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1 Use of terrestrial photosieving and airborne topographic LiDAR to assess bed

2 grain size in large rivers: potentials and limits

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14

15 Abstract (300 mots-max)

16 Most grain size monitoring is still being conducted by manual sampling in the field, 17 which is time consuming and has low spatial representation. Due to new remote 18 sensing methods, some limitations have been partly overcome, but methodological 19 progress is still needed for large rivers as well as in underwater conditions. In this 20 paper, we tested the reliability of two methods along the Old Rhine River 21 (France/Germany) to estimate the grain size distribution (GSD) in above-water 22 conditions: (i) a low-cost terrestrial photosieving method based on an automatic 23 procedure using Digital Grain Size (DGS) software and (ii) an airborne LiDAR topo-24 bathymetric survey. We also tested the ability of terrestrial photosieving to estimate 25 the GSD in underwater conditions. Field pebble counts were performed to compare 26 and calibrate both methods. The results showed that the automatic procedure of

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27 terrestrial photosieving is a reliable method to estimate the GSD of sediment patches 28 in both above-water and underwater conditions with clean substrates. Sensitivity 29 analyses showed that environmental conditions, including solar lighting conditions and petrographic variability, significantly influence the GSD from the automatic 30 31 procedure in above-water conditions. The presence of biofilm in underwater conditions significantly altered the GSD estimation using the automatic procedure. 32 33 but the proposed manual procedure overcame this problem. The airborne LiDAR 34 topographic survey is an accurate method to estimate the GSD of above-water 35 bedforms and is able to generate grain size maps. The combination of terrestrial 36 photosieving and airborne topographic LiDAR methods is adapted to assess the 37 GSD along large rivers in entire sections that are several kilometers long.

Key words: Grain size, Large rivers, above-water and underwater conditions, 38 39 Methodological study, Terrestrial photosieving, Airborne topographic LiDAR.

1. Introduction 40

Quantification of the GSD of a riverbed surface is important for assessing sediment 41 42 transport and for geomorphological and ecological studies, notably regarding river 43 restoration (Graham, Rice, and Reid, 2005b; MacKenzie, Eaton, and Church, 2018). 44 Many studies have been carried out during recent decades to characterize the GSD, 45 but its assessment remains difficult because the grain size variability depends notably on the study scale (Church, Mclean, & Wolcott J.F, 1987; Graham et al., 46 2005b). GSD assessment of a sediment patch requires a large set of particles whose 47 number depends on the shape of the distribution (Rice & Church, 1996). Most grain 48 49 size monitoring was performed by using the classic "pebble count" manual procedure 50 (Wolman, 1954). These different procedures are all time consuming and show low 51 spatial representation, especially for large rivers (Warrick et al. 2009).

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52 From the beginning of the 1970s, terrestrial photosieving methods were carried out to 53 estimate the GSD in above-water conditions to reduce field time, increase the 54 sampling density and limit bed disturbance (Butler, Lane, and Chandler 2001). Data processing requires manually digitizing the B-axis of each visible particle, increasing 55 56 the time and lab effort (Kellerhals & Bray, 1971; Ibbeken & Schleyer, 1986). 57 Thereafter, semiautomatic or automatic procedures were developed to reduce the 58 processing time. They were based either on oriented-object approaches (McEwan et 59 al., 2000; Sime & Ferguson, 2003; Graham, Reid, and Rice, 2005a; Lucas & Strom, 60 1987; Detert & Weitbrecht, 2012; Strom, Kuhns, & Lucas, 2010; Sulaiman et al., 61 2014) or on statistical approaches (Buscombe, 2010, Buscombe, 2013; Sime & 62 Ferguson, 2003; Warrick et al., 2009). However, this kind of method is suitable only 63 for studies where prompt GSD data are needed.

64 Over the last two decades, new methods of remote sensing have been developed to 65 estimate the GSD at larger spatial scales in above-water conditions (Dugdale, Carbonneau & Campbell, 2010). Some studies tested the reliability of airborne digital 66 67 imagery processing, such as airborne multispectral (Rainey et al., 2003; Black et al., 68 2014) or color photography, by performing textural analyses to estimate the GSD 69 over scales from several hundred meters to several dozen kilometers (Carbonneau, 70 Lane, & Bergeron, 2004; Carbonneau, Bergeron, & Lane, 2005; Verdú, Batalla, & 71 Martínez-Casasnovas, 2005; Lejot et al., 2011; Carbonnneau, Bizzi, & Marchetti, 72 2018; Woodget, Fyffe, & Carbonneau, 2018). The accuracy of these methods to 73 predict the GSD is dependent on the resolution of the images, which must be 74 commensurate with the particle size (Lejot et al., 2011). Three-dimensional data acquired by terrestrial LiDAR or UAV photogrammetry were also used to predict the 75 76 GSD by using the bed surface roughness as a proxy (Heritage & Milan, 2009;

77 Brasington, Vericat, & Rychkov, 2012; Storz-Peretz & Laronne, 2013; Woodget & 78 Austrums, 2017; Vázguez-Tarrío et al., 2017). The first empirical relation between the 79 roughness height metric (rh) and the median grain size was found by Gomez (1993) 80 from the bed surface profile and vertical photographs. These methods have the 81 advantage that they simultaneously provide various information, such as roughness 82 maps, channel morphological dynamics, and grain size maps (Marteau et al., 2017; 83 Vázquez-Tarrío et al., 2017). However, the application of terrestrial LiDAR and UAV 84 photogrammetry techniques is not applicable in large study reaches in underwater 85 conditions.

86 During the last decade, airborne topographic LiDAR techniques have been 87 increasingly employed, notably in fluvial geomorphological and hydrologic studies (Charlton, Large, & Fuller, 2003; Demarchi, Bizzi, & Piégay, 2016; Bizzi et al., 2019; 88 89 Shaker, Yan, & LaRocque, 2019). Dataset collection is performed by using the nearinfrared wavelength (Mandlburger et al., 2015). The data collection is fast and may 90 91 cover large areas. This method provides not only accurate point clouds in three 92 dimensions but also intensity values that correspond to the amplitude of the return 93 signal (Kashani et al., 2015). Kukko, Kaasalainen, & Litkey, (2008) showed that this 94 metric is impacted partly by surface roughness, suggesting a probable link between 95 the intensity values and the bed grain size.

Some studies have been carried out to qualitatively estimate the GSD in underwater
conditions, but they are rare due to technical limitations in constraining field
conditions.

99 Qualitative underwater substrate mapping was produced by using side-scan sonar
100 imagery (Buscombe, Grams, & Kaplinski, 2017, Buscombe, Grams, & Smith, 2015;
101 Hamill, Buscombe, & Wheaton, 2018). Rüther (2013) used the terrestrial

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photosieving method in underwater conditions along the Surna River to estimate the
bed GSD following an automatic procedure but without a control dataset and
calibration with field GSD.

This paper addresses the inference of the GSD in large rivers from remote sensing in both above-water and underwater conditions. Two methods are tested in above-water conditions: (i) terrestrial photosieving, a low-cost technique to rapidly estimate the bed GSD, and (ii) airborne topographic LiDAR data analysis using a laser wavelength λ =1064 nm. For underwater conditions, we tested the terrestrial photosieving method. This paper follows three objectives: (i) compare the reliability between the terrestrial photosieving technique and the airborne LiDAR topometric survey in above-water conditions, (ii) test the reliability of the terrestrial photosieving technique to estimate the GSD in underwater conditions and (iii) determine the parameters that can influence the accuracy of both techniques in both environmental conditions.

126 2. Materials and methods

127 2.1 <u>Study area</u>

128 The Rhine is the third largest river in Europe with a drainage basin of approximately 129 185,000 km² and a length of 1250 km. The Upper Rhine runs from Basel to Bingen-130 am-Rhein (300 km long) into the Upper Rhine graben, where the hydrological regime 131 is nivo-glacial (Figure 1.a). The mean annual discharge is 1059 m³/s at Basel 132 (Uehlinger & Wantzen, 2009). After two engineering phases of correcting and 133 regulating the flow (Arnaud, 2012; Schmitt, Morris, & Kondolf, 2018), the Old Rhine 134 River was bypassed by the French Grand Canal d'Alsace (GCA) along 50 km from Kembs to Breisach. Most of the flow of the Rhine River into the GCA is regulated by 135 136 the Kembs derivation dam. The GCA has four power plants. An instream flow is 137 maintained in the Old Rhine between 52 and 115 m³/s, which is the monthly variation corresponding to the natural hydrological discharge of the Rhine River (Figure 1.b). 138 Spillovers occur into the Old Rhine River when the Rhine discharge exceeds 1400 139 140 m³/s at Basel, which corresponds to the maximum discharge of the GCA capacity. 141 The channel bottom of the Old Rhine River is composed of gravels to cobbles. The 142 mean slope and mean width are equal to 0.09% and 100 m, respectively (Figure 1.b).

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Figure 1: (a) The Rhine Basin and the location of the study reach, (b) the Old Rhine River and the GCA, (c) the range of digital images collected in this study, and (d) and (e) maps of the intensity values and the Rh roughness metric of an above-water deposit along the study reach. In (a), the black rectangle indicates the location of the Old Rhine River. In (b), the black arrows, the black cross and the gray circles

represent the study reach, the Rheinweiler gauging station and the power plants, 151 152 respectively.

153 **Data collection** 2.2

2.2.1 Collection of digital images 154

Between winter and autumn 2017, terrestrial photosieving surveys were carried out 155 on both above-water and underwater patches by using a 12-MP Olympus TG-4 156 157 waterproof camera. The camera was placed in a plan view by using a telescopic rod. The recorded elevation ranged from 0.6 m to 1.0 m, and the pixel size ranged from 158 159 0.18 mm to 0.30 mm in above-water conditions and from 0.24 mm to 0.40 mm in underwater conditions. A square gabarit with an area of 1 m² placed on the bed 160 surface and a rigid rule were used for scale in above-water and underwater 161 162 conditions, respectively. All the digital images recorded in above-water conditions were characterized as clean substrate (n=10), while the digital images collected in 163 164 underwater conditions were composed of both clean substrate (n=4) and substrate 165 with biofilm (n=6).



167 Figure 2. (a) Framework of the study and maximum daily flow at the Rheinweiler gauging station during 2017 and (b) the GSD of the field pebble counts (truncated at 168 3 psi). * indicates the collection period of the field pebble counts used for the 169

calibration of the airborne topo-bathymetric LiDAR survey. The value of the criticaldischarge was extracted from (El Kadi Abderrezzak, 2009).

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173 2.2.2 Airborne topographic LiDAR survey

In March 2017, airborne LiDAR data were acquired by using a Teledyne Optech Titan DW sensor. The flight was carried out at an altitude of 400 m along a reach of 35 km between KP 174,00 and KP 209.00. The Titan DW sensor is a topobathymetric sensor operating a near-infrared (NIR) laser (λ =1064 nm) typical of airborne topographic LiDAR and a green laser (λ =532 nm) with shallow-water bathymetry mapping capability (Fernandez-Diaz et al. 2016) In this study, only the NIR laser data were used on above-water bars.

181 The divergence angle of the NIR laser is 0.3 mrad, resulting in a laser spot size of 182 approximately 0.12 m at nadir. The range density points and range mean distance 183 between points, 38 to 49 points/m² and 0.08 m to 0.09 m, respectively, were 184 calculated on three-point clouds located on three above-water deposits. To estimate 185 the range noise of the flight, we estimated the variability of the z-values and intensity 186 values on three ground control areas (sections of roads) by assuming that the difference in the point values should be equal to 0 on planar control areas (Lague, 187 188 Brodu, & Leroux, 2013). The uncertainties of the survey along the z-axis were less than 2 cm and equal to 2.10 cm for the intensity values (Table 1). 189

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Standard deviation of z values deviation (cm)	Standard deviation of Rh metric deviation (cm)	Standard deviation of intensity values deviation	Standard deviation of intensity metric deviation
1.00	0.18	2.10	6.51
0.90	0.17	2.10	1.50

197 Table 1: Precision of the LiDAR topographic survey along three ground control areas.

198 LiDAR metrics were computed for a kernel size equal to 0.4 m.

199 2.2.3 Collection of field pebble counts

200 The collection of field pebble counts was based on the random surface sampling of 201 100 particles for each sediment patch during February 2017 and October 2017 202 (Wolman, 1954). A sampling of 21 pebble counts was collected in both above-water 203 (n=18) and underwater conditions (n=3) in a large range of sediment patches (Figure 204 2). The low number of field samplings in underwater conditions resulted from adverse survey conditions due to bed imbrication, high water depth and flow velocity and the 205 206 locally important thickness of fine sediments (greater than 0.1 m). On above-water 207 surfaces, each particle was collected at every 2*Dmax (Dmax=maximum B-Axis) spacing along a decameter. In underwater conditions, the particles were sampled 208 209 following the random step-toe procedure (Bunte & Abt, 2001). A caliper was used to 210 measure the B-axis of each particle. The distribution was truncated at 3 psi according 211 to the results of Rice & Church, (1996), who demonstrated an underestimation for 212 these particles during pebble count sampling. Each pebble count area was 213 georeferenced by using a global positioning system (centimetric planimetric 214 precision). For calibration purposes, ten field pebble counts in above-water

215 conditions and three field pebble counts in underwater conditions were compared to 216 the terrestrial photosieving results. On the other hand, 18 field pebble counts were 217 used to calibrate the LiDAR metrics. The ranges of the 50th and 84th percentiles of the 218 sampled sediment patches were between 4.75 psi and 7.02 psi and between 5.04 psi 219 and 7.49 psi, respectively.

220 2.3 Data processing

221 2.3.1 Automated processing of digital images

Digital Grain Size (DGS) software developed by Buscombe (2013) was used to automatically estimate the GSD of the apparent particle B-axis. This software, which is based on the wavelet statistical approach, provided the distribution in grid by number form. From the recommendations of Barnard et al., (2007) and Buscombe (2010), a control dataset composed of twenty digital images was used to evaluate the accuracy of the software. The control dataset was performed by using the grid tool implemented in ImageJ software.

229 2.3.2 Manual processing of digital images

A manual method was also tested to process the digital images to compare with the automatic procedure. The B-axis of particles was manually digitalized following a grid in which nodes were spaced by one Dmax to avoid sampling the same particle twice. This was made by the same operator to minimize the subjective bias during the Baxis choice. This procedure was performed by using the grid tool implemented on ImageJ software. Sampling areas were equal to 100 times the area of the largest particle following Petrie & Diplas (2000) recommendation.

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237 2.3.3 Processing the airborne topographic LiDAR survey

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2.3.3.1 Computation of the Rh metric

239 First, all vegetation areas were excluded from the point cloud to avoid computation 240 errors by empirically filtering the intensity values because it can be a more accurate 241 method than geometric classification approaches (Reymann & Lacroix, 2015). The 242 Rh metric was computed by using the roughness tool implemented in CloudCompare 243 v.2.9.1 software (EDF R&D). For each point, the computation of the Rh metric is given by the distance between the point elevation and the ordinary least-squares 244 245 best fitting plane computed on its nearest neighbors (Woodget, 2015; Woodget et al., 2017; Vázquez-Tarrío et al., 2017). The nearest neighbors are selected within a 246 247 specified kernel size from the selected point. Third, according to the methodology of Vázquez-Tarrío et al., (2017), the point cloud was clipped by a buffer with a radius of 248 249 five meters, and the center corresponded to the location of the field pebble counts to 250 compare the Rh metric distribution with the field GSD. This step was performed by 251 using ArcGIS software.

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2.3.3.2 <u>Computation of the standard deviation of the intensity values</u>

253 The intensity values of the return pulses of the NIR wavelength are influenced by 254 several parameters, including internal instrument amplification, environmental effects 255 (wetness and atmospheric transmittance), data acquisition geometry (range and 256 incidence angle) and surface characteristics (reflectance and roughness) (Li et al., 257 2014; Kashani et al., 2015). In our case study, instrumental and environmental 258 parameters had a limited impact on intensity values because the same instrument 259 was used, and environmental conditions, including the flight elevation, were relatively 260 constant during flight. Considering the data acquisition geometry, Kukko, Kaasalainen, & Litkey (2008) and Kaasalainen et al., (2011) showed that intensity 261

values are significantly sensitive to the incidence angle when the latter is greater than 262 263 20°. In our case, the incidence angle did not exceed 16°, and we assumed that the 264 data acquisition geometry had no influence. Hence, we tested the standard deviation of the raw values of intensity as a proxy for the surface GSD. The first step consisted 265 266 of calculating the standard deviation of the raw intensity values for each point of the point cloud for a given area by computing a buffer with a specific radius. We 267 268 performed this step by using ArcGIS software. The second step was identical to the 269 third step of the computation of the Rh metric (see section 2.3.4).

270 2.4 Sensitivity analyses

271 2.4.1 <u>Effect of environmental conditions on GSD estimation by the DGS software</u>
272 Sensitivity analyses were performed on three parameters:

1. The influence of the textural variation of the digital image induced by 273 274 petrographic variability. This study was performed by using a median filter that homogenized the textural differences within individual particles and reduced 275 276 the oversegmentation (Strom, Kuhns, & Lucas, 2010). The kernel size of the median filter was increased progressively to 1%, 2.5%, and 5% for underwater 277 conditions (n=6) and increased progressively to 1%, 2.5%, 5%, 10% and 15% 278 of the maximal B-axis of the largest particle observed on each digital image for 279 280 above-water conditions with controlled solar lighting conditions (n=10). The 281 GSDs estimated by the software were compared to the control dataset.

282
2. The light conditions during digital image acquisition. We recorded two
283 photographs for each sampling patch (n=10) with and without sun exposure by
284 using an umbrella on the above-water clean substrate. The time recording was
285 extracted from the raw data digital image to calculate the influence of the solar
286 angle on the GSD estimation.

13

287 3. The quality of the substrate on the DGS error estimations as clean substrate288 or substrate with the presence of biofilm.

289 2.4.2 Selection of minimal sampling area in the DGS software

To evaluate the effect of the minimal sampling area on the estimation fluctuations of the DGS software, for each sediment patch in above-water conditions (n=10), we increased the minimal sampling area progressively from 10 to 100 times the area of the largest particle by steps of 10 by using a montage of digital images performed with GIMP software. We calculated a mobile slope coefficient to determine from which sampling area the fluctuation estimations were low as follows:

296 Slope coefficient $= \frac{i}{6} \frac{i}{6}$

297 2.4.3 Airborne topographic LiDAR

298 The accuracy of the GSD predicted by the Rh metric can be influenced by the kernel 299 size computation of the metric (Vázquez-Tarrío et al., 2017; Woodget & Austrums, 300 2017). A sensitivity analysis was performed by computing the Rh metric for kernel 301 sizes ranging between 0.4 m and 2.0 m, by steps of 0.1 m from 0.4 m to 1.0 m, and 302 by steps of 0.2 m from 1.0 m to 2.0 m. This procedure was performed using 303 CloudCompare v.2.9.1 software. The same procedure was performed for the 304 standard deviation of the intensity values using ArcMap v10.3 software by 305 progressively increasing the size of the radius of the computed buffer.

We computed linear regressions between the two proxies with the field GSD for each kernel size to define the best relationship between the two variables and consequently to identify the best kernel size.

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309 **3.** <u>Results</u>

310 3.1 Accuracy of the GSD estimation in above-water conditions using 311 terrestrial photosieving

312 3.1.1 Accuracy of the DGS software

Figure 3 shows that the percentiles estimated by the DGS software in clean above-313 water conditions with clean substrate and controlled solar lighting conditions were 314 315 systematically underestimated compared with the percentile values of the control dataset. For the 50th percentile, the values of the NRMSE were equal to 72% for the 316 digital images with clean substrate in above-water conditions (Table 2). Error 317 estimations decrease as the percentiles increase for these two types of ground digital 318 images. The NRMSE values were 88% and 32% for the 5^{th} percentile and the 95^{th} 319 320 percentile, respectively.

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323 values of the control dataset. The dashed lines correspond to the 1:1 line. The digital

324 images were taken with controlled solar lighting conditions in above-water conditions.

	Above-wate	r condition		Underwater conditi	on
Decile	Clean substrate with	Clean substrate with	Clean substrate	Biofilm	Biofilm with median

	controlled solar lighting condition (n=10)	median filter (5%) (n=10)	(n=4)	(n=6)	filter (2.5%) (n=6)
D ₅	88	22	42	92	27
D ₁₀	84	21	28	83	21
D ₁₆	83	25	23	77	20
D ₂₅	80	25	20	72	23
D ₅₀	72	29	12	70	45
D ₇₅	58	23	9	56	40
D ₈₄	51	18	10	60	40
D ₉₀	43	16	12	56	39
D ₉₅	32	15	8	47	31

Table 2: Values of the normalized root mean square error (NRMSE) in percentage for each type of data. The RMSE values were normalized by the mean particle size of the corresponding percentile of the control dataset and multiplied by 100.

329 3.1.2 Effects of environmental conditions

330 3.1.2.1 Effects of solar lighting conditions

Figure 4 compares the percentiles estimated by the DGS software for the same digital image in sunny and shadow conditions. An overprediction below 10% was observed before 10:00 am for sunny conditions by comparison with shadow conditions. In contrast, underprediction was observed in sunny conditions with a peak of 20% for 2:00 pm. In any light condition, coarse percentiles are less impacted than small percentiles.





338 Figure 4: Impact of the solar lighting conditions on the GSD estimated by DGS339 software.

340

3.1.2.2 Effects of the particle petrography

Figure 5.a-c shows the influence of the application of a median filter on a digital 341 image recorded in above-water conditions for a clean substrate. The filter produced 342 343 both a smoothing and a reduction in intravariability of the gray values of the pixels 344 that composed the particles, thus limiting intra-particle noise (Figure 5.b). Applying the median filter reduced the NRMSE value of the estimated percentiles by the DGS 345 346 software up to a certain threshold. Figure 6.a shows that 5% of the B-axis of the largest particle was the best compromise to minimize the estimated errors for all 347 348 percentiles. The application of this filter on the raw-clean substrate reduced the 349 estimated error percentiles by twice to four times (Table 2) and significantly reduced 350 the over-segmentation by the software (Figure 3). The NRMSE values decreased from 83% to 25%, from 72% to 29% and from 51% to 18% for the 16^{th} , 50^{th} and 84^{th} 351 352 percentiles, respectively.

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The use of a median filter increased the data processing time. As shown in Figure 6.b, the computation of the median filter increased with increasing kernel size following a power function. For example, the computation time of a digital image with a size equal to 2748*2808 pixels was processed from 7 to 95 seconds for a kernel size equal to 1% and 5% of the B-axis of the largest particle.

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360 Figure 5: Effect of applying a median filter on gray values of digital images in different conditions: (a) and (d) correspond to a digital image of clean substrate in controlled 361 362 solar lighting conditions in above-water conditions with and without the application of 363 a median filter, respectively; (b) and (e) correspond to a digital image of clean substrate in underwater conditions with and without the application of a median filter, 364 365 respectively; (c) and (f) correspond to a digital image of substrate with the presence 366 of biofilm in underwater conditions with and without the application of a median filter, respectively. The gray line in (g), (h) and (i) corresponds to the gray values of pixels 367

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extracted from the raw image, and the red line corresponds to the gray values ofpixels extracted after the application of the median filter.



Figure 6: (a) Effect of applying the median filter to the model deviation for each percentile as a function of the kernel size. Percentage values correspond to the kernel size of the median filter divided by the B-axis of the largest particle, multiplied by 100.

375 3.1.3 Effect of sampling area

376 For all percentiles, a significant negative exponential relationship (95% confidence 377 level) was found between the slope coefficient and the dimensionless sampling area 378 (sampling area divided by the largest particle area; Figure 7.a). A stabilization of the values of the slope coefficient was observed from a sampling area equal to 80 times 379 380 the area of the largest particle (Figure 7.b). The mean values of the slope decreased from 2.41 to 0.17 for dimensionless sampling areas from 20 to 80. It has been 381 observed that the slope coefficients were higher for the sediment patches 382 383 characterized by a high sediment sorting index than for sediment patches with low 384 sediment sorting for the same sampling area (Figure 7.a).





Figure 7: (a) Evolution of the slope coefficient as a function of the dimensionless sampling area and the sorting index, where black lines correspond to the relationship, and (b) boxplots of the slope values according to the dimensionless sampling area. Intervals correspond to the 25th and 75th percentiles, and the lower and upper whiskers correspond to 1.5 times the interval quartile range. Black lines correspond to the median values, and the red points correspond to the mean values.

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392 3.1.4 <u>Comparison of the estimated GSD with field pebble counts</u>

393 Figure 8.a compares the percentiles estimated by field pebble counts with the percentiles estimated by the automatic procedure of the digital images in controlled 394 395 environmental conditions (controlled solar lighting condition, application of the median filter at 5%, and sampling area greater than 80 times the largest particle). 396 397 The terrestrial photosieving method guasi-systematically underestimated the field 398 pebble-count percentiles. The bias of the terrestrial photosieving method has been 399 corrected by linear regression (Figure 8.b). The RMSE values decreased from 0.55 psi to 0.29 psi by applying the correction. The comparison of our results with other 400 401 studies using automatic procedures shows the same range of errors (Table 3).

	Approach	Form	Lighting	Range of grain	Truncations	Irreducible
Study	дриоасн	distribution	conditions	size (psi)	Huncations	error (e) (psi)
This study	Statistical approach	Pebble counts	Controlled	3.00 – 8.13	3 psi	0.29
This study	Manual approach	Pebble counts	Not controlled	3.00 - 8.13	3 psi	0.29
Sime & Ferguson, (2003)	Object-oriented approach	Pebble counts	Not specified	Not specified	3 psi	0.27
Graham et al., (2005.b)	Object-oriented approach	Pebble counts	Controlled	0.10 – 7.64	3 psi	0.18 ^(a)
Strom et al., (2010)	Object-oriented approach	Pebble counts	Not specified	2.32 – 7.60	2.32 psi	0.26

Table 3: Comparison of the performance of the procedures used in this study with those used in other published studies. All values are in psi. The irreducible error (e) of Graham et al. (2005b) was transformed to grid by number distribution. ^(a) Mean irreducible error calculated on three rivers.



407 Figure 8: Percentiles estimated by field pebble counts according to percentiles
408 estimated by the automatic procedure of digital images (a) before the bias correction
409 and (b) after the bias correction. RMSE and MAE values are in psi. The distributions
410 were truncated at 3 psi.

411 3.2 <u>Accuracy of the GSD estimation in above-water conditions by using</u> 412 <u>airborne topographic LiDAR data</u>

413 3.2.1 Rh metric and standard deviation of intensity values as proxies of the GSD

The percentiles calculated using the distribution of the standard deviation of the intensity values were higher than the threshold uncertainties for all percentiles (Figure 9.a). For the Rh metric, only the percentiles equal to or greater than the 25th were greater than the threshold uncertainties.



Figure 9: Values of percentiles estimated by (a) the standard deviation of the
intensity values and (b) the Rh metric extracted from the airborne topographic LiDAR
survey. The black line corresponds to the threshold uncertainties of the two metrics
estimated on the three control areas (see section 2.2.2).

Significant power law correlations at the 95% confidence level were found between the percentiles of the Rh metric distribution and the GSD of the field pebble counts in a range of grain sizes equal to or higher than the 25th percentile (Table 4). The strongest correlation was found for the 84th percentile with an R² coefficient equal to 0.85 (p-value=4.9e-08). Significant power law correlations at the 95% confidence level were also found between the percentiles of the distribution of the standard deviation of the intensity values and the GSD of the field pebble counts (Table 4). The strongest correlation is also found for the 84th percentile with an R² coefficient equal to 0.85 (p-value=9.6e-07) (Table 4). Figure 10.a-b shows that the relationship

between the predicted percentiles by both metrics and the estimated percentiles by the field pebble counts are close to the 1:1 line. The mean values of the RMSE and MAE of the predicted GSD were equal to 0.34 psi and 0.29 psi for the Rh metric for the 16th and 95th percentile, respectively, while for the standard deviation of the intensity values, the mean values of the RMSE and MAE were equal to 0.38 psi and 0.30 psi for the 5th and 95th percentile, respectively (Figure 10.a-b).

Rh metric					Standar	d deviati	on of intensi	ty values		
		(n=18)					(n=18)		
Percentile	Equation	R ²	p-value	RMSE	MAE	Equation	R ²	p-value	RMSE	MAE
D ₅	NE	NE	NE	NE	NE	y=2.528x ^{0.154}	0.32	0.013	0.40	0.31
D ₁₀	NE	NE	NE	NE	NE	y=2.41x ^{0.180}	0.41	0.0048	0.39	0.31
D ₁₆	NE	NE	NE	NE	NE	y=12.138x ^{0.219}	0.61	0.00035	0.32	0.28
D ₂₅	y=30.280x ^{0.345}	0.62	9.4e-05	0.36	0.30	y=1.800x ^{0.264}	0.67	0.00015	0.34	0.30
D ₅₀	y=23.994x ^{0.319}	0.69	2.2e-05	0.38	0.31	y=1.450x ^{0.318}	0.78	3.2e-05	0.32	0.26
D ₇₅	y=23.654x ^{0.341}	0.79	8.8e-07	0.34	0.28	y=1.110x ^{0.387}	0.82	2.2e-06	0.33	0.25
D ₈₄	y=29.015x ^{0.410}	0.85	4.9e-08	0.29	0.26	y=1.103x ^{0.386}	0.85	9.6e-07	0.31	0.24
D ₉₀	y=28.590x ^{0.422}	0.81	3.5e-07	0.33	0.32	y=1.096x ^{0.386}	0.83	1.9e-06	0.33	0.23
D ₉₅	y=24.781x ^{0.398}	0.84	8.0e-08	0.29	0.26	y=1.35x ^{0.338}	0.76	8.9e-06	0.36	0.28

Table 4: Statistical relationships between the percentiles of the distributions of the Rh metric and the standard deviation of the intensity values and the GSD of the field pebble counts. The RMSE and MAE metrics are in psi. NE corresponds to no estimation.



Figure 10: Predicted percentiles by (a) the Rh metric and (b) the standard deviationof the intensity values for different percentiles.

445 3.2.2 Effects of the kernel size computation

Figure 11.a shows the evolution of the R^2 coefficient of the relation between the 446 percentiles of the distribution of the Rh metric and the GSD of the field pebble counts 447 as a function of the kernel size computation of the metric. The relations were strong 448 with a mean R^2 coefficient ranging from 0.64 to 0.77 in a range of kernel sizes from 449 450 0.4 m to 1.2 m and decreased for a kernel size equal to 1.4 m (Figure 11.a). The best 451 correlation was found for a kernel size equal to 1.0 m, which corresponds to three to four times the B-axis of the largest particle. Figure 11 b shows the evolution of the R^2 452 453 coefficient of the relation between the percentiles of the distribution of the standard deviation of the intensity values and the GSD of the field pebble counts as a function 454 of the kernel size computation of the metric. A small decrease in the mean R² 455 coefficient from 0.72 to 0.62 was observed for a kernel size increasing from 0.1 to 2.0 456 m. The highest R^2 was found for a kernel size equal to 0.4 m (grain size ranging 457 between the 25th and 95th percentiles). For the percentiles ranging between the 5th 458 and 95th percentiles, R² decreases from 0.62 to 0.58 when the kernel size increases 459

460 from 0.1 to 2.0 m. No clear threshold of kernel size appears for the standard 461 deviation of the intensity, contrary to the Rh metric.



Figure 11: Impact of the kernel size used for the computation of the two proxies for (a) the Rh metric and (b) the standard deviation of the intensity values on the statistical relationships between the distribution of the metrics and the GSD of the field pebble count. Black points correspond to the mean values of R^2 from the 25th to the 95th percentiles; the gray points correspond to the mean values of R^2 for the 5th to the 95th percentiles. Error bars correspond to +/- one standard deviation.

469 3.2.3 Effect of sediment characteristics

Figure 12 compares the relation between the 84th percentile of the GSD of the field pebble counts and the 84th percentile of the Rh metric distribution found in this study with that found in the literature. The equation slopes show a large variability, indicating that multiple values of the Rh metric can be found in the same grain size range. Vázquez-Tarrío et al., (2017) found a relation close to the 1:1 line with a slope value equal to 0.79, while Woodget et al., (2017) found a very high slope equal to

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476 12.35. Our empirical relation is enclosed between these two relations with a slope477 value equal to 6.46.

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Figure 12: Relation between the 84th percentile of the field pebble-count distribution according to the 84th percentile of the distribution of the Rh metric compared with the literature results. The calibration of Woodget et al., (2017) was based on a grid count on ground digital images (0.4 m x 0.4 m), whereas Vázquez-Tarrío et al., (2017) used field pebble counts. Values of α correspond to the slope of the linear relations found between the two variables.

486 3.2.4 <u>Computation of the predicted grain size maps</u>

Figure 13 shows the predicted maps of the median grain size at the cell scale (1 m x 1 m) from the standard deviation of the intensity values (Figure 14.a) and Rh metric (Figure 14.b). The maps show similar spatial predictions of the grain size patterns with bed refinement in the downstream direction and from the thalweg to the bank direction, which are generally observed on above-water bars and in accordance with our qualitative field observations. However, the relationship obtained by the standard deviation of the intensity values shows a lower spatial variability than that obtained

with the Rh metric. Significant differences exist in the predicted 84th percentile between the two proxies with a standard deviation of the difference equal to 0.78 psi (Figure 13.c).



Figure 13: Predicted maps of the median grain size on an above-water bar by using (a) the standard deviation of the intensity values and (b) the Rh metric as a proxy. The differences in the predictions between the two proxies are given in (c). The blue and red dashed lines correspond to the mean and +/- 1 standard deviation of the differences between the two metrics, respectively.

503 3.3 Accuracy of the GSD estimation in underwater conditions by terrestrial

504 photosieving

505 3.3.1 The automatic procedure

506 The results showed that the accuracy of the GSD estimated by DGS software was 507 dependent on the type of substrate. Low values of the NRMSE were obtained for 508 clean substrate, while the NRMSE values exceeded 40% for all percentiles for 509 substrate with the presence of biofilm (Table 2). For both types of substrate, the NRMSE decreased when the percentiles increased. Low values of the NRMSE for 510 511 clean substrate are explained by low particle intravariability and high particle intervariability, whereas high NRMSE values for substrate with the presence of 512 biofilm and/or presence of deposition are due to both low particle intravariability and 513 intervariability of gray values (Figure 5). Considering sensitivity analyses, the best 514 515 kernel size for digital image computation with the presence of biofilm to significantly 516 reduce error estimations by the DGS software is equal to 2.5% of D_{max} (Figure 14, 517 Table 2). In this case, the median filter increases the intervariability between the particles (Figure 5). However, the NRMSE values are still too high to use DGS 518 519 software to estimate the GSD for substrate with biofilms (Table 2).

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527 Figure 14: Effect of the application of the median filter on the NRMSE values for each 528 percentile according to the kernel size computation. Percentages correspond to the 529 kernel size of the median filter divided by the B-axis of the largest particle multiplied 530 by 100.

531 3.3.2 Exploring manual processing of ground digital images to process all contexts

532 Manual processing was tested because the majority of the digital images collected in 533 underwater conditions were impacted by the presence of biofilm, notably due to 534 relatively low bedload mobility along the study reach. The manual method offers the 535 advantage of being less influenced by environmental conditions than the automatic 536 procedure (see section 3.1.2). Similar to the automatic procedure. an 537 underestimation of the field pebble count was observed with the manual procedure in 538 both above-water and underwater conditions (Figure 15.a). The bias was corrected 539 by a linear regression (Figure 15.c), inducing a significant reduction in the RMSE in 540 both conditions that was equivalent for both environmental recording conditions 541 (Figure 15.b-d).



Figure 15: (a) Manual procedure before the bias correction, (b) boxplots of the RMSE values before the bias correction for each environmental recording condition, (c) manual procedure after the bias correction and (d) boxplots of the RMSE values after bias correction for each environmental recording condition. Black lines correspond to the linear regression, and dashed lines correspond to the 1:1 relation. The RMSE and MAE values are in psi, and n corresponds to the number of field pebble counts.

549 4. Discussion

550 4.1 Above-water conditions

551 4.1.1 <u>Accuracy of terrestrial photosieving and airborne topographic LiDAR to</u>

552 estimate the GSD in above-water conditions

553 Our results demonstrate that both terrestrial photosieving and proxies extracted from the airborne topographic LiDAR are reliable for estimating the GSD in above-water 554 555 conditions once calibrated. Differences between the results of the two procedures suggest that terrestrial photosieving is more accurate than the Rh metric and 556 557 standard deviation of intensity values extracted from the airborne topographic LiDAR data (Table 3, Table 4). This can be explained by the fact that photosieving estimates 558 559 grain size in the plan view, which is less affected by sediment patch imbrication than three-dimensional views (Carbonneau et al., 2005; Woodget et al., 2018). 560

The automatic procedure of the digital images systematically underestimated the GSD of the field pebble counts, as also reported by Sime & Ferguson, (2003), Strom et al., (2010) and Warrick et al., (2009), but it can be corrected by simple linear regressions (Figure 8). This underestimation by photosieving is explained by burial, overlapping, foreshortening and the C-axis not being oriented perpendicularly to the plane of some particles (Graham et al., 2010). The irreducible errors found in this study are in the same range as those in other studies (Table 3).

568 Comparison between the two proxies extracted from the airborne topographic LiDAR 569 survey shows that the standard deviation of intensity seems to predict the GSD with 570 higher accuracy than does the Rh metric and allows an estimation of the low 571 percentiles of the distribution, contrary to the Rh metric. We explain this by the fact 572 that the intensity values are less affected by recording uncertainties (Table 1). The 573 comparison of our results with previous studies shows a large variability in the

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empirical relationships between the Rh metric (D₈₄) and GSD (D₈₄) for the same 574 575 range of grain sizes (Figure 12). Our empirical relation is located between the 576 relations of Woodget & Austrums, (2017) and Vázquez-Tarrío et al., (2017). Pearson 577 et al., (2017) showed that bed roughness is influenced by several parameters, 578 including the shape of particles, packing and bed imbrication of particles, and 579 distribution shape and survey errors, and can explain differences in roughness 580 values for the same range of grain sizes. Vázguez-Tarrío et al., (2017) reported that their sediment patches were composed of well-rounded and subspherical granitic 581 and metamorphic gravels and cobbles. In our case, particles were mostly flat and 582 583 imbricated, generating lower roughness values for a given GSD. Woodget & 584 Austrums, (2017) also reported that their sediment patches were mostly composed of packed and imbricated particles. As intensity values are dependent on the bed 585 586 surface roughness, it is very likely that various relationships could also be found between the standard deviation of the intensity values and the bed grain size for the 587 same range of GSD. The approach of Pearson et al., (2017) in laboratory conditions 588 with the objective of assessing the influence of the sedimentary characteristics on the 589 590 roughness - grain size relationship could also be performed in the field to try to build 591 an abacus and derive from it several universal calibration laws usable for the two 592 methods based on LiDAR data. It should be noted that this technique is limited only 593 to sections of rivers where the roughness is relatively high and higher than the 594 georeferenced error of the survey along the z-dimension.

595 Both methods have their own advantages: terrestrial photosieving allows the GSD to 596 be followed at a high temporal frequency with rapid grain size information and is 597 cheaper, whereas airborne topographic LiDAR can predict the GSD in large above-

water areas and produce grain size maps, which is crucial to surveying the grain size
evolution, notably for restorations along large rivers (Figure 13).

600 4.1.2 Toward an optimization of the two methods

601 Our study reveals that the accuracy of the automatic procedure of digital images to 602 estimate the GSD is dependent on both the environmental conditions and the 603 sampling area. The higher NRMSE values in our study compared to those published 604 by Buscombe (2013) may be explained by the petrographic variability of the particles, which induces oversegmentation due to high intravariability of the gray values of 605 606 pixels (Figure 5). However, the use of a median filter can significantly reduce the 607 oversegmentation with a decrease in the NRMSE value, close to the results of 608 Buscombe (2013). Moreover, our study shows that DGS estimations were influenced 609 by solar lighting in the majority of the cases with an underestimation using sunny 610 photographs by comparison with photographs with shadow conditions. Changes in 611 underestimation values are explained by the changes in the solar angle during a day. 612 These observations are in accordance with Warrick et al., (2009) and may be explained by the fact that bed roughness generated by the coarser particles induced 613 614 large shadow areas in low sun angles Warrick et al., (2009) and explain why low 615 percentiles were more impacted by solar conditions than were coarse percentiles. Thus, the variation in solar lighting conditions can alter the calibration step between 616 the GSD estimated by digital images and the field pebble counts. In addition, our 617 618 study reveals that sensitivity analyses must be conducted to define the minimal 619 sampling area from which the fluctuation of the DGS software becomes low to 620 minimize variability during the calibration step with the field pebble counts. For our 621 sediment patches, our study reveals that fluctuations were significantly reduced for a 622 sampling area 80 times larger than the largest particle area. This sampling area is

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dependent on the sorting index of the sampling sediment patches (Figure 7), but other parameters of the distribution shape (e.g., skewness, bimodality) can also influence the accuracy for a given surface sampling (Rice & Church, 1996).

For the airborne topographic LiDAR, our study highlights that the accuracy of the Rh metric to predict the GSD can be dependent on the kernel size computation, contrary to the standard deviation of the intensity values, which requires no presensitivity analysis and significantly reduces the processing time (Figure 11).

The best kernel size to compute the Rh metric is four times larger than Dmax, which is twice the values found by Vázquez-Tarrío et al., (2017). We hypothesize that this difference is the consequence of a lower point density in our study (38 to 49/m²) compared to that of Vázquez-Tarrío et al., (2017; 36 to 1052/m²).

Supplementary research is needed to evaluate the impact of the density of the point cloud on the reliability of the bed GSD estimation by the intensity metric. Vázquez-Tarrío et al., (2017) showed that 10 pts/m² is the minimal threshold to estimate the bed GSD by the Rh metric with accuracy for their range of sediment sizes. Research must also be conducted to evaluate the influence of the spot size of the beam, which depends both on the flight elevation and on the open angle of the captor.

640 **4.2** <u>Underwater conditions: accuracy of digital images</u>

Our results show that the automatic procedure is a reliable method to estimate the GSD for clean substrate. Contrary to above-water conditions, there is no need to apply a median filter to reduce estimation errors by the DGS software. This is explained by the absorption of solar light by the water column, which significantly reduces the variability of the gray values on the digital images, thus minimizing the oversegmentation by the DGS software. However, this method does not allow substrate with biofilms to be processed even with the application of a median filter for

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percentiles equal to and greater than the 50th percentile. An alternative approach 648 649 must be conducted to process this kind of data, as this situation is very frequent for rivers with weak bedload dynamics and/or with high wash loads. The manual 650 651 approach proposed in this paper is a reliable method to estimate the GSD of substrate with biofilms and has the advantages of requiring no preprocessing step 652 653 and is independent of environmental conditions (Figure 15). This approach can also 654 be applied in above-water conditions if photosieving was conducted in limiting environmental conditions (e.g., solar light for calibration purposes with field pebble 655 counts, local growth of small pioneer vegetation). Unfortunately, it presents a 656 657 nonnegligible operator-introduced bias during the manual B-axis determination.

658 4.3 Methodological recommendations

659 To perform data calibration from terrestrial photosieving with field pebble counts in above-water conditions, we recommend the following: 660

- (i) Collect the dataset during cloudy days as proposed by (Warrick et al., 2009; 661 Buscombe et al., 2010) and when the vegetation is not yet developed 662 663 (Graham et al., 2005b).
- (ii) Use a median filter in case of large variability in particle petrography to reduce 664 the oversegmentation by the DGS software. The best kernel size for the 665 666 median filter computation found in this study can vary as a function of the petrographic characteristics of the sediment patches studied; thus, new 667 sensitivity analyses must be conducted for studies performed on other 668 669 rivers.
- (iii) Perform sensitivity analyses to evaluate the minimal sampling area from which 670 the estimation fluctuations of the DGS software are judged to be low in 671 relation to the characteristics of sediment patches studied. 672

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To perform data calibration from the two metrics extracted from the airborne topographic LiDAR survey with the field pebble counts in above-water areas, we recommend the following:

(i) Prioritize the dataset collection in winter due to the absence of vegetation to
limit estimation errors during the computation of the two metrics and
evaluate the GSD on the largest possible area. Preferentially use the
standard deviation of the intensity values rather than the Rh metric
because the accuracy prediction of the metric is weakly dependent on the
kernel size computation of the metric and reduces processing time.

(ii) In the case when intensity values are not available, the Rh metric can be a
useful proxy, but sensitivity analyses must be performed to find the best
size of the kernel computation of the metric.

The relationships found in this study have been performed for a maximum beam size equal to 12 cm and a minimal density of points greater than 30 pts/m². Supplementary research should be conducted to evaluate the influence of these parameters on the relation between the two proxies tested in this study and the bed GSD.

690 For digital image collection in underwater conditions, we recommend the following:

(i) Perform a survey once the water turbidity is low and biofilm is not yet
developed as during low water temperature or just after critical flood
events.

(ii) Collect the data by using the video option of the camera rather than the
photographs option to limit blurred images due to the movement of the
boat, which does not allow the captor to make the adjustment and requires
less time in the field.

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We used between ten and twenty field data calibrations for the two methods used in this study deployed along several kilometers of river reach. However, the number of these survey calibrations may be higher for studies covering several tens of kilometers because the heterogeneity of the GSD may be relatively important due to various sedimentary contexts (e.g., influence of tributaries, bedload inputs, contacts with lateral hillslope), which can generate various sediment patch characteristics (Vázquez-Tarrío et al., 2017).

705 5. Conclusion

706 This study highlights the ability of terrestrial photosieving and, for the first time, the capacity of airborne topographic LiDAR surveys based on the computation of two 707 metrics, the Rh metric and the standard deviation of the intensity values, to estimate 708 709 the GSD of above-water deposits. The errors of both methods are similar with a 710 range of MAE values from 0.23 to 0.31 psi. Airborne topographic LiDAR allows the production of maps of the GSD, while rapid GSD estimations can be produced only 711 by terrestrial photosieving. The results also show that the accuracy of automatic 712 713 processing of terrestrial photosieving depends on the environmental conditions and 714 areal sampling. For both proxies derived from airborne topographic LiDAR, the 715 accuracy of the predicted GSD for the Rh metric is dependent on the size of the 716 kernel computation, contrary to the standard deviation of the intensity values. The 717 latter allows the estimation of all grain size percentiles, whereas the Rh metric allows 718 the estimation of only the grain size percentiles coarser than the 25th due to the 719 larger uncertainties of recording. The automatic procedure of terrestrial photosieving 720 is also a reliable method to estimate the GSD in underwater conditions for clean 721 substrates, but it cannot be adapted in the presence of biofilm. The manual procedure can be a relevant alternative to overcome these constraints. Thus, 722

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combining terrestrial photosieving with airborne topographic LiDAR appears a relevant compromise for surveying the GSD in large rivers, along reaches of several kilometers and over the whole channel cross section with rapid GSD data in underwater conditions and continuous GSD data in above-water conditions. In the future, one important challenge is to develop universal laws according to sediment patch characteristics for both terrestrial photosieving and airborne topographic LiDAR surveys.

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