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1 **Terrestrial structure-from-motion: spatial**
2 **error analysis of roughness and**
3 **morphology**

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24 **Abstract**

25 Structure-from-Motion (SfM) photogrammetry is rapidly becoming a key tool
26 for morphological characterisation and change detection of the earth surface.
27 This paper demonstrates the use of Terrestrial Structure-from-Motion (TSfM)
28 photogrammetry to acquire morphology and roughness data at the reach-
29 scale in an upland gravel-bed river. We quantify 1) spatially-distributed error in
30 TSfM derived Digital Elevation Models (DEMs) and 2) identify differences in
31 roughness populations acquired from TSfM photogrammetry versus TLS. We
32 identify an association between local topographic variation and error in the
33 TSfM DEM. On flatter surfaces (e.g. bar and terrace surfaces), the difference
34 between the TSfM and TLS DEMs are generally less than ± 0.1 m. However,
35 in areas of high topographic variability (>0.4 m) such as berm or terrace
36 edges, differences between the TSfM and TLS DEMs can be up to ± 1 m. Our
37 results suggest that grain roughness estimates from the TSfM point cloud
38 generate values twice those derived from the TLS point cloud on coarse berm
39 areas, and up to four-fold those derived from the TLS point cloud over finer
40 gravel bar surfaces. This finding has implications when using SfM data to
41 derive roughness metrics for hydrodynamic modelling. Despite the use of
42 standard filtering procedures, noise pertains in the SfM DEM and the time
43 required for its reduction might partially outweigh the survey efficiency using
44 SfM. Therefore, caution is needed when SfM surveys are employed for the
45 assessment of surface roughness at a reach-scale.

46

47 Keywords: Digital Elevation Model (DEM), error, roughness, SfM
48 photogrammetry, Terrestrial Laser Scanning (TLS)

49

50 **1. Introduction**

51 The last ten years have seen a step-change in our ability to capture data
52 remotely for geomorphological and hydrological applications (Entwistle et al.,
53 2018). In fluvial geomorphology, Terrestrial Laser Scanning (TLS) has
54 established itself as a key tool in the retrieval of data that allows detection of
55 morphological change at high resolution at the reach-scale (Milan et al., 2007,
56 Heritage and Milan, 2012; Wheaton et al., 2013), and in the characterisation
57 of grain-scale topographic and roughness data over dry (Heritage and Milan,
58 2009; Hodge et al., 2009; Huang and Wang, 2012), and submerged (Smith et
59 al., 2012; Miura and Asano, 2015) gravel surfaces capturing complex spatial
60 patterns and changes after floods (Milan et al., 2009).

61

62 More recently, however, Structure-from-Motion (SfM) photogrammetry has
63 emerged as a more cost-effective alternative to TLS with the ability to retrieve
64 high density point cloud data for a range of geomorphological applications
65 (Westoby et al., 2012; Fonstad et al., 2013; Smith et al., 2015; Dietrich, 2016;
66 Carrivick and Smith, 2019), with most studies employing the technique from an
67 unmanned drone (e.g. Marteau et al., 2017; Carbonneau and Dietrich, 2017;
68 Entwistle and Heritage, 2017). Photogrammetry is well established in
69 geomorphology (Lane et al., 1993; Barker, et al., 1997; Butler et al., 1998;
70 Heritage et al., 1998; Chandler, 1999; Westaway et al., 2001), as a rapid
71 survey technique that can be used to generate highly accurate grain-scale
72 DEMs (Wang et al., 2015). SfM photogrammetry utilises mathematical models
73 derived from early photogrammetry studies, including coplanarity and

74 collinearity, and self-calibrating bundle adjustment (Kenefick et al., 1972; Faig,
75 1975; Ullman, 1979). The emergence of SfM photogrammetry has also been
76 accompanied with the development of software (Snavely et al., 2006; Lague
77 et al., 2013) capable of merging large digital image datasets, and the
78 development of algorithms capable of producing dense point clouds from the
79 imagery (Buscombe, 2016). SfM photogrammetry has been shown to produce
80 reliable data for DEM production when survey design such as photo overlap,
81 camera angle, distribution of ground control points, and environmental
82 conditions is appropriate (see James and Robson, 2012 and James et al.,
83 2017a for details) or corrections are applied during processing (James and
84 Robson, 2014). Additional corrections such as for refraction at the water
85 surface even allows construction of high quality DEMs from submerged areas
86 of the bed (e.g. Woodget et al., 2015; Entwistle and Heritage, 2017; Dietrich,
87 2017). Retrieval of grain size and roughness data using SfM photogrammetry
88 is a recent further development (Langhammer et al., 2017; Woodget and
89 Austrums, 2017; Pearson et al., 2017; Woodget et al., 2018). The ability to
90 retrieve morphology data from dry and submerged parts of the bed, and grain
91 roughness information, allows for seamless surveys of the aquatic
92 environment that may not be achieved using red-wavelength LiDAR systems,
93 thus providing new opportunities for assessing spatial patterns in sediment
94 budgets at the reach-scale, and improved hydrodynamic modelling within river
95 systems.

96

97 Despite the increasing number of studies deploying SfM photogrammetry from
98 unmanned drones, the challenges that exist when using this platform have

99 received only limited attention. A number of potential issues exist (e.g. Duffy
100 et al. 2017) as follows. 1) Access to a drone and a trained operator requires
101 considerable initial cost and reliance on the availability of the drone operator.
102 2) The trained drone operator may not always be familiar with
103 geomorphological or hydrological processes, and may therefore not capture
104 the required information to the satisfaction of the geomorphologist. 3) Time
105 needs to be taken for pre-flight planning of the site (Duffy et al., 2017). 4)
106 Flights need to comply with local legislation, and permissions may not always
107 be granted to fly at certain sites, and may take considerable time before being
108 secured. It may therefore not be possible to retrieve data at short notice, as is
109 often required in fluvial and hydrological projects (e.g. during or immediately
110 after a flood event). Furthermore, drone flights are not possible at all in no-fly
111 zones. 5) Weather conditions may not be suitable for drone flights. For
112 example, it may not possible to deploy a drone during high wind speeds, yet
113 still possible to take photographs from a terrestrial platform. 6) Shadow and
114 sun angle effects caused by vegetation or coarse sediment can be
115 problematic. 7) Drone battery life may limit photograph data retrieval,
116 particularly when working in remote areas, where it may be difficult to
117 recharge batteries. As a consequence, deployment of SfM photogrammetry
118 from a terrestrial platform (TSfM) could offer a more reliable and cost-effective
119 alternative in some instances. Indeed, some sites with steep slopes and near-
120 vertical surfaces, such as river banks and landslides, might be more suitable
121 for ground-based approaches (Westoby et al., 2012).

122

123 Although SfM has made it easier for non-specialists to use photogrammetry
124 for landform measurement and change detection, this simplification has
125 resulted in the introduction of new types of measurement errors, previously
126 precluded by the strict application of camera calibration techniques and other
127 controls in classical photogrammetry. Studies quantifying SfM
128 photogrammetric errors, particularly at the reach-scale are lacking, largely due
129 to the difficulties in acquiring suitable control datasets. Assessing the
130 accuracy of SfM-derived point clouds and DEMs and appropriate error
131 analyses are fundamental to the success of the approach in geomorphological
132 change detection studies (e.g. Hugenholtz et al., 2013; Javernick et al., 2014;
133 Entwistle and Heritage, 2017; James et al., 2017a; Cook, 2017), and grain
134 size assessment (Westoby et al., 2015). Although SfM photogrammetry can
135 have geometric distortion issues (e.g. James et al., 2017a), occlusion is less
136 of an issue due to the multi-view geometry achieved thanks to the high
137 number of photograph loci. In contrast, TLS does not suffer from systematic
138 warping, although can suffer from occlusion issues, particularly when
139 insufficient scans are taken with adequate overlap. In this paper we use a
140 TLS-derived DEM as ground-truth data to assess the spatial distribution of
141 SfM photogrammetric error. This paper aims to 1) interrogate spatial error in
142 both morphology and grain roughness data, and 2) critically evaluate the
143 ability of SfM photogrammetry with a terrestrial platform (TSfM) to capture
144 morphology and roughness data.

145

146 **2. Study site**

147 This investigation focused on a 500 m reach of the Thinhope Burn, a small
148 tributary catchment to the River South Tyne situated in the north Pennines in
149 Cumbria, UK (OS National grid reference NY680550, latitude 54° 52' 48.31"
150 N, longitude 2° 31' 09.57" W, 180-595 m Above Ordnance Datum, catchment
151 area 12 km²; Fig. 1). The river here is a sinuous single thread channel,
152 displaying pool-riffle and rapid morphology, with a mean bed slope of 0.031 m
153 m⁻¹. The role of high flow events is significant in this catchment, with coarse
154 berm deposits with a typical D_{50} of 200 mm mobilised by infrequent
155 catastrophic events (Macklin et al., 1992; Milan, 2012), and finer more mobile
156 deposits ($\sim D_{50}$ 30 mm) in the annually inundated areas of the channel making
157 up the bed and point bars that are typically reworked by winter high flow
158 events. The channel at this location has a Strahler (1952) stream order of 3,
159 and drains a catchment underlain by Carboniferous sandstones, limestones,
160 and shales, overlain by glacial diamicton. In the headwaters of the catchment,
161 peat overlays the diamicton with depths of up to 2 m. The variety of grain
162 sizes and morphological units in the reach provided an excellent opportunity
163 to test the utility of TSfM photogrammetry to detect fluvial form and
164 roughness.

165

166 The morphological development of Thinhope Burn over the Holocene and the
167 more recent flood history has been reconstructed by Macklin et al. (1992),
168 where three phases of incision were identified over the late Holocene,
169 resulting in the formation of a series of terraces. Superimposed on these
170 terraces were a series of boulder berm deposits, which Macklin et al. (1992)
171 linked to 21 different large flood events occurring post 1766. In 2007, a large

172 flood event caused significant mobilisation to the valley floor, fully reworking
173 many of the old berms reported in Macklin et al. (1992), however depositing
174 new berms and reconfiguring channel morphology (Milan, 2012; Milan and
175 Schwendel 2019).

176

177 **3. Methods**

178

179 *3.1. Field based approach*

180 Smith (2015) reviewed TLS error sources, highlighting random and systematic
181 instrument errors, error relating to the imaging geometry, the nature of the
182 reflecting surface (e.g. shiny versus dull objects), environmental errors (e.g.
183 atmospheric conditions), and methodological error (including registration and
184 georeferencing errors) as possible sources. Despite this, TLS is still
185 considered to currently be the best method available for producing accurate
186 point clouds and DEMs, and has been shown to produce DEMs with
187 millimetric accuracy which have been used for morphological and boundary
188 roughness characterisation and change detection in a range of fluvial studies
189 (e.g. Milan et al., 2007; Hodge et al., 2009; Williams et al., 2014). TLS has
190 also been used to produce 'control' DEMs whereby the spatial error found in
191 other survey techniques can be quantified (e.g. Heritage et al., 2009; Nadal-
192 Romero et al., 2015). A GLS 2000 red-pulse TLS (Topcon Corporation,
193 Tokyo, Japan) was used to gather sub-aerial data for the control DEM in this
194 study. Eight overlapping scans were taken of the 500 m reach of Thinhope
195 Burn from the valley sides and high terraces, where clear unobstructed views
196 to the reach were available (Fig. 2). A series of overlapping tiepoints were

197 surveyed, allowing the scans to be merged using Scanmaster software
198 (Topcon Corporation, Tokyo, Japan). Topcon (2019) report a 'single point
199 accuracy of 3.5 mm surveyed between 1 and 150 m (1σ) away from the
200 scanner (as in this study), with a spot size of 4 mm at 20 m.

201

202 In union with the TLS survey, a total of 365 overlapping photographs were
203 taken from 55 vantage points overlooking the channel (Fig. 2), using a Lumix
204 TZ30 camera (Panasonic Corporation, Osaka, Japan). Thirty-six Ground
205 Control Points (GCPs), scattered throughout the study site (Fig. 2), were used
206 to help merge the photographs and produce a point cloud using Agisoft
207 Photoscan software (Agisoft LLC, St. Petersburg, Russian Federation).
208 Overlap between individual adjacent images was >70%, with all parts of the
209 valley floor covered from at least nine camera stations. The average distance
210 between the camera stations and the study area was 72.5 m with a total area
211 of 0.036 km² covered. Both the tiepoints for the TLS survey and the GCPs
212 were surveyed using a Leica dGPS 1200 (Leica Geosystems, Heerbrugg,
213 Switzerland), allowing both point clouds to be georeferenced into the same
214 coordinate system. The reported static accuracy of post-processed dGPS
215 data is 5 mm + 0.5 ppm for horizontal, and is 10 mm + 0.5 ppm for vertical
216 (Leica, 2008). Whilst the photogrammetric survey was carried out over a little
217 more than one hour, the scanning required a full day.

218

219 *3.2. Data analysis and processing*

220 The images taken were aligned and underwent the Scale-Invariant-Feature-
221 Transform (SIFT) algorithm using high accuracy setting in Photoscan. The

222 sparse SFM point cloud (1777170 points) was subject to removal of points
223 that did not suffice certain criteria (e.g. reprojection error) which reduced the
224 sparse cloud by 7.5%. This resulted in an *RMSE* value of all tie points on all
225 images of 1.76 pixels with an effective ground resolution of 8.93 mm per pixel,
226 and ensured every point was projected based on the overlap of more than
227 nine images. After application of the Multi-View Stereo (MVS) algorithm to the
228 sparse SFM cloud, both, the dense TSfM and the TLS point cloud, underwent
229 manual and automated low pass filtering (search radius 1 m, maximal
230 variation in elevation 2 m and angle of $<30^\circ$ between a ground class point and
231 a preliminary ground surface consisting of the lowest point in each search) in
232 order to remove outlying points below and above the actual ground surface.
233 The TSfM-derived point cloud was additionally classified by pixel colour in
234 order to identify vegetation and points scattered below the coherent layer of
235 ground surface points (i.e. the latter as identified by their grey gravel colour).
236 This resulted in a point density of 1237 m⁻² and 7322 m⁻² for the TLS and
237 TSfM clouds respectively. These clouds were subsequently reduced to the
238 valley floor and the channel area. DEMs were produced in Surfer (Golden
239 Software, Golden, USA) using triangulation with linear interpolation as the
240 interpolation algorithm (Schwendel et al., 2012), with a grid spacing of 0.1 m
241 for the entire reach and 0.05 m for separately investigated patches within the
242 reach.

243

244 It is arguable whether remote sensing approaches actually measure grain size
245 (e.g. Woodget and Austrums, 2017; Pearson et al., 2017; Woodget et al.,
246 2018), as grains on a natural river bed are imbricated, partially buried and the

247 particle edges partially obscured by neighbouring clasts. However, remote
248 sensing approaches can measure roughness height of clasts, reflecting the
249 degree of protrusion into the flow. Heritage and Milan (2009) demonstrated a
250 linear relationship between twice the standard deviation of local elevation
251 ($2\sigma_z$) and ground-truth measurements of clast c-axes, reflecting flow
252 orientation of the primary axis in the streamwise direction exposing the
253 shortest axis to the flow. We adopt this approach as a roughness measure in
254 this study.

255

256 Grain roughness grids were produced through interrogating the point cloud by
257 measuring the standard deviation of elevations in a moving window equivalent
258 to the largest clast in the area of interest (Heritage and Milan, 2009). Within
259 the entire reach the search radius was 0.8 m, while for the two selected
260 coarser grained patches (S5 and S6) the search radius was 0.6 m, and for
261 two finer-grained patches (S7 and S8) the search radius was 0.15 m. The
262 standard deviation statistic is a measure of spread within the sample
263 population, and is unaffected by sample size, thus allowing this statistic to be
264 used on point clouds with different densities, and in situations where there are
265 spatial differences in point density. However, standard deviation values
266 become more stable with increasing sample size, and as such we deployed a
267 minimum sample size of 30 points within the moving window. Populations of
268 grain roughness values for these patches were produced through both survey
269 methods, and the grain roughness populations were compared to identify
270 differences.

271

272 *3.3. Spatial error analysis*

273 Spatial variation in difference (error) between the TSfM and TLS datasets
274 were assessed by subtracting the latter from the former with the TLS surface
275 regarded as reference (Heritage et al., 2009; Nadal-Romero et al., 2015). This
276 permitted a visual assessment of the spatial patterns and magnitude of the
277 differences throughout the reach (Fig. 3a). Cross-sections from the DEM of
278 difference were also taken from a sub-reach containing several morphological
279 features including bars, berms, terraces and banks, to further visualize the
280 spatial differences in 2D.

281

282 The error inherent in DEMs for river survey datasets is known to be spatially
283 variable, and linked to local topographic variation; with greater errors found at
284 breaks of slope such as bank edges, as opposed to flatter bar surfaces
285 (Heritage and Milan, 2009; Milan et al., 2011). We adopted the Milan et al.
286 (2011) approach to characterize this effect through interrogating the
287 relationship between local surface topographic variation and the local
288 elevation difference between the two DEM surfaces. Local surface
289 topographic (morphological) variability is defined by taking the local elevation
290 standard deviation in a 0.8-m radius moving window over the point cloud, to
291 produce a standard deviation of elevations grid (Fig. 4a). Elevation errors for
292 each coordinate are established from the difference between TLS and TSfM
293 elevations (Fig. 3a) and are used to create a spatially variable Level of
294 Detection (LoD).

295

296 Greater topographic roughness values are generally found at breaks of slope
297 in both clouds, however roughness is generally below 0.6 m with the TLS
298 product having lower values (Fig. 4). Within the channel TLS derived
299 roughness is generally less than 0.2 m, and elevated values are restricted to
300 mid-channel bars throughout the reach and coarse flood-berms, particularly in
301 the lower part of the reach. The TSfM product shows roughness of up to 0.5
302 m with high values in the central part and at a riffle in the lower part of the
303 reach. Otherwise roughness of up to 0.2 m is found in similar locations than in
304 the TLS cloud but spatially more extensive.

305

306 The plot of elevation error against local surface variation (Fig. 5a), established
307 from digitising 2000 randomly distributed points from the TSfM-TLS difference
308 grid, shows that on flatter surfaces (e.g. bar and terrace surfaces) with a local
309 surface elevation variation of $<\pm 0.05$ m, the difference between the TSfM and
310 TLS DEMs is generally less than ± 0.3 m. The variability around the mean
311 error clearly increases within increasing topographic variability. In areas of
312 high topographic variability (>0.4 m) such as berm or terrace edges,
313 differences between the TSfM and TLS DEMs (error) can be up to ± 3 m.
314 Using the data in Fig. 5a, the standard deviation of elevation error was
315 established for different classes of local surface variation. The relationship
316 between standard deviation of elevation error and local surface variation
317 classes is shown in Fig. 5b. The standard deviation of elevation error shows a
318 strong power law relationship with local surface elevation variability (Fig. 5b).
319 This relationship may be used to filter spatial error after two further steps
320 (*sensu* Milan et al., 2011) are taken: 1) the regression equation (Fig. 5b) is

321 applied to the grid of local topographic variability, produced here through
322 taking the standard deviation of elevations in a 0.8-m moving window over the
323 point cloud, to generate a spatial error grid, and 2) a spatially distributed root
324 mean square error grid is produce through the application of

$$325 \quad U_{crit} = t\sqrt{(\sigma_e)^2}$$

326 to the spatial error grid, where U_{crit} is the LoD; and σ_e is the standard deviation
327 of elevation error, and t is the critical t -value at the chosen confidence level
328 here set at a value of 1.96 (2σ), in which case the confidence limit is equal to
329 95%.

330

331 **4. Results**

332

333 *4.1. Digital Elevation Models*

334 The surface of difference between the DEMs based on TSfM data and TLS
335 data (Fig. 3) shows the highest deviation near the lateral edges of the valley
336 floor and the channel as well as on the inside of some bends. Field
337 observations and photographs identify these areas as locations where the
338 channel actively erodes valley slopes and terraces, and sudden breaks in
339 slope such as channel banks and terraces edges. Actively eroding slopes and
340 terraces (marked A in Fig. 3a) are underestimated in the TSfM DEM, in
341 particular the grassy surface of slumped blocks. Similarly, actively eroding
342 banks (marked B in Fig. 3a) tend to be lower and therefore appear more
343 retreated in the TSfM dataset. Some former cut-banks, now protected by bars
344 or berm deposits (marked C in Fig. 3a), also show this pattern. In contrast,
345 banks dominated by coarse, bulldozed cobbles and boulders (marked D in

346 Fig. 3a) appear to be overestimated in elevation and less retreated in the
347 TSfM DEM. This also applies to currently inactive coarse bar deposits such as
348 the berms marked E in Fig. 3a. The maximum vertical deviation between the
349 DEMs is up to 4 m. Fig. 3b demonstrates how the majority of error has been
350 removed following the filtering procedure; based upon the relationship
351 between elevation error (difference between TSfM and TLS DEMs) and
352 topographic variability (local morphological roughness). Most of the
353 differences evaluated here are within the topography-dependant LoD and that
354 genuine differences between the two DEMs are within ± 1 m. Within the
355 channel the deviations are variable, usually within a range of 0.1 m around 0,
356 except for a coarse substrate area showing substantial underestimation of the
357 TSfM DEM in the centre of the reach (marked F in Fig. 3a). Open water
358 surfaces are represented generally lower in the TSfM DEM. Homogeneous
359 gravel bars (marked G in Fig. 3a) appear to show the least deviation between
360 the two DEMs.

361

362 The long-profile for the lower part of the study reach (Fig. 6) shows a more
363 'noisy' profile for the TSfM data compared with the TLS DEM, particularly at
364 riffles. Cross-section A–A' traverses a series of flood berms and a point bar
365 and ends at a slumping hillslope. The strongest deviations between the two
366 DEMs occur in the North on vegetated berms but there appears to also be a
367 systematic shift to the South West of the TSfM DEM which is also apparent in
368 Section C–C' (Fig. 6). Section B–B' is located between two terraces and
369 shows the highest deviation at the terrace edges and in an area with coarse
370 flood deposits to the East of the current channel. Section C–C' shows

371 considerable underestimation of the surface elevation by the TSfM DEM in an
372 area dominated by a riffle. In addition, the partially vegetated surface of a
373 terrace in the SW and a boulder berm show much higher variability for this
374 DEM. Section D–D' traverses the channel from the slumping valley side, over
375 a relatively smooth point-bar onto a terrace. Despite the vegetation on the
376 latter, here both DEMs are largely in good agreement. However, in this
377 section and others, the angle of nearly vertical slopes subject to erosion
378 appears to be greater in the TLS DEM compared to the TSfM product. Slopes
379 extracted from the TSfM product appear to be more retreated and have less
380 steep slopes at A', B' and D while the opposite, more stable, side may show a
381 steeper slope (e.g. at B).

382

383 *4.2. Roughness comparison*

384 Accurate measurement of boundary roughness is needed as input to
385 hydrodynamic modelling, and techniques such as TLS and TSfM now allow
386 fully spatially distributed roughness information to be included in flow
387 simulations. Here we explore the difference in roughness characterisation
388 using the two techniques. Grain roughness populations were investigated at
389 four patches representative of different morphological units. Patch S5 (Fig. 7),
390 a boulder berm, shows similar spatial distribution of roughness in the southern
391 half between both DEMs, while in the northern part there are three distinct
392 zones with elevated roughness in the TSfM DEM. Patch S6 covers a boulder
393 berm deposited in 2007 (Fig. 8). The measured roughness is of similar
394 magnitude in both DEMs (Table 1) with two zones of elevated roughness
395 present in the TSfM DEM (a North-East edge and a North–South aligned

396 ridge) that are not shown in the TLS product. The differences between the two
397 DEMs are shown as a shift of the maximum frequency to higher roughness
398 and a bimodal distribution for the SFM product which account for these zones
399 (Fig. 9, Table 1).

400

401 The two fine-grained patches S7 and S8 differ in their roughness
402 measurement between the two approaches (Figs. 10 and 11). The TLS DEM
403 is much smoother than the TSfM DEM and the spatial distribution of
404 roughness does not match. The TSfM DEMs show more variability in
405 roughness which is reflected in their relatively wide frequency distribution (Fig.
406 9). In contrast, the roughness range of the TLS DEMs is rather narrow and
407 centred at considerably lower roughness compared to the TSfM DEM (Table
408 1).

409

410 **5. Discussion**

411

412 The differences between DEMs generated from TSfM photogrammetry and
413 TLS are spatially variable and showed an association with local topographic
414 variability. Substantial DEM differences were restricted to small areas
415 following error filtering. While the degree of vegetation appears to be
416 important, a clear attribution of these differences to specific morphological
417 units was not evident. The channel and most bars show little detectable
418 difference which reflects the quality of the DEMs in areas of little topographic
419 variability. Even in the wet channel, differences of more than a few
420 centimetres were only detected in areas where their magnitude and their

421 incongruence with geomorphological units (riffle) suggest outlying points that
422 escaped the filtering process of the TSfM point cloud (F in Fig. 3a). The level
423 of detection in the channel was rather low due to it being derived from a
424 comparison with the TLS dataset which shows very little topographic variation
425 within the channel (Fig. 4) and contains patches of water, detected as very
426 smooth surfaces (Fig. 6). Therefore, the general minor differences between
427 the two DEMs are remarkable given the difficulties introduced by the
428 differential penetration of water surfaces, reflection and refraction (Woodget et
429 al., 2015). The different representation of water surfaces, also evident in some
430 parts of the long-profile (Fig. 6), can be attributed to the reconstruction of
431 some sub-aqueous surfaces with the TSfM approach while red laser
432 wavelengths are absorbed in water (Cook, 2017). A detailed assessment of
433 the suitability of the two techniques for measurement of topography and
434 roughness in sub-merged areas is beyond the scope of this paper, and ideally
435 these would have been excluded from the analysis. While manually blanking
436 patches of water surface in the DEMs could address this issue, in shallow
437 gravel-bed reaches of this size this is very time consuming and can be
438 impractical. Because the true-colour TSfM pixel might not allow distinction
439 between shallow submerged channel and dry channel, the use of the intensity
440 of laser signal returns to detect the water edge might be preferable (Flener et
441 al., 2013). However, in this instance differences between the DEMs at
442 patches of water were of small magnitude not exceeding the level of
443 detection, hence light penetration issues in the submerged areas appear to
444 have not significantly reduced DEM accuracy.

445

446 In contrast to the channel, more elevated bars and berms, terraces and
447 actively eroding slopes coupled to the channel showed in places substantial
448 differences of up to 1 m between the two DEMs (Fig. 3). Locations affected
449 can be separated in two categories: areas affected by vegetation and breaks
450 in slopes. Foliage of vegetation can lead to differential penetration of light and
451 therefore will affect surveys utilising light waves (Heritage and Hetherington,
452 2007; Cook, 2017). This study suggests that vegetation was a cause of
453 difference between the datasets as well as topographic variability, however
454 we are unable to quantify this in the present investigation. Although the area
455 of interest of this study largely consists of unvegetated river channel, bars and
456 banks, some of the stable floodplain and terraces were covered in short
457 herbaceous vegetation. The filters applied to the point clouds eliminated high
458 points but were unable to exclude gradual transition from a bare surface to
459 low vegetation (Cook, 2017; James et al., 2017a). Although vegetated
460 surfaces will always be problematic for TSfM and TLS surveys (Lane, 2000;
461 Castillo et al., 2012; Tonkin et al., 2014; Cook, 2017), fresh deposition of
462 sediment between vegetation or the gradual encroachment of plants on bars
463 mean that the presence of vegetation in peripheral areas cannot always be
464 excluded in geomorphological studies.

465

466 The greatest elevation differences between the two DEMs are located at
467 breaks in slope such as eroding terrace edges, valley slopes and banks but
468 they exceed the spatially variable level of genuine detection based on the
469 local topographic variation only in a small number of places (Fig 3). The
470 reason for significant elevation differences can be found in different

471 representation of slope angles: actively eroding slopes appear steeper in the
472 TLS DEM, while stable breaks in slope are often shown as steeper in the
473 TSfM DEM (Fig. 3). Deviations at steep slopes and near vertical surfaces are
474 a common problem, particularly in aerial photogrammetry (Lague et al., 2013;
475 Carbonneau and Dietrich, 2017; Cook, 2017; Huang et al., 2017). Since the
476 slopes in the two DEMs have common toe points, these deviations are not
477 likely due to a uni-directional relative shift in DEM position, for example due to
478 GCP precision, or tilt but rather a result of distortion during the SfM-multi-
479 view stereo process (Fonstad et al., 2013; James et al., 2017a). Smoothing of
480 breaks in slopes and misrepresentation of slope angles in SfM DEMs, e.g. as
481 reported by Kolzenburg et al. (2016), can be attributed to filtering processes
482 during image matching (James and Robson, 2017b). This study used a
483 variety of camera positions and camera angles from the terrestrial vantage
484 points to minimise this problem. The slopes with considerable differences are
485 distributed throughout the DEM thus localised distortion or issues with
486 individual images or GCPs can be excluded. Conversely, steep slopes facing
487 up-valley or down-valley and thus captured from both valley sides are equally
488 affected as slopes mostly captured only from one valley side. James et al.
489 (2017b) found systematic differences between SfM and TLS DEMs along
490 steep slopes which indicate horizontal error in the relative georeferencing of
491 the DEMs, and indicate that cloud-to-cloud comparison in combination with
492 photogrammetric precision estimates can to some extent account for this
493 error. If image capture or processing issues can be ruled out, the different
494 representation of slope shape could potentially also be related to

495 characteristics of actively eroding slopes such as roughness and colour which
496 may be relevant during the SFM image matching process.

497

498 As for the entire DEM, within the channel, the variation between the two
499 DEMs appears to increase with topographic variation. Although DEM
500 accuracy generally tends to show this tendency (e.g. Milan et al., 2011, Cook,
501 2017 but not Kolzenburg et al., 2016), the steepness of the regression line
502 (Fig. 5b) suggests that the TSfM DEM differs not only at the discussed,
503 significant breaks in slopes, but generally in areas with high topographic
504 roughness.

505

506 By using twice the standard deviation of elevation values within a moving
507 window equivalent to the largest clast, Heritage and Milan (2009) were able to
508 show how dense point clouds may be used to provide bar-scale grain
509 roughness information, and showed relationships between the roughness and
510 grain size. Due to the purely comparative nature of this study, only one
511 standard deviation is reported here. The measured roughness over the entire
512 reach compounds types of roughness at a range of scales from skin (surface)
513 roughness of large boulders, over grain roughness, to vegetation and bedform
514 roughness. Gravel-cobble bar surfaces such as patches 7 and 8 (Figs. 10 and
515 11) provide the opportunity to compare the assessment of grain roughness
516 based on the two datasets. The ratio of respective percentiles of roughness
517 height is up to four with barely any similarity between the spatial distribution of
518 roughness. Although both sets of frequency distributions (Fig. 9) retain their
519 single-modal shape, there is a distinct shift in modal values and spread.

520 James and Robson (2017b) suggest that the representation of small
521 roughness elements can be affected by filtering and smoothing processes
522 during the image matching process (Hirschmuller, 2008). At the coarser
523 patches S5 and S6 (Figs. 7 and 8), the difference between the roughness
524 representation between the two DEMs is smaller, i.e., there is some
525 agreement in spatial distribution of roughness elements. Both patches
526 encompass boulder berms deposited in the 2007 flood (Milan, 2012). Patch
527 S5 was deposited on the inside of a bend, and its roughness has been
528 affected since then by gradual covering in finer sediment and partially
529 stripping of the latter by smaller floods. Its mean roughness height derived
530 from the TLS and TSfM datasets of respectively 228 mm and 452 mm
531 substantially exceed the mean b-axis length of a visually very similar berm
532 situated nearby that has been reworked in 2007 (130 mm, berm 2 in Milan,
533 2012). Given that roughness height is better correlated with the smaller c-axis
534 length (Heritage and Milan, 2009) and standard deviation of elevation may be
535 much lower than measured particle size (Brasington et al., 2012), this shows
536 a considerable potential overestimation of measured roughness despite the
537 fine sediment cover. Since 2007 patch S6 has been subject to in-channel
538 reworking (Milan and Schwendel, 2019) of fines and thus has developed a
539 bimodal grain size distribution which is shown by both survey methods (Fig.
540 9). For both coarse patches, the mean roughness height of the SFM dataset
541 is approximately twice that of the TLS DEM with a remarkable consistency
542 between percentiles (Table 1) and their frequency distributions are of similar
543 character, e.g., are comparable after a simple exponential transformation.
544 This shows that the representation of grain roughness scales with grain size,

545 although it remains unclear to which extent the differences are due to
546 systematic smoothing within the TSfM process or may be attributed to higher
547 random noise in the TSfM point cloud (Cook, 2017) as evident in the
548 roughness frequency distributions (Fig. 9).

549

550 Over the entire valley floor, both surveys agreed in identifying highest
551 roughness at areas of vegetation, at breaks in slope and coarse boulder
552 berms (Fig. 5). While in the first two locations, the values are an artefact of the
553 interrogation method or due to differential penetration of the vegetation cover
554 (Lane, 2000; Castillo et al., 2012; Tonkin et al., 2014), in the latter location
555 they may represent actual grain roughness. The gradual nature of
556 encroachment of vegetation onto bare surfaces as well as sediment deposited
557 on top of vegetation provides difficulties for the exclusion of vegetation from
558 the analysis. Investigation focussing on morphometric changes also cannot
559 neglect these marginal sites.

560

561 **6. Conclusions**

562

563 The comparison channel DEMs derived from interpolated point clouds based
564 on TSfM and TLS surveys showed that on smooth gravel bars and terrace
565 surfaces, the vertical difference does not exceed 0.3 m which reduces to 0.1
566 m after a threshold of genuine change detection is applied. Here the surface
567 roughness, assessed as the standard deviation of local elevation, is
568 considerably higher in the TSfM DEM compared with the TLS DEM
569 suggesting that removal of random noise by filtering remains a key issue in

570 order to make full use of the survey efficiency of the technique. Caution
571 should be exercised when using TSfM point clouds to provide roughness data
572 for hydrodynamic modelling; perhaps through field calibration. In areas of
573 higher relief such as breaks in slopes, roughness estimates vary most
574 between the two approaches and differences between the DEMs can
575 approach 1 m on terrace edges or slips on the valley sides. In these areas
576 inaccuracies introduced by differential penetration of vegetation play a role as
577 well, and might be of higher relative magnitude than noise. This is supported
578 by the similarities in the roughness frequency distributions in coarse grained
579 patches. The representation of near vertical surfaces varies between the two
580 DEMs, in particular at the upper edge which could be improved by the use of
581 direct comparison of point clouds. This research highlights that in fluvial
582 landscapes, where spatial heterogeneity of relief, surface material and
583 roughness is high, finding suitable filtering processes for point clouds is
584 challenging. Despite using a range of point cloud filtering processes and high-
585 quality settings in the analysis software, the TSfM dataset does not achieve
586 comparable results to the TLS DEM in key areas of the reach. Thus, for the
587 accurate assessment of surface roughness on a reach-scale the higher
588 surveying time using the TLS technique might be in part offset by shorter data
589 processing time.

590

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823

824

825 Figure captions

826

827 Fig. 1. The South Tyne catchment (dashed line shows its divide) in the North
828 Pennines with the River South Tyne and its major tributaries (thick line) and
829 smaller tributaries (thin lines). The location of the study reach is shown by a
830 point within the Thinhope Burn sub-catchment (shaded rectangle). The inset
831 on the right indicates the location of the catchment within the boundaries of
832 the UK.

833

834 Fig. 2. DEM of the studied reach with position of TLS stations (open circles),
835 camera positions (filled circles), ground control points for TSfM (open
836 squares) and the location of the patches P5 to P8. The full 500 m long study
837 reach is highlighted by the boundary line.

838

839 Fig. 3. DEM of difference (SfM – TLS) of the study reach at Thinhope Burn.
840 (a) For highlighting the raw differences without a Level of Detection (LoD) and
841 (b) with a spatially variable LoD applied. Grey areas indicate no difference.
842 The annotated letters are referred to in the text. Coordinates are given in
843 British National Grid (units are metres).

844

845 Fig. 4. Surface topographic roughness height (in metres) derived from the a)
846 TLS and b) SfM dense point clouds by assessing the standard deviation of
847 local topographic elevation within a 0.8 m search radius. Coordinates are
848 given in British National Grid (units are metres).

849

850 Fig. 5. Error assessment between the TLS and TSfM DEMs based on 2000
851 randomly selected points, (a) differences between the two DEMs versus local
852 surface elevation within a 0.8 m radius, and (b) standard deviation of the
853 difference between the DEMs plotted against local topographic variability.

854

855 Fig. 6. Transverse and longitudinal channel cross-sections of the TLS and
856 TSfM DEMs.

857

858 Fig. 7. Surface roughness (in metres) of the TLS and TSfM DEMs as one
859 standard deviation of local topographic variability using a search radius of 0.6
860 m at patch S5 (location within the study reach given in Fig. 2), a boulder berm
861 deposited in 2007 as illustrated in the inset photograph. Coordinates are given
862 in British National Grid (units are metres).

863

864 Fig. 8. Surface roughness (in metres) of the TLS and TSfM DEMs as one
865 standard deviation of local topographic variability using a search radius of 0.6
866 m at patch S6 (location within the study reach given in Fig. 2), a boulder berm
867 deposited in 2007 as illustrated in the inset photograph. Coordinates are given
868 in British National Grid (units are metres).

869

870 Fig. 9. Frequency distributions of roughness height derived from the TLS and
871 TSfM DEMs at the patches S5 to S8.

872

873 Fig. 10. Surface roughness (in metres) of the TLS and TSfM DEMs as one
874 standard deviation of local topographic variability using a search radius of

875 0.15 m at patch S7 (location within the study reach given in Fig. 2), a lateral
876 gravel bar as illustrated in the inset photograph. Coordinates are given in
877 British National Grid (units are metres).

878

879 Fig. 11. Surface roughness (in metres) of the TLS and TSfM DEMs as one
880 standard deviation of local topographic variability using a search radius of
881 0.15 m at patch S8 (location within the study reach given in Fig. 2), a gravel
882 bar as illustrated in the inset photograph. Coordinates are given in British
883 National Grid (units are metres).

884

885

886

887

888 Table 1. Percentiles of a grain roughness measure (in cm) derived from the
889 standard deviation of elevation within two coarse-grained patches (S5 and S6)
890 and two fine-grained patches (S7 and S8) at Thinhope Burn.

| | Patch S5 | | Patch S6 | | Patch S7 | | Patch S8 | |
|-----------------------------|-----------------|------|-----------------|------|-----------------|-----|-----------------|-----|
| | TSfM | TLS | TSfM | TLS | TSfM | TLS | TSfM | TLS |
| 25 th percentile | 16.0 | 8.3 | 14.5 | 9.4 | 5.8 | 1.1 | 5.2 | 1.7 |
| 50 th percentile | 22.6 | 11.4 | 22.7 | 11.7 | 7.4 | 1.6 | 6.5 | 2.0 |
| 75 th percentile | 30.3 | 16.1 | 30.2 | 16.2 | 10.8 | 2.0 | 7.5 | 2.3 |
| 99 th percentile | 57.4 | 29.8 | 52.5 | 34.0 | 22.8 | 4.2 | 10.7 | 3.8 |

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