS-borne LIDAR systems currently available on the market. Thus, LIDAR and photogrammetry generally require extraction of the elevation of the “water-edge” points, i.e. points at the interface between land and water, for identifying the WSE. We demonstrate highly accurate WSE observations with a new radar altimetry solution, which comprises a 77 GHz radar chip with full waveform analysis and an accurate dual frequency differential Global Navigation Satellite System (GNSS) system. The radar altimetry solution shows the lowest standard deviation (σ) and RMSE on WSE estimates, ca. 1.5 cm and ca. 3 cm respectively, whilst photogrammetry and LIDAR show a σ and an RMSE at decimetre level. Radar altimetry also requires a significantly shorter survey and processing time compared to LIDAR and especially to photogrammetry.

1. Introduction

46 According to Tauro et al. (2018) new measurement techniques, equipment and sensors are needed
47 to characterize the hydrological cycle. The global decline of measuring stations and systems for
48 hydrology continues (Lawford et al., 2013). However, in recent years, there has been a general
49 trend towards data mining and hydrological modelling rather than experimental research (Blume et
50 al., 2017; Sidle, 2006). Accurate and high spatial resolution observations of water surface elevation
51 (WSE) are essential for validation and calibration of hydraulic models (Giustarini et al., 2011;
52 Langhammer et al., 2017; Tarpanelli et al., 2013) and for flood forecasting (Asadzadeh Jarihani et
53 al., 2013; Domeneghetti, 2016; Montesarchio et al., 2015). Hydrodynamic models would require
54 spatially distributed calibration and validation of WSE (Alsdorf et al., 2007), however in-situ
55 campaigns or gauge stations can retrieve only point-based measurements and do not ensure the
56 adequate spatial coverage to characterize the river networks.

57 Conversely, spaceborne WSE measurements are currently constrained by the spatial and temporal
58 resolutions of satellite altimeters, with a vertical accuracy of decimetres to meters (Asadzadeh
59 Jarihani et al., 2013; Biancamaria et al., 2017; Calmant and Seyler, 2006). The upcoming SWOT
60 mission (Durand et al., 2010; Neeck et al., 2012) is expected to provide 2D measurements of WSEs
61 for many of the world's prominent rivers, lakes, and wetlands with decimetre-level accuracy over 1
62 km² areas (Biancamaria et al., 2016; Pavelsky et al., 2014). Altenau et al. (2017) demonstrated that
63 AirSWOT, an airborne instrument that produces radar measurements analogous to SWOT, can
64 obtain observations with an RMSE of 9.0 cm for WSEs averaged over 1 km² areas and 1.0 cm/km for
65 slopes along 10 km reaches. However, the spaceborne SWOT is expected to be capable of
66 monitoring only rivers whose width exceeds 100 m ([https://earth.esa.int/web/eoportal/satellite-](https://earth.esa.int/web/eoportal/satellite-missions/s/swot)
67 [missions/s/swot](https://earth.esa.int/web/eoportal/satellite-missions/s/swot)), therefore is not expected to deliver WSE observations of small rivers (less than
68 100 m), which remain currently ungauged by satellite observations. However, small rivers are an
69 essential part of the river network, because they govern connectivity at the watershed-scale (e.g.

70 Wohl, 2017), constitute the whole river network in some geographical regions or countries and can
71 cause major floods in both rural and urban areas.

72 Manned aerial LIDAR instruments can measure WSE and slope also in small rivers. However,
73 accurate determination of the water surface (WS) is not trivial for LIDAR instruments (Guenther,
74 1981). WSE can be extracted from the “water-edges” of the LIDAR point cloud with a vertical
75 accuracy at the decimetre level (Legleiter, 2012), or in case LIDAR instruments have a suitable
76 frequency, pulse energy and pulse width for directly detecting the WS, WSE can be directly
77 measured with an accuracy from few cm to a few tens of cm (Hopkinson et al., 2011; Schumann et
78 al., 2008). Generally, Near-Infrared (NIR) is reflected by the air-water interface and does not
79 penetrate below the WS, while blue/green LIDAR pulses penetrate below the WS and travel through
80 the water column (e.g. Andersen et al., 2017). Because the green water surface returns include
81 returns from the air–water interface but also from the volume backscatter and the bed, Guenther
82 et al. (2000) suggested to avoid the use of green LIDAR for measuring the WS. On the other hand,
83 the use of NIR LIDAR data for WS detection is documented in several studies (e.g. Allouis et al., 2010;
84 Brzank et al., 2008; Collin et al., 2008; Höfle et al., 2009).

85 Compared to manned aircrafts, Unmanned Aerial Systems (UAS) are low cost, portable flight
86 platforms that can ensure inexpensive and versatile flight operations. UAS can fly at a lower altitude,
87 i.e. closer to the stream, and can be deployed at short notice, for example during a period of
88 hydrological interest. UAS are customizable with different payloads, but with limited size and
89 weight available for the sensors, which significantly limits the availability of UAS-borne LIDAR
90 systems. Mandlburger et al. (2016) tested the novel topo-bathymetric laser profiler system
91 (RIEGLBDF-1) onboard RIEGL BathyCopter (RIEGL, Austria). This LIDAR system implements a green
92 wavelength and is able to detect WS and also bathymetry (penetration up to 1.5 Secchi depth). The
93 authors demonstrated that the system can measure WSE, with a median vertical error of ca. 4.5 cm,

94 mainly due to penetration of green LIDAR below the WS. Furthermore, the authors report a standard
95 deviation of 6 cm in measurements, which was assumed to be caused by the short-term variability
96 of the WS (e.g. roughness). The authors specified that a combined NIR/green LIDAR solution would
97 be optimal for WS detection.

98 Huang et al. (2018) tested a lightweight and relatively cheap scanning laser (UTM-30LX, Hokuyo
99 Automatic Co., LTD., Japan) onboard a UAS to measure WSE of the sea, including wave heights. The
100 NIR laser system could receive only 10%–35% of useful data returns from a height of 6 m over the
101 sea, and for this reason, it was operated at altitudes of 6–10 m above sea level. The vertical RMSE
102 in sea WSE observation was 5 cm for a flight height of 10 m in hover mode. The major factors
103 affecting system accuracy were the accuracy of i) the Inertial Measurement Unit (IMU), ii) the Real
104 Time Kinematic (RTK) Global Navigation Satellite System (GNSS) system, iii) the scanning laser and
105 iv) the synchronization between the sensors.

106 Due to the weight and price of airborne LIDAR systems, in recent years researchers have
107 experimented with UAS-photogrammetry to measure WSE. Photogrammetric Digital Elevation
108 Models (DEMs) can generally estimate the elevation of solid surfaces with a vertical accuracy of few
109 cm (Bühler et al., 2017; Carbonneau and Dietrich, 2017; Ouédraogo et al., 2014; Santise et al., 2014).

110 However, WS is notoriously difficult to reproduce: shadows, aquatic vegetation, lack of stable visual
111 key points on the WS, and through-water penetration of visible light complicate the reconstruction
112 of the WS with Structure-from-Motion (SfM) algorithms. Westaway et al. (2001, 2000) suggested
113 that WS maps could be produced by interpolating WS information from data points acquired from
114 dry locations (“water-edge”) adjacent to inundated areas. Using this “water-edge” technique,
115 Woodget et al (2015) have demonstrated that WSE can be estimated by i) visually identifying the
116 “water-edge” interface on the UAS-orthophoto and ii) extracting the elevation of the “water-edge”
117 at small intervals from the digital surface map derived from UAS-imagery. The “water-edge” can

118 be successfully identified along streambanks which exhibit clearly identifiable edges (e.g. vegetation
119 does not protrude over the stream) and gentle bank slopes (Javernick et al., 2014; Pai et al., 2017).
120 Different automatic algorithms have been developed to identify the “water-edge”, particularly on
121 images captured by in-situ static optical camera, e.g. supervised methods (Young et al., 2015) based
122 on Canny’s edge detection algorithm (Canny, 1986), or similarly methods based on analysis of grey-
123 scale image profiles to detect the water-solid surface transition signal (Leduc et al., 2018). Pai et al.
124 (2017) attempted to identify the “water-edge” on UAS-imagery via Normalized Water Difference
125 Index (NDVI) or NIR thresholds estimated from multispectral images, but did not report a substantial
126 improvement compared to visual identification. Ridolfi and Manciola (2018) proved that the “water-
127 edge” between WS and the solid surface constituting a dam can be clearly identified on UAS-imagery
128 via Canny algorithms.

129 The accuracy of WSE observations estimated via photogrammetric techniques depends on the
130 accuracy of the photogrammetric DEM and on “water-edge” identification accuracy. In general,
131 photogrammetry requires high computational power and time-consuming human-computer
132 interaction to visually identify the ground control points (GCPs) and inspect the “water-edge” points.
133 Given the current limitations of LIDAR and photogrammetry systems, Bandini et al. (2017b)
134 retrieved WSE observations of a lake with different UAS-sensors, i.e. sonar system, radar and
135 camera-laser based prototype, in order to test precision, accuracy and beam divergence of each of
136 the sensors. The radar system was demonstrated to provide a ranging accuracy of ca. 0.5% of range.
137 With GNSS system delivering a vertical accuracy better than 3-5 cm, the radar-GNSS system was
138 proven to measure WSE of the lake with an overall accuracy better than 5–7 cm.

139 In this paper, we describe a new UAS-based radar altimetry solution with full waveform analysis,
140 together with LIDAR and photogrammetric methods. The performance of a LIDAR, photogrammetric
141 and radar estimates of WSE are quantified and compared to an independent conventional manual

142 gauging in a small stream reach. The advantages and limitations of the different sensor technologies
143 are reviewed, and both the accuracy and operating costs compared. We find that the radar
144 observations are approximately an order of magnitude better than either LIDAR or
145 photogrammetry.

146 2. Materials and methods

147

148 Firstly, this study aims to show that UAS-borne WSE measurements retrieved with an innovative full
149 waveform radar system are more reliable and accurate than photogrammetry or LIDAR WSE
150 estimates. Secondly, the study aims to demonstrate the applicability of this UAS-borne radar
151 technique with full waveform analysis also in a very small stream (1-2 m wide) that is fully covered
152 by dense vegetation over most of its length.

153 To demonstrate this, UAS-borne WSE observations were retrieved in two case studies:

154

- 155 i) in a ca. 2.3 km stretch of the stream Åmose Å (Denmark) on November 21, 2018. This
156 stretch had a WS width of ca. 3-4 m and was overhung by sparse deciduous trees. This
157 campaign shows a comparison of UAS-borne estimates from the 3 different techniques,
158 i.e. radar, LIDAR and photogrammetry, benchmarked with ground-truth observations.
- 159 ii) In a ca. 0.8 km stretch of the stream Nivå Å (Denmark) on June 25, 2019. This stretch
160 had a WS maximum width of only 1.5-2 m. The stretch is almost fully covered by dense
161 canopy: this survey shows that the radar altimetry solution with full waveform can
162 identify the WS also in locations where the WS is not visible with optical imagery (e.g.
163 photogrammetry) because the WS is fully covered by trees during their growth season.

164 This campaign shows the radar observations benchmarked with ground-truth
165 observations.

166

167

168 Fig. 1 shows the location of the 2 streams, while Table 1 summarizes the morphological and
169 hydraulic characteristics of the 2 river stretches.

170

171 *Table 1, morphological and hydraulic characteristics of the 2 river stretches*

Stream name	Coordinates Latitude/Longitude (WGS84) Total length:	Annual average WSE slope	Mean annual discharge	Maximum water depth	Water turbidity	Mean water surface width	Vegetation status
Åmose Å	From 55.566056/ 11.644617 To 55.567107/ 11.672163 Total length: 2.3 km	0.2-0.5 per mille	ca. 0.8 m ³ /s, large annual variation	Ca. 1.5 m	High turbidity. Secchi depth: ca. 0.7 m	2-4 m	<ul style="list-style-type: none">• Sparse riparia n vegetat ion• Dense aquatic vegetat ion
Nivå Å	From 55.93008/ 12.48708 To	0.1-0.2 per mille	ca. 0.2 m ³ /s, large	Ca. 0.6 m	Secchi depth: ca. 1-1.2 m	1-2 m	<ul style="list-style-type: none">• Very dense riparia n

	55.92900/ 12.49894 Total length: 0.8 km		annual variation				vegetat ion overha nging the stream • Dense aquatic vegetat ion
--	--	--	---------------------	--	--	--	--

172

173

174 Fig. 1, General map of Zealand island (Denmark) with the location of the two stretches. Map tiles by Stamen Design,
175 with Data by OpenStreetMap (Maps.stamen.com, 2019).

2.1. Åmose Å case study

Observations in Åmose Å were retrieved with our radar altimetry solution, a LIDAR system and UAS-borne photogrammetry. The flight paths for LIDAR and radar are shown in Fig. 2, while the flight path for photogrammetry is shown in Fig. 3.

Fig. 2. Map showing the surveyed Åmose Å stretch and its corresponding chainage, which is the linear distance along watercourse from stream origin. The map includes the location of the poles used to retrieve in-situ measurements and the route flown by both the radar and the LIDAR. The red dot shows an in-situ gauging station to measure WSE. Map background is an orthophoto from the Danish Geodata Agency (Styrelsen for Dataforsyning og Effektivisering, 2018).

Fig. 3, map showing the flight route for photogrammetry and the Ground Control Points (GCPs) for photogrammetry for Åmose Å. The LIDAR route (equivalent to the 2nd route for radar) is also shown in this map together with GCPs for LIDAR. Map background is an orthophoto from the Danish Geodata Agency (Styrelsen for Dataforsyning og Effektivisering, 2018)

The radar observations were obtained along the entire ca. 2.3 km stretch, while observations for the LIDAR and photogrammetry were limited to a smaller stretch. A shorter stretch (ca. 0.9 km) was covered with photogrammetry because photogrammetry requires: i) multiple flight strips to monitor an area, and ii) GCPs. For this reason, photogrammetry is the most labour demanding technique. The total number of flights with LIDAR and photogrammetry was also limited by the need to obtain the UAS-borne and the in-situ ground-truth observations in a time lag of a few hours to avoid WSE fluctuation between the surveys. The maximum WSE variation was 1-2 cm during the survey, as measured by the gauging station shown in Fig. 2 (hydrometric data available online at Orbicon (2018)). The photogrammetry flight was conducted in daylight conditions to have sufficient

illumination for optical imagery, while the LIDAR flight was conducted just after sunset, i.e. when the light conditions (absence of sunlight) were ideal for an active NIR sensor.

The radar flight paths consist of three consecutive routes (each route lasted ca. 12 minutes). For each route, the UAS is flown in a round trip (double-pass) along the river centreline.

The LIDAR path follows only one of the three radar routes (2nd route). The GCPs for LIDAR were used only as check points to evaluate the LIDAR accuracy, but GCPs are not used to directly georeference the LIDAR point cloud. These LIDAR GCPs consist of features clearly distinguishable with the LIDAR because of their elevation contrast with the surroundings. 7 LIDAR GCPs were chosen in total: 4 points on the roof of the car, 1 point on a small bridge crossing the stream and 2 points on flat hay bales.

The photogrammetry consists of two routes at different altitudes (30 and 70 meters above ground level). The camera was facing nadir for the route at 30 m. During the route at the highest altitude, the camera was facing nadir in one flight and it was tilted ca. 30° (from vertical, in a forward direction) in the other flight. Obtaining images at different altitudes and different angles ensured the highest accuracy in surfaces generation and DEM (e.g. Rossi et al., 2017; Wackrow and Chandler, 2011). 22 GCPs are used for photogrammetry (spatial distribution of GCPs is shown in Fig. 3, vertical variability range was ca. 1 m), of which 16 are directly used to geo-reference the model and 6 are check points to assess the absolute accuracy of the model.

Details about flight settings for each specific payload are given in Table 2.

226

2.2. Nivå case study

228

229 Fig. 4 shows a UAS-borne orthophoto map obtained with photogrammetric technique of the stream
 230 Nivå Å during the survey day. The river chainage is also shown in the figure.

231
 232 *Fig. 4, UAS-borne orthophoto of Nivå Å. (a) Orthomosaic showing the river stretch that was surveyed for*
 233 *WSE. (b) detail of the stream. The stream has a width of 1-2 m at maximum. In most locations (in*
 234 *more than 90% of stretch length), the stream is fully covered by vegetation canopy.*

235
 236 The stream appears to be fully covered by dense canopy during the survey day, with WS that is
 237 visible on UAS-borne imagery only in sparse locations (less than 10% of the stretch length). This case
 238 study is a demonstration of the capabilities of the radar altimetry solution in environments where
 239 photogrammetry and LIDAR would fail to detect the WS because they would lack line-of-sight to the

240 WS. Also UAS navigation is complicated in this stream, indeed, the centerline is not clearly
241 identifiable in the locations covered by vegetation, thus the UAS planned route can significantly
242 differ (a few meters) from the river centerline.

243

244 2.3. Ground-truth observations

245 In-situ observations were obtained with the levelling technique (Fig. 5).

246 19 metal poles were installed along the surveyed stretch in Åmose Å and 4 poles were located along
247 Nivå Å, in order to have stable in-situ reference points. The horizontal and vertical coordinates of
248 these poles were measured on multiple days (one measurement every month during the period
249 March-November 2018) with a GNSS rover station Trimble RTK GNSS R8s (Trimble Inc., USA).

250

251 *Fig. 5, levelling system for in-situ WSE ground-truth observations. Vertical absolute poles*
252 *coordinates were measured with an RTK GNSS system.*

253 The offset between the metal pole and the closest WS point was measured with the levelling
254 instrument Leica Sprinter 50 Digital Level (Leica Geosystems, Switzerland). Levelling generally
255 ensures sub-mm accuracy in height difference determination. However, the positioning of the
256 measuring rod on the WS can generate an uncertainty of 1-2 cm, e.g. because of waves, ripples and

257 operator errors. Furthermore, the absolute vertical coordinates of the poles were measured on
258 different days to average the RTK GNSS errors, but an uncertainty of 1-2 cm is expected. Because of
259 these sources of uncertainty, we can expect an accuracy of ground-truth in-situ observations of 2-3
260 cm.

261

262

263 **2.4. UAS platforms and GNSS/IMU sensors**

264

265 Observations with LIDAR and radar were retrieved with a DJI Matrice 600 PRO (DJI, China), as shown
266 in Fig. 6, and imagery for the photogrammetry model was retrieved with a DJI Phantom 4 Pro (DJI,
267 China).

268

269

270 *Fig. 6, UAV flight to retrieve WSE observations in Åmose Å, Denmark.*

271

272

273 The Matrice 600 Pro was equipped with the GNSS system OEM7700 (NovAtel, Canada) integrated
274 through NovAtel's Synchronous Position, Attitude and Navigation (SPAN) technology with the IMU
275 OEM-ADIS-16488 (Analog Devices, Inc., USA). To obtain cm-level accurate drone position, the GNSS
276 (comprising GPS and GLONASS constellations) observations are post-processed with post-processed
277 kinematic (PPK) technique with the software Inertial Explorer version 8.70 (NovAtel, Canada). A
278 NovAtel Flexpack6 receiver with a NovAtel GPS-703-GGG pinwheel triple frequency (GPS and
279 GLONASS) antenna was used as basestation. The IMU system was used to measure drone angles
280 and processed with Inertial Explorer in a solution tightly coupled with the GNSS system, in order to
281 filter GNSS observations and increase the position acquisition rate (Falco et al., 2017; Nouredin et
282 al., 2013).

283 Observations of LIDAR and radar systems are saved and synchronized with GNSS and IMU
284 observations on the single-board computer BeagleBone Black (BeagleBoard.org).

285 **2.5. Radar**

286 Bandini et al. (2017b) describe the UAS radar altimetry solution. As with satellite altimetry, the GNSS
287 measures the altitude of the UAS above the reference ellipsoid (or sea level if geoid undulation is
288 known), while the radar measures the range between UAS and the WS. By subtracting the range to
289 WS from the GNSS-derived altitude, WSE can be determined. The accuracy in WSE estimates is a
290 combination of the accuracy of both the ranging sensor and the GNSS system. The radar system
291 used for this study is different from Bandini et al. (2017b). In this study, we adopted the Evaluation
292 Module (IWR1443BOOST) of the IWR1443 radar chip from Texas Instrument (USA). The module
293 costs ca. \$300 (USD) and weighs ca. 50 g.

294 IWR1443 is a Frequency-Modulated Continuous-Wave (FMCW) radar chip capable of operating in
295 the 76-81 GHz band with up to 4 GHz bandwidth continuous chirp (Texas Instruments, 2017). It is a

296 fully configurable radar which supports 3 transmitting and 4 receiving antennas. Texas Instrument
 297 currently provides a mmWave Software Development Kit (SDK) for radar hardware and firmware
 298 configuration. The main advantage of this radar compared to the automotive radar used in Bandini
 299 et al. (2017b) is the possibility to obtain the full waveform of radar return. Appendix A reports the
 300 radar configuration parameters used for this research. This current configuration enables 2 receiving
 301 antennas and 1 transmitting antenna, 5 Hz frame rate (5 observations per second), 1024 range bins,
 302 and a range resolution of ca. 0.036 m. The radar field of view and the flight settings are given in
 303 Table 2, while details about radar configuration are given in Appendix A.

304 Fig. 7 shows the full waveform plot, obtained after applying a Fast Fourier transform (FFT) on the
 305 digitized samples corresponding to each chirp (Appendix A). The peak in each waveform is
 306 representative of the WS, because in the microwave spectrum WS has a higher reflectivity
 307 compared to soil and vegetation.

308 Analysing the waveform, a measuring accuracy value higher than range resolution can be achieved.
 309 Our experimental results, conducted in a laboratory with water tanks, showed that the optimal
 310 range value is obtained by extracting the range and power return of the maximum peak and of the
 311 previous and subsequent range bins, as according to experimental Eq. (1).

$$R = R_{peak} - \frac{res}{2} * \frac{pw_{peak} - pw_{next}}{(pw_{peak} - pw_{next}) + (pw_{peak} - pw_{previous})} + \frac{res}{2} * \frac{pw_{peak} - pw_{previous}}{(pw_{peak} - pw_{next}) + (pw_{peak} - pw_{previous})} = \quad (1)$$

$$R_{peak} + \frac{res}{2} * \frac{(pw_{next} - pw_{previous})}{2pw_{peak} - pw_{next} - pw_{previous}}$$

312 R is the range between the radar and the target (e.g. water surface), R_{peak} is the range corresponding
 313 to the range bin of the peak, res is the radar resolution (i.e. distance between two range bins, ca.
 314 0.036 m in the current configuration), pw_{peak} , $pw_{previous}$, pw_{next} are the return power (e.g. in

315 Decibels) of the range bin corresponding to the peak, the previous and the next range bin. In the
316 equation, the range of the peak is adjusted by subtracting (in second term) and adding (in third
317 term) a quantity equal to half the resolution multiplied by the difference between the peak return
318 power and the return power of the next bin (in second term) or the previous bin (in third term), with
319 each difference normalized by the sum of the two differences. Eq. (1) allows to estimate a range
320 that was shown to be more accurate than extraction of just the range of the peak.

321 Laboratory experiments were performed under controlled conditions and the application of this
322 formula has shown that a sub-centimetre accuracy can be obtained in range determination.

.

Fig. 7, waveform of a single radar observation above a river. (a) full waveform plot of the range bins of the radar (maximum range bin is ca. 36.78 m). The peak is representative of the WS. The

first and last bins show high returns but these are due to the direct wave and FFT numerical artefacts. (b) detail of the returns, highlighted by a black rectangle in (a), that are representative of the actual range to the water surface (estimated range to the WS is ca. 29.6186 m after applying Eq. (1)).

323

324 The gimbal Gremsy T1 (Gremsy Co., Ltd, Vietnam) is currently used to stabilize and maintain the
325 radar to a position facing nadir. The UAS-borne payload is shown in Fig. 8.

326

327 *Fig. 8, UAS-borne radar. The current radar is stabilized through a gimbal. The gimbal is also equipped*
328 *with an RGB camera for airborne pictures and videos.*

329

330 The current UAS platform includes an accurate PPK GNSS system for post-processing UAS positions
331 but does not include an RTK GNSS system for navigation. For this reason, UAS navigation showed to
332 have a deviation of a couple of meters in both the vertical and the horizontal compared to the
333 planned flight route. The UAS-radar altimetry observations include a few observations retrieved at
334 locations where WS of this small stream was not visible to the radar antenna beam, because the
335 UAS was not navigating above the stream but in the surroundings. These observations had to be

336 filtered. In this study, this filtering is performed by including only radar observations that were
337 captured when the UAS was positioned above the river mask, which was approximated using a
338 polygon. This polygon was centred along the river centerline and its width (3 m Åmose and 1.5 m
339 for Nivå) was chosen according to the stream size to approximate the river mask, for this reason we
340 refer to this polygon as river polygon. Furthermore, altimetry observations were filtered to remove
341 the few outliers (e.g. trees, bridges) that were at an elevation significantly different (more than 1
342 m) than WS. Another efficient option for filtering, which is not shown in this study, would be to
343 determine a return power threshold to distinguish waveform peaks caused by land/trees/bridges
344 from predominant peaks caused by the WS.

345

346

347

348

349 **2.6. Photogrammetry**

350 The UAS-imagery for the photogrammetry model was obtained with the CMOS RGB camera sensor
351 (1 inch sensor, 20MP resolution) onboard Phantom 4 Pro. Camera settings for the flights are
352 summarized in Table 2. UAS-imagery are processed in the software AgiSoft PhotoScan Professional
353 (Version 1.4.5) retrieved from <https://www.agisoft.com/>.

354 We compared 3 different methods to estimate WSE from photogrammetry observations: i)
355 extraction of elevation of the photogrammetric point cloud values contained in the river polygon
356 (to be consistent with radar) ii) extraction of photogrammetric DEM elevation values along river
357 centreline iii) extraction of the elevation of points at the “water-edge” to be consistent with the
358 previously published methodology (Westaway et al., 2001, 2000; Woodget et al., 2015).

2.7. LIDAR

The LIDAR system is a Puck LITE™ (Velodyne LIDAR, US). It costed ca. \$8,000 and weighs ca. 590 g. It provides dual return with a NIR wavelength of 903 nm. With 16 Channels, it is able to generate 300,000 points/second. Field of view and resolution are summarized in Table 2. Its typical accuracy over solid surfaces is ± 3 cm: this accuracy corresponds to the accuracy of LIDAR only, without including GNSS or IMU errors.

LIDAR data are post-processed with the software LAStools (version 181119, academic), obtained from <http://rapidlasso.com/LAStools>. LAStools is used to visualize the point cloud, filter observations, and create the Digital Surface Model (DSM).

We found that the WS is not reflective enough to acquire direct LIDAR returns, so WSE cannot be directly measured. The main reason for this is probably the low energy that the LIDAR emits. This is a very common issue (e.g. Huang et al., 2018; Mandlbürger et al., 2017) in the current lightweight LIDAR sensors (e.g. that can be deployed in small (less than 25 kg) UASs. Given this limitation in detecting the WS, LAStools needs to extrapolate from the “water-edge” points to construct a DEM of the stream.

We apply two methods to estimating WSE: i) extraction of all LIDAR point cloud elevation values contained in the river polygon (to be consistent with radar and photogrammetry) ii) extraction of the LIDAR DSM values along the river centreline.

379 *Table 2, platform, flight route and payload settings for the different sensors as used in this study*

Payload	Platform	Measurement rate	Altitude (above ground level)	Flight speed (m/s)	Image overlapping	Sensor orientation	Field of view (FOV) Resolution
Radar	DJI Matrice 600 PRO	5 Hz	28 m	3	-	Nadir	<ul style="list-style-type: none">• Full waveform Estimated FOV at 77 GHz: <ul style="list-style-type: none">• horizontal 3dB-beamwidth is ca. $\pm 28^\circ$• elevation 3dB-beamwidth is ca. $\pm 14^\circ$

Photogrammetry	DJI Phantom 4 Pro	3 sec	30 m	2.5	>80% <i>frontal</i> >60% <i>side</i>	Nadir	<ul style="list-style-type: none"> FOV: 84° Ground Sample Distance (GSD) At 30 m: 0.9 cm/px, At 70 m: 2.10 cm/px
		3 sec	70 m	6	>80% <i>frontal</i> >60% <i>side</i>	Nadir	
						30° (from vertical)	
LIDAR	DJI Matrice 600 PRO	300,000 points/second	28 m	3	-	Nadir	<ul style="list-style-type: none"> FOV (Vertical): +15.0° to -15.0° Angular Resolution (Vertical): 2.0° FOV (Horizontal): 360° Angular Resolution

							(Horizontal/Azimuth): 0.1° – 0.4°
--	--	--	--	--	--	--	-----------------------------------

380

381

382 3. Results

383 3.1. Radar

384

385 Fig. 9 shows the elevation bins obtained by subtracting the radar waveform from the GNSS altitude
386 data. The colour map reflects the measured return power. The highest return power has an intense
387 blue colour.

388

389 *Fig. 9, colour map of the radar power returns of the flights above Åmose Å. X-axis shows river*
390 *chainage, Y-axis shows the elevation bins (i.e. radar range bins subtracted from GNSS-derived*
391 *altitude).*

392 Fig. 9 depicts a clear WS profile, with a few outliers. The solid yellow colour at the bottom and top
393 sides of the figure indicates elevation values that are above the flight altitude and below the
394 minimum theoretical elevation bin, which is obtained by subtracting the maximum unambiguous
395 range bin from the actual GNSS-derived altitude. The lowest and highest elevation bins vary
396 depending on the flight altitude. The strong returns at the lowest and highest bins are not significant
397 and can be generally ignored. Some of the outliers are caused by tree canopy or river structures
398 above the WS (e.g. a bridge), as highlighted in the figure. Generally, trees with dense leaves cause
399 a clear hyperbolic signal; however, at the time of the flight, trees were without leaves. Thus, the
400 hyperbolic signal from trees is attenuated, with only perennial trees or large branches showing some
401 returns predominant with respect to the WS.

402 WSE was extracted from the full waveform radar observations, as according to the waveform shape
403 analysis technique described by Eq. (1).

404

405 Fig. 10 shows the in-situ ground-truth observations, the radar observations extracted from the
406 waveform analysis and a spatial average of UAV observations at 5 m intervals.

407

Fig. 10, WSE observations (in meters above mean sea level (mamsl)) retrieved by UAV-borne radar-GNSS technology and with in-situ levelling-RTK GNSS technique in Åmose Å. The size of the squares representing in-situ observations is arbitrary.

Fig. 10 shows that the radar solution is able to determine WSE with an accuracy better than 3 cm (Table 3 reports the statistics about error with comparison to ground-truth observations). This accuracy depends on two components: i) radar ranging accuracy and ii) vertical accuracy of the GNSS system.

3.2. Photogrammetry

Fig. 11 shows the orthophoto and the DEM model retrieved in the river stretch where photogrammetry was flown. Fig. 12 shows a detail (portion of the river stretch) of the orthophoto and DEM, with colour scale adapted to highlight the DEM estimation of WSE. The Ground Sample Distance (GSD) in final orthomosaic is ca. 2.1 cm/px.

422

423

424

Fig. 11, Åmose Å: (a) shows the orthophoto, (b) shows the DEM computed with AgiSoft PhotoScan from the UAS-borne pictures.

425

Fig. 12, Åmose Å: detail of (a) orthophoto and (b) DEM from UAS-photogrammetry

426 Fig. 13 shows a comparison of the WSE estimates of three different methods: i) cloud points values
 427 extracted inside the area contained by the river polygon, ii) DEM values extracted along centreline,
 428 iii) DEM values extracted along the “water-edge”. Observations were filtered by removing the few
 429 outliers (e.g. trees, bridges) that were at an elevation significantly different (more than 1 m) from
 430 WSE and then subsequently removing observations below the 15th and above 85th percentile.

Fig. 13. Photogrammetry in Åmose Å: comparison of the elevation of the point cloud in the river polygon with the DEM values extracted along centerline and along the edge.

Fig. 13 shows peaks that are caused by the trees and the bridge. The point cloud shows the larger standard deviation, with the DEM centrelines values and the DEM “water-edge” having lower dispersion. The “water-edge” values are at a higher elevation compared to the other two datasets, this is mainly due to the streambank grass protruding over the stream and affecting the “water-edge” elevation.

3.3. LIDAR

443 The LIDAR instrument was not directly able to detect the WS. Even at nadir, where we expect the
444 highest reflection from the WS (Hopkinson et al., 2011), WS returns were not acquired by the
445 instrument.

446 Fig. 14 shows that the point cloud includes observations in the stream area only in the patches
447 where surface vegetation plants are present.

Fig. 14, Åmose Å: detail of photogrammetry and LIDAR point cloud in a stream portion. (a) shows the orthophoto obtained in the same location as (b), which is the LIDAR point cloud.

448

449

450

Fig. 15, Åmose Å: DSM obtained from LIDAR point cloud. The red diagonals are caused by the academic trial license of LAs tool.

Because the LIDAR could not acquire sufficient reflection from the WS and the DSM shown in Fig. 15 is estimated by the software LAs tools mainly by extrapolating the observations obtained at the streambank points.

Fig. 16 shows the LIDAR observations extracted i) along the river centerline from the DSM and ii) from the point cloud contained in the river polygon. Similarly to photogrammetry, LIDAR observations were filtered by altimetry observations were filtered to remove the few outliers (e.g.

463 trees, bridges) that were at an elevation significantly different (more than 1 m) from WSE and then
464 subsequently removing observations below the 15th and above the 85th percentile.

465
466 *Fig. 16, Åmose Å: comparison of different methods to extract WS from LIDAR DSM and point cloud.*

467
468 As shown in Fig. 16, the LIDAR observations show large standard deviation: trees and the bridge
469 overhanging the stream induce the most evident peaks, but also in areas where there are no
470 overhanging trees the observations show large dispersion. This is mainly due to the fact that the WS
471 is not reflective enough. Therefore, the LIDAR does not directly acquire WS returns, but instead
472 mainly retrieves observations of aquatic surface plants and of streambank grass that protrudes over
473 the stream.

3.4. Comparing radar altimetry, photogrammetry and LIDAR

Check point to evaluate measurement accuracy of land elevation

The accuracy of the photogrammetric DEM on estimating land elevation is evaluated on the 16 GCPs directly used in the geo-referencing process and on the 6 check points. A vertical RMSE of less than 2.5 cm and a horizontal RMSE of 2 cm are estimated by AgiSoft PhotoScan on the geo-referencing GCPs, while a vertical RMSE of 3 cm and a horizontal RMSE of 2.5 cm are computed on the check points. Therefore, the photogrammetric DEM could estimate land elevation with an RMSE generally better than 3 cm.

The LIDAR accuracy in land elevation estimates was lower: an RMSE of 30 cm on the horizontal and 15 cm on the vertical were estimated when comparing the LIDAR designated GCPs. This large LIDAR error is mainly due to the inaccuracy in the IMU estimates, especially on the azimuth angle, and on the uncertainty in determining the angle offset between the IMU and the LIDAR reference planes. A horizontal angle uncertainty of 1-2 degrees can result in large horizontal errors in the LIDAR DSM. This could be improved in the future by using a system with 2 GNSS antennas to provide accurate heading and improve the a priori knowledge of the angle offsets between the IMU system and the LIDAR reference planes.

The radar system is not developed to monitor land elevation, thus the accuracy of the radar in land elevation measurements was not assessed.

WSE estimates

498 Fig. 17 compares the LIDAR, photogrammetry and radar observations extracted from the point cloud
 499 contained in the river polygon.

500
 501 *Fig. 17. Åmose Å: Comparison of radar, photogrammetry and LIDAR elevation values extracted in*
 502 *the point clouds.*

503 Table 3 shows a comparison of the accuracy and standard deviation of the 3 different techniques in
 504 WSE determination.

505
 506 *Table 3, statistics showing measurement standard deviation and accuracy of the different UAV-*
 507 *borne technology when compared to in-situ measurements in Åmose Å. Average Standard deviation*
 508 *(σ) is computed by averaging the standard deviation of the 5 meters intervals in which the stream*
 509 *reach (~2.3 km) was discretized. Mean Absolute Error (MAE), Mean Bias Error (MBE), Root Mean*
 510 *Square Error (RMSE) were computed by comparing the in-situ observations with the average of UAV*
 511 *observations obtained at intervals of 5 m, i.e. 2.5 m before and 2.5 m after the in-situ measurement*
 512 *location. Lidar and photogrammetry were compared with the ground-truth observations in the 800*
 513 *m stretch that is covered by both Lidar and photogrammetry flights, radar statistics are shown both*
 514 *for the 2.3 km stretch and for the 800 m stretch in common with Lidar and photogrammetry.*

Technology	σ (m)	MAE (m)	MBE (m)	RMSE (m)
------------	--------------	---------	---------	----------

Radar (2.3 km stretch- 19 ground-truth observations)	0.014	0.029	0.019	0.031
Radar (800 m stretch, only ground-truth observations in common with LIDAR and photogrammetry)	0.012	0.033	0.033	0.03
Photogrammetry DEM centerline	0.048	0.15	-0.151	0.164
Photogrammetry DEM “water-edge”	0.106	0.385	0.385	0.450
Photogrammetry Point cloud	0.073	0.160	-0.160	0.180
LIDAR DSM centerline	0.120	0.238	0.076	0.358
LIDAR point cloud	0.15	0.159	0.033	0.2218

515

516 Table 3 shows that the radar observations have a standard deviation and accuracy that are
517 approximately one order of magnitude higher than LIDAR or photogrammetry.

518 In this specific study, the “water-edge” method for photogrammetry showed higher values for the
519 error metrics compared to the extraction of observations from both the river centerline and the
520 point cloud contained in the river polygon. The extraction of LIDAR values from the point cloud
521 values shows values for the error metrics relatively similar to the LIDAR centerline technique: this is
522 because the LIDAR does not obtain any return from the WS and LAsTools software needs to
523 extrapolate observations from the edges to create the DEM in the stream area. These results suggest
524 that the current LIDAR and photogrammetry methods do not provide an accuracy below the

525 decimetre level in a stream with streambank vegetation (e.g. herbaceous plants) that affects the
526 water-edge detection.

527

528 **3.5. Result-Nivå Å survey**

529

530 Fig. 18 shows the full waveform of the radar for Nivå Å. The stream appears to be fully covered by
531 tree canopy (blue “shadows” are the hyperbolic signatures of the tree canopy). However, a high
532 return power signal clearly depicts the WS in the colour plot. The WS signal is lost where the UAS
533 navigation fails to accurately follow the river course, especially where the stream is very narrow and
534 the canopy very dense.

535

536

537 *Fig. 18, radar full waveform in Nivå Å. Blue shadows are the hyperbolic signatures of trees.*

538

539

540 WS was extracted from the return peak of each waveform, as shown in Fig. 19, and compared with
541 ground-truth observations.

542
543 *Fig. 19, WSE observations (in meters above mean sea level (mamsl)) retrieved by UAV-borne radar-*
544 *GNSS technology and with ground-truth levelling-RTK GNSS technique in Nivå Å. The size of the*
545 *squares representing ground-truth observations is arbitrary.*

546
547 Fig. 19 shows that the radar retrieved observations also in this challenging environment, with very
548 narrow stream covered by vegetation. Only in few areas, the radar failed to capture observations of
549 the stream WSE.

550 The RMSE of the observations showed a MBE of 1.7 cm, a MAE of 3 cm, a RMSE of ca. 3.2 cm and
551 an average standard deviation, computed by averaging the standard deviation of the 5 meters
552 intervals, of ca. 2.4 cm.

553

554

555

556 4. Discussion

557 We demonstrated that UAS platforms can retrieve highly accurate WSE observations. UAS ensure a
558 spatial resolution higher than spaceborne or airborne remote sensing technique, with a spatial
559 coverage and survey time significantly lower than ground-truth techniques. A few days of field work
560 are needed for retrieving WSE, at the same accuracy and same spatial resolution level as UAS-radar
561 altimetry observations, with in-situ instrumentations (e.g. with RTK-GNSS systems, levelling systems
562 or terrestrial laser scanners). Furthermore, GNSS floaters or remotely operated aquatic vehicles are
563 not practical autonomous solutions in densely vegetated streams and cannot retrieve WSE
564 observations at the same accuracy level as UAS-radar altimetry. Indeed, in small rivers with dense
565 aquatic and riparian vegetation, GNSS antennas positioned at the WS level do not have a clear sky
566 view, furthermore, signal multipath caused by the WS and by the surroundings reduces the GNSS
567 accuracy.

568 Table 4 compares the estimated market price of the three different UAS-borne WSE measuring
569 techniques: radar, LIDAR and photogrammetry.

570 *Table 4, comparison of the market price of the different UAS-borne techniques to measure WSE*

Technique	Cost of the UAS-borne payload (US dollars)	Weight	Deployed UAS Platform	GCPs required	Time to survey 1 km stretch	Time to process 1 km stretch
Radar	Radar: ca. \$300 Gimbal: ca. \$300-2000 PPK/RTK GNSS+IMU: \$1000-10000	Radar: 0.05 kg Gimbal: 0.5-1.5 kg PPK/RTK GNSS+IMU: ca. 0.15-0.4 kg	DJI Matrice 600 Pro ¹	NO	ca. 10 minutes	ca. 10 minutes

			Ca. \$6400			
LIDAR	LIDAR: ca. \$8000 PPK/RTK GNSS+IMU: \$1000-10000	LIDAR: ca. 0.6 kg PPK/RTK GNSS+IMU: ca. 0.15-0.4 kg	DJI Matrice 600 PRO Ca. \$6400	NO	ca. 10 minutes	A few hours
Photogrammetry	RGB Camera: \$400-5000 Gimbal: \$300-2000 GNSS+IMU: \$300-10000	Camera+gimbal: 0.1-3 kg GNSS+IMU: ca. 0.1-0.4 kg	DJI Phantom 4 Pro \$2000 (includes GNSS and IMU)	Generally required	30-120 minutes	A few days

571 ¹A smaller and cheaper UAS platform could potentially be used.

572 Table 4 shows that in terms of price, the radar sensor is the most competitive. However, this solution
573 requires a GNSS rover receiver (preferably dual frequency) on the UAS and a base station (i.e.
574 differential GNSS system with either PPK or RTK processing), which should be included in the cost.
575 Furthermore, the radar solution could also include an IMU, which may be integrated to the GNSS to
576 improve the position solution or could be used to retrieve the UAS angles when the radar is not
577 stabilized with a gimbal. In case GCPs are used, the photogrammetry solution does not require a
578 dual frequency GNSS receiver and a base station, i.e. low-cost GNSS could be used for
579 photogrammetry. Only if direct geo-referencing (Carbonneau and Dietrich, 2017; Cramer et al.,
580 2000; Rehak et al., 2013; Turner et al., 2014) was adopted, GCPs could be reduced or theoretically
581 avoided, but in this case the UAS would require: i) accurate GNSS receivers and IMU sensors (similar
582 to the ones deployed in our radar payload) that should be accurately synchronized with the camera
583 solution ii) high-accuracy calibration of the UAS camera.

584 The radar and LIDAR sensors show the shortest survey time. Differently, UAS-photogrammetry
585 requires longer flight time: multiples flight strips to acquire images at different angles and flight
586 routes at different altitudes and with different camera angles should be performed.

587 For the radar, processing time is short (in the orders of few minutes with consumer grade laptops).
588 The post-processing of radar observations is already automatized, with most of the human-
589 computer interaction (generally a few minutes) that needs to be spent to import and process GNSS
590 radar in the GNSS processing software. LIDAR has shown longer processing time because of the high
591 point density, with human-computer interaction required to filter observations according to river
592 mask and create DSM and DTM. Photogrammetry is the most demanding application in terms of
593 computational times. A few days are normally required to process the high resolution RGB images
594 also with the current optimized computer server, which consists of AMD Ryzen Threadripper 1950X
595 processor with 16 cores, 3400 Mhz with two graphic cards (Nvidia GeForce GTX 1080). Furthermore,
596 the processing time is not deterministic and varies depending on the image match points that are
597 identified by the software. Significant human-computer interaction time is required to identify the
598 “water-edge” and to extract WSE observations along this “water-edge”.

599 The accuracy of UAS-borne radar WSE does not depend on water depth and water turbidity.
600 Furthermore, as shown in this study, UAS-borne WSE can be retrieved also in small stream covered
601 by dense vegetation canopy. This is a clear advantage compared to WSE measurements with UAS-
602 borne lidar and photogrammetry, which are effected by water turbidity, water depth (e.g. a visible
603 riverbed or aquatic vegetation in the imagery can complicate construction of the WSE
604 photogrammetric model) and require line-of-sight with the WS, which is limited in case of dense
605 vegetation overhanging the stream.

606 UAS-WSE observations represent a new dataset in hydrology: radar altimetry can capture WSE
607 profiles, in agreement with the 1-D WSE simulation of most of the hydrodynamic river models (e.g.

608 MIKE 11, HEC-RAS, etc.). In case of large rivers or floodplains, multiple flight routes can be easily
609 conducted to measure the WSE at different points across the river. Accurate WSE slope
610 measurements can improve understanding of how spatial irregularities in river bathymetry affect
611 river hydraulics (Garambois et al., 2017), enhance knowledge about surface water-groundwater
612 interaction processes (Bandini et al., 2017a; Pai et al., 2017) and resolve channel roughness with
613 high spatial resolution (Schneider et al., 2018).

614 WSE can be retrieved autonomously during extreme events (e.g. floods) with our radar altimetry
615 solution, without any GCP and without sunlight. Indeed, radar is not affected by light conditions,
616 while e.g. photogrammetry relies on sunlight. Regarding the current UAS-platform, the main
617 limitation is the weather condition during an extreme event: the UAS platforms deployed in this
618 study can withstand a wind of at least 8-10 m/s but can fly only in light rain conditions.

619 Furthermore, discharge could be better estimated with UAS-borne observations, e.g. by informing
620 Manning's equation or hydrodynamic models with WSE slope measurements and by deriving rating
621 curves (e.g. Bjerklie et al., 2005; LeFavour and Alsdorf, 2005; Tarpanelli et al., 2013).

622 WSE measurements in combination with discharge (Q) can be used to construct rating curves, which
623 are essential for estimating discharge based on real-time WSE measurements. Discharge
624 computation requires wetted area (Ω) and mean flow velocity (V), which are usually measured with
625 in-situ surveys that are generally time-consuming and labour intensive, especially in large rivers
626 during extreme conditions. Manfreda (2018) describes an approach to express V and Ω both as a
627 function of WSE and river bed geometry.

628

629 5. Conclusions

630

631 We compare the WSE estimates from 3 different UAS-borne methods: LIDAR, photogrammetry and
632 an innovative radar altimetry solution:

- 633 • The radar altimetry solution with full waveform analysis shows the best accuracy in WSE
634 estimates, with RMSE ca. 3 cm and σ ca. 1.5 cm, while photogrammetry and LIDAR show an
635 RMSE and σ of decimetres.
- 636 • The LIDAR and the radar solution do not require GCPs and allow for single-pass routes, while
637 photogrammetry requires longer survey times because it requires GCPs and multiple flight
638 strips.
- 639 • The developed radar solution requires significantly shorter computational and human-
640 computer interaction time. The computational time that is required to process observations
641 of a 1 km stretch is in the order of minutes for radar, hours for LIDARs, days for
642 photogrammetry.
- 643 • The main advantage of the LIDAR and photogrammetry compared to radar is the capability
644 of producing a DEM of the riverbank topography, while radar can only determine the WSE
645 and its slope.

646 In our view, UAV-borne WSE observations can be defined as a new datatype in river hydrology: i)
647 compared to other remote sensing techniques they ensure high accuracy and can be acquired also
648 in the smallest vegetated streams ii) compared to in-situ measurements they ensure high spatial
649 resolution and higher spatial coverage at lower cost. UAV-borne WSE observations can significantly
650 improve flood forecast models, improve our knowledge about the effect of river geometry and
651 hydraulic roughness on WSE and contribute to construction of rating curves.

652

653 **Acknowledgments**

654 We thank Karsten Stæhr Hansens from Orbicon A/S for having retrieved the in-situ ground-truth
655 observations. The choice of having in-situ observations acquired by a professional operator from
656 Orbicon engineering company was motivated with the need to perform an independent accuracy
657 validation test of the radar WSE observations.

658 **Funding**

659 This work was partly funded within the RIVERSCAPES project by the Innovation Fund Denmark under
660 file number 7048-00001B.

661

662 **Code and data availability.**

663 Datasets used in the study are available online in the repository archived in Zenodo.org
664 (<http://doi.org/10.5281/zenodo.3519888>). The repository contains UAS-borne observational
665 datasets and programming scripts to analyze data.

666

667 **Appendix A**

668 The report from Dham (2017) provides a short overview on the chirp timing parameters that are
669 needed to configure an FMCW radar, as shown in Fig. A1.

670

671 *Fig. A1, chirp configuration, Source: Dham, Texas Instrument (2017)*

672 An FMCW radar typically sends out a sequence of chirps (i.e. a sinusoid whose frequency increases
673 linearly with time), equally spaced in time, in a unit called a frame (Rao, 2017).

674

675 *Table A1, chirp parameters chosen for the radar configuration*

Chirp timing parameters	Parameter value
ADC Sampling Rate	8.580 millions of sample per seconds
ADC sampling time	106.29 μ s
number of ADC samples collected during ADC sampling time	912
frequency slope	35 MHz/ μ s
frequency start	77 GHz
ramp end time	114.3 μ s
ADC valid start time	7 μ s
Idle time	2929 μ s

676

677 The radar was configured with 1 transmitting antenna and 2 receiving antennas, with the chosen
678 chirp configuration resulting in a bandwidth of 4 GHz, a measurements rate of 5 Hz, maximum
679 unambiguous range of ca. 30 m, and vertical resolution of ca. 0.036 m. Table A1 shows the specific
680 radar configuration parameters. The specific configuration parameters are shown in Table A1.

681

682

683

684 ***Reference list***

685 Allouis, T., Bailly, J.S., Pastol, Y., Le Roux, C., 2010. Comparison of LiDAR waveform processing
686 methods for very shallow water bathymetry using Raman, near-infrared and green signals.
687 Earth Surf. Process. Landforms 35, 640–650. <https://doi.org/10.1002/esp.1959>

688 Alsdorf, D.E., Rodriguez, E., Lettenmaier, D.P., 2007. Measuring surface water from space. Rev.
689 Geophys. 45, 1–24. <https://doi.org/10.1029/2006RG000197>

690 Altenau, E.H., Pavelsky, T.M., Moller, D., Lion, C., Pitcher, L.H., Allen, G.H., Bates, P.D., Calmant, S.,
691 Durand, M., Smith, L.C., 2017. AirSWOT measurements of river water surface elevation and
692 slope: Tanana River, AK. Geophys. Res. Lett. <https://doi.org/10.1002/2016GL071577>

693 Andersen, M.S., Gergely, Á., Al-Hamdani, Z., Steinbacher, F., Larsen, L.R., Ernstsén, V.B., 2017.
694 Processing and performance of topobathymetric lidar data for geomorphometric and
695 morphological classification in a high-energy tidal environment. Hydrol. Earth Syst. Sci.
696 <https://doi.org/10.5194/hess-21-43-2017>

697 Asadzadeh Jarihani, A., Callow, J.N., Johansen, K., Gouweleeuw, B., 2013. Evaluation of multiple
698 satellite altimetry data for studying inland water bodies and river floods. J. Hydrol. 505, 78–90.
699 <https://doi.org/10.1016/j.jhydrol.2013.09.010>

700 Bandini, F., Butts, M., Jacobsen, T.V., Bauer-Gottwein, P., 2017a. Water level observations from
 701 unmanned aerial vehicles for improving estimates of surface water-groundwater interaction.
 702 Hydrol. Process. <https://doi.org/10.1002/hyp.11366>

703 Bandini, F., Jakobsen, J., Olesen, D., Reyna-Gutierrez, J.A., Bauer-Gottwein, P., 2017b. Measuring
 704 water level in rivers and lakes from lightweight Unmanned Aerial Vehicles. J. Hydrol. 548, 237–
 705 250. <https://doi.org/10.1016/j.jhydrol.2017.02.038>

706 Biancamaria, S., Frappart, F., Leleu, A.S., Marieu, V., Blumstein, D., Desjonqueres, J.D., Boy, F.,
 707 Sottolichio, A., Valle-Levinson, A., 2017. Satellite radar altimetry water elevations performance
 708 over a 200 m wide river: Evaluation over the Garonne River. Adv. Sp. Res. 59, 128–146.
 709 <https://doi.org/10.1016/j.asr.2016.10.008>

710 Biancamaria, S., Lettenmaier, D.P., Pavelsky, T.M., 2016. The SWOT Mission and Its Capabilities for
 711 Land Hydrology. Surv. Geophys. <https://doi.org/10.1007/s10712-015-9346-y>

712 Bjerklie, D.M., Moller, D., Smith, L.C., Dingman, S.L., 2005. Estimating discharge in rivers using
 713 remotely sensed hydraulic information. J. Hydrol. 309, 191–209.
 714 <https://doi.org/10.1016/j.jhydrol.2004.11.022>

715 Blume, T., van Meerveld, I., Weiler, M., 2017. The role of experimental work in hydrological
 716 sciences—insights from a community survey. Hydrol. Sci. J.
 717 <https://doi.org/10.1080/02626667.2016.1230675>

718 Brzank, A., Heipke, C., Goepfert, J., Soergel, U., 2008. Aspects of generating precise digital terrain
 719 models in the Wadden Sea from lidar-water classification and structure line extraction. ISPRS
 720 J. Photogramm. Remote Sens. <https://doi.org/10.1016/j.isprsjprs.2008.02.002>

721 Bühler, Y., Adams, M.S., Stoffel, A., Boesch, R., 2017. Photogrammetric reconstruction of
 722 homogenous snow surfaces in alpine terrain applying near-infrared UAS imagery. Int. J. Remote
 723 Sens. <https://doi.org/10.1080/01431161.2016.1275060>

724 Calmant, S., Seyler, F., 2006. Continental surface waters from satellite altimetry. *Comptes Rendus -*
725 *Geosci.* 338, 1113–1122. <https://doi.org/10.1016/j.crte.2006.05.012>

726 Canny, J., 1986. A Computational Approach to Edge Detection. *IEEE Trans. Pattern Anal. Mach. Intell.*
727 <https://doi.org/10.1109/TPAMI.1986.4767851>

728 Carbonneau, P.E., Dietrich, J.T., 2017. Cost-effective non-metric photogrammetry from consumer-
729 grade sUAS: implications for direct georeferencing of structure from motion photogrammetry.
730 *Earth Surf. Process. Landforms* 42, 473–486. <https://doi.org/10.1002/esp.4012>

731 Collin, A., Archambault, P., Long, B., 2008. Mapping the shallow water seabed habitat with the
732 SHOALS, in: *IEEE Transactions on Geoscience and Remote Sensing*.
733 <https://doi.org/10.1109/TGRS.2008.920020>

734 Cramer, M., Stallmann, D., Haala, N., 2000. Direct georeferencing using gps/inertial exterior
735 orientations for photogrammetric applications. *Int. Arch. Photogramm. Remote Sens.*
736 <https://doi.org/10.1017/CBO9780511777684>

737 Dham, V.-T.I., 2017. Programming Chirp Parameters in TI Radar Devices Application, Report [WWW
738 Document]. URL <http://www.ti.com/lit/an/swra553/swra553.pdf> (accessed 1.3.19).

739 Domeneghetti, A., 2016. On the use of SRTM and altimetry data for flood modeling in data-sparse
740 regions. *Water Resour. Res.* <https://doi.org/10.1002/2015WR017967>

741 Durand, M., Fu, L.L., Lettenmaier, D.P., Alsdorf, D.E., Rodriguez, E., Esteban-Fernandez, D., 2010. The
742 surface water and ocean topography mission: Observing terrestrial surface water and oceanic
743 submesoscale eddies, in: *Proceedings of the IEEE*. pp. 766–779.
744 <https://doi.org/10.1109/JPROC.2010.2043031>

745 Falco, G., Pini, M., Marucco, G., 2017. Loose and tight GNSS/INS integrations: Comparison of
746 performance assessed in real Urban scenarios. *Sensors (Switzerland)*.
747 <https://doi.org/10.3390/s17020255>

748 Garambois, P.A., Calmant, S., Roux, H., Paris, A., Monnier, J., Finaud-Guyot, P., Samine Montazem,
 749 A., Santos da Silva, J., 2017. Hydraulic visibility: Using satellite altimetry to parameterize a
 750 hydraulic model of an ungauged reach of a braided river. *Hydrol. Process.*
 751 <https://doi.org/10.1002/hyp.11033>

752 Giustarini, L., Matgen, P., Hostache, R., Montanari, M., Plaza, D., Pauwels, V.R.N., De Lannoy, G.J.M.,
 753 De Keyser, R., Pfister, L., Hoffmann, L., Savenije, H.H.G., 2011. Assimilating SAR-derived water
 754 level data into a hydraulic model: A case study. *Hydrol. Earth Syst. Sci.*
 755 <https://doi.org/10.5194/hess-15-2349-2011>

756 Guenther, G., 1981. Accuracy and penetration measurements from hydrographic trials of the AOL
 757 system, in: *Proc. 4th Laser Hydrography Symposium*. Salisbury, pp. 108–150.

758 Guenther, G.C., Cunningham, a G., Larocque, P.E., Reid, D.J., Service, N.O., Highway, E., Spring, S.,
 759 2000. Meeting the Accuracy Challenge in Airborne Lidar Bathymetry. *EARSeL eProceedings* 1,
 760 1–27.

761 Höfle, B., Vetter, M., Pfeifer, N., Mandlbürger, G., Stötter, J., 2009. Water surface mapping from
 762 airborne laser scanning using signal intensity and elevation data. *Earth Surf. Process.*
 763 *Landforms*. <https://doi.org/10.1002/esp.1853>

764 Hopkinson, C., Crasto, N., Marsh, P., Forbes, D., Lesack, L., 2011. Investigating the spatial distribution
 765 of water levels in the Mackenzie Delta using airborne LiDAR. *Hydrol. Process.* 25, 2995–3011.
 766 <https://doi.org/10.1002/hyp.8167>

767 Huang, Z.-C., Yeh, C.-Y., Tseng, K.-H., Hsu, W.-Y., Huang, Z.-C., Yeh, C.-Y., Tseng, K.-H., Hsu, W.-Y.,
 768 2018. A UAV–RTK Lidar System for Wave and Tide Measurements in Coastal Zones. *J. Atmos.*
 769 *Ocean. Technol.* 35, 1557–1570. <https://doi.org/10.1175/JTECH-D-17-0199.1>

770 Javernick, L., Brasington, J., Caruso, B., 2014. Modeling the topography of shallow braided rivers
 771 using Structure-from-Motion photogrammetry. *Geomorphology*.

772 <https://doi.org/10.1016/j.geomorph.2014.01.006>

773 Langhammer, J., Bernsteinová, J., Miřijovský, J., 2017. Building a high-precision 2D hydrodynamic
 774 flood model using UAV photogrammetry and sensor network monitoring. *Water* (Switzerland).
 775 <https://doi.org/10.3390/w9110861>

776 Lawford, R., Strauch, A., Toll, D., Fekete, B., Cripe, D., 2013. Earth observations for global water
 777 security. *Curr. Opin. Environ. Sustain.* 5, 633–643.
 778 <https://doi.org/10.1016/j.cosust.2013.11.009>

779 Leduc, P., Ashmore, P., Sjogren, D., 2018. Technical note: Stage and water width measurement of a
 780 mountain stream using a simple time-lapse camera. *Hydrol. Earth Syst. Sci.* 22, 1–11.
 781 <https://doi.org/10.5194/hess-22-1-2018>

782 LeFavour, G., Alsdorf, D., 2005. Water slope and discharge in the Amazon River estimated using the
 783 shuttle radar topography mission digital elevation model. *Geophys. Res. Lett.* 32, L17404.
 784 <https://doi.org/10.1029/2005GL023836>

785 Legleiter, C.J., 2012. Remote measurement of river morphology via fusion of LiDAR topography and
 786 spectrally based bathymetry. *Earth Surf. Process. Landforms* 37, 499–518.
 787 <https://doi.org/10.1002/esp.2262>

788 Mandlbürger, G., Pfeifer, N., Soergel, U., 2017. Water Surface Reconstruction In Airborne Laser
 789 Bathymetry From Redundant Bed Observations, in: *ISPRS Annals of the Photogrammetry,*
 790 *Remote Sensing and Spatial Information Sciences.* [https://doi.org/10.5194/isprs-annals-IV-2-](https://doi.org/10.5194/isprs-annals-IV-2-W4-123-2017)
 791 [W4-123-2017](https://doi.org/10.5194/isprs-annals-IV-2-W4-123-2017)

792 Mandlbürger, G., Pfennigbauer, M., Wieser, M., Riegl, U., Pfeifer, N., 2016. Evaluation Of A Novel
 793 Uav-Borne Topo-Bathymetric Laser Profiler. *ISPRS - Int. Arch. Photogramm. Remote Sens. Spat.*
 794 *Inf. Sci.* XLI-B1, 933–939. <https://doi.org/10.5194/isprs-archives-XLI-B1-933-2016>

795 Manfreda, S., 2018. On the derivation of flow rating curves in data-scarce environments. *J. Hydrol.*
 50

796 <https://doi.org/10.1016/j.jhydrol.2018.04.058>

797 Maps.stamen.com, 2019. maps.stamen.com [WWW Document]. URL
798 <http://maps.stamen.com/#watercolor/12/37.7706/-122.3782> (accessed 10.11.19).

799 Montesarchio, V., Napolitano, F., Rianna, M., Ridolfi, E., Russo, F., Sebastianelli, S., 2015.
800 Comparison of methodologies for flood rainfall thresholds estimation. Nat. Hazards.
801 <https://doi.org/10.1007/s11069-014-1357-3>

802 Neeck, S.P., Lindstrom, E.J., Vaze, P. V., Fu, L.-L., 2012. Surface Water and Ocean Topography (SWOT)
803 mission, in: Conference on Sensors, Systems and Next-Generation Satellites XVI. p. 85330G.
804 <https://doi.org/10.1117/12.981151>

805 Noureldin, A., Karamat, T.B., Georgy, J., 2013. Fundamentals of inertial navigation, satellite-based
806 positioning and their integration, Fundamentals of Inertial Navigation, Satellite-Based
807 Positioning and their Integration. Springer. <https://doi.org/10.1007/978-3-642-30466-8>

808 Orbicon, 2018. Hydrometri.dk [WWW Document]. URL <http://www.hydrometri.dk/hyd/> (accessed
809 12.12.18).

810 Ouédraogo, M.M., Degré, A., Debouche, C., Lisein, J., 2014. The evaluation of unmanned aerial
811 system-based photogrammetry and terrestrial laser scanning to generate DEMs of agricultural
812 watersheds. Geomorphology. <https://doi.org/10.1016/j.geomorph.2014.02.016>

813 Pai, H., Malenda, H.F., Briggs, M.A., Singha, K., González-Pinzón, R., Gooseff, M.N., Tyler, S.W., 2017.
814 Potential for Small Unmanned Aircraft Systems Applications for Identifying Groundwater-
815 Surface Water Exchange in a Meandering River Reach. Geophys. Res. Lett.
816 <https://doi.org/10.1002/2017GL075836>

817 Pavelsky, T.M., Durand, M.T., Andreadis, K.M., Beighley, R.E., Paiva, R.C.D., Allen, G.H., Miller, Z.F.,
818 2014. Assessing the potential global extent of SWOT river discharge observations. J. Hydrol.
819 <https://doi.org/10.1016/j.jhydrol.2014.08.044>

820 Rao, S.-T.I., 2017. Introduction to mmwave Sensing: FMCW Radars [WWW Document]. URL
821 https://training.ti.com/sites/default/files/docs/mmwaveSensing-FMCW-offlineviewing_3.pdf
822 (accessed 1.3.19).

823 Rehak, M., Mabillard, R., Skaloud, J., 2013. A micro-UAV with the capability of direct georeferencing.
824 Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. [https://doi.org/10.5194/isprsarchives-XL-](https://doi.org/10.5194/isprsarchives-XL-1-W2-317-2013)
825 1-W2-317-2013

826 Ridolfi, E., Manciola, P., 2018. Water level measurements from drones: A Pilot case study at a dam
827 site. Water (Switzerland) 10. <https://doi.org/10.3390/w10030297>

828 Rossi, P., Mancini, F., Dubbini, M., Mazzone, F., Capra, A., 2017. Combining nadir and oblique uav
829 imagery to reconstruct quarry topography: Methodology and feasibility analysis. Eur. J. Remote
830 Sens. <https://doi.org/10.1080/22797254.2017.1313097>

831 Santise, M., Fornari, M., Forlani, G., Roncella, R., 2014. Evaluation of dem generation accuracy from
832 UAS imagery, in: International Archives of the Photogrammetry, Remote Sensing and Spatial
833 Information Sciences - ISPRS Archives. <https://doi.org/10.5194/isprsarchives-XL-5-529-2014>

834 Schneider, R., Tarpanelli, A., Nielsen, K., Madsen, H., Bauer-Gottwein, P., 2018. Evaluation of multi-
835 mode CryoSat-2 altimetry data over the Po River against in situ data and a hydrodynamic
836 model. Adv. Water Resour. <https://doi.org/10.1016/j.advwatres.2017.11.027>

837 Schumann, G., Matgen, P., Cutler, M.E.J.E.J., Black, A., Hoffmann, L., Pfister, L., 2008. Comparison of
838 remotely sensed water stages from LiDAR, topographic contours and SRTM. ISPRS J.
839 Photogramm. Remote Sens. 63, 283–296. <https://doi.org/10.1016/j.isprsjprs.2007.09.004>

840 Sidle, R.C., 2006. Field observations and process understanding in hydrology: Essential components
841 in scaling. Hydrol. Process. <https://doi.org/10.1002/hyp.6191>

842 Styrelsen for Dataforsyning og Effektivisering, 2018. Aerial orthophoto [WWW Document]. URL
843 <https://download.kortforsyningen.dk/> (accessed 2.17.19).

844 Tarpanelli, A., Barbetta, S., Brocca, L., Moramarco, T., 2013. River discharge estimation by using
 845 altimetry data and simplified flood routing modeling. *Remote Sens.*
 846 <https://doi.org/10.3390/rs5094145>

847 Tauro, F., Selker, J., Van De Giesen, N., Abrate, T., Uijlenhoet, R., Porfiri, M., Manfreda, S., Caylor, K.,
 848 Moramarco, T., Benveniste, J., Ciraolo, G., Estes, L., Domeneghetti, A., Perks, M.T., Corbari, C.,
 849 Rabiei, E., Ravazzani, G., Boga, H., Harfouche, A., Brocca, L., Maltese, A., Wickert, A.,
 850 Tarpanelli, A., Good, S., Lopez Alcala, J.M., Petroselli, A., Cudennec, C., Blume, T., Hut, R.,
 851 Grimaldia, S., 2018. Measurements and observations in the XXI century (MOXXI): Innovation
 852 and multi-disciplinarity to sense the hydrological cycle. *Hydrol. Sci. J.* 63, 169–196.
 853 <https://doi.org/10.1080/02626667.2017.1420191>

854 Texas Instruments, 2017. IWR1443 Single-Chip 76-to 81-GHz mmWave Sensor 1 Device Overview
 855 [WWW Document]. URL <http://www.ti.com/lit/ds/symlink/iwr1443.pdf> (accessed 1.1.19).

856 Turner, D., Lucieer, A., Wallace, L., 2014. Direct georeferencing of ultrahigh-resolution UAV imagery.
 857 *IEEE Trans. Geosci. Remote Sens.* 52, 2738–2745. <https://doi.org/10.1109/TGRS.2013.2265295>

858 Wackrow, R., Chandler, J.H., 2011. Minimising systematic error surfaces in digital elevation models
 859 using oblique convergent imagery. *Photogramm. Rec.* 26, 16–31.
 860 <https://doi.org/10.1111/j.1477-9730.2011.00623.x>

861 Westaway, R.M., Lane, S.N., Hicks, D.M., 2001. Remote sensing of clear-water, shallow, gravel-bed
 862 rivers using digital photogrammetry. *Photogramm. Eng. Remote Sensing* 67, 1271–1281.

863 Westaway, R.M., Lane, S.N., Hicks, D.M., 2000. The development of an automated correction
 864 procedure for digital photogrammetry for the study of wide, shallow, gravel-bed rivers. *Earth*
 865 *Surf. Process. Landforms* 25, 209–226. [https://doi.org/10.1002/\(SICI\)1096-9837\(200002\)25:2<209::AID-ESP84>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1096-9837(200002)25:2<209::AID-ESP84>3.0.CO;2-Z)

867 Wohl, E., 2017. The significance of small streams. *Front. Earth Sci.* <https://doi.org/10.1007/s11707-53>

868 017-0647-y

869 Woodget, A.S., Carbonneau, P.E., Visser, F., Maddock, I.P., 2015. Quantifying submerged fluvial
870 topography using hyperspatial resolution UAS imagery and structure from motion
871 photogrammetry. *Earth Surf. Process. Landforms* 40, 47–64. <https://doi.org/10.1002/esp.3613>
872 Young, D.S., Hart, J.K., Martinez, K., 2015. Image analysis techniques to estimate river discharge
873 using time-lapse cameras in remote locations. *Comput. Geosci.*
874 <https://doi.org/10.1016/j.cageo.2014.11.008>

875