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Journal:	*Earth Surface Processes and Landforms*
Manuscript ID	Draft
Wiley - Manuscript type:	Letters to ESEX
Date Submitted by the Author:	n/a
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Keywords:	drone, river, grain size, structure from motion photogrammetry, gimbal

Drones for fluvial grain size measurement?

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Abstract

Fluvial grain size plays a fundamental role in determining the condition and availability of aquatic habitats. Remote sensing provides rapid and objective methods of quantifying fluvial grain size, and typically provide coarse grain size outputs (c. 1m) at the catchment scale (up to 80km channel lengths) or fine resolution outputs (c. 1mm) at the patch scale (c. 1m^2). Recently, drone based approaches have started to fill the gap between these scales, providing hyperspatial resolution data (<10cm) over reaches up to a few hundred metres in length. This 'mesoscale' is of importance to habitat assessments and is aligned with the ideals of the 'Riverscape' concept. Most drone based grain size measurement approaches use textural variables computed from drone orthoimagery. To date however, no published works provide quantitative evidence of the success of this approach, despite significant differences in platform stability and the image quality obtained by manned aircraft versus drones. With interest in drone surveys growing rapidly, such error quantification is essential for making reliable, evidence-based recommendations about the suitability of drones for routine management of fluvial environments. Here we provide an initial assessment of the accuracy and precision of grain size estimates produced using two different drone-based methods; (1) the image textural variable ‘negative entropy’, and; (2) the roughness of point clouds derived from drone imagery processed using structure from motion photogrammetry. Data is collected from a small gravel-bed river in Cumbria, UK. Results from jack knife analyses show that the point cloud roughness method gives more accurate and precise measures of grain size at this site, as indicated by the mean (0.0002m) and standard deviation (0.0184m) of residual errors. However, both methods struggle to provide grain size measures with sub-centimetre precision. We suggest that blur within the drone imagery prevents better precision, resulting from an inadequate camera gimbal.

Introduction

The mapping and quantification of fluvial grain (or substrate) size is important in the study of fluvial process, within both science and management. Grain size data are a key input to hydraulic models, and are essential for quantifying sediment entrainment, transfer and deposition. Our understanding of the interaction between channel substrate and near-bed flow hydraulics relies on mapped grain size distributions. Furthermore, the heterogeneity of bed material is an important determinant of fluvial habitat availability, especially for spawning fish and benthic macroinvertebrates (Wise and Molles, 1979; Keeley and Slaney, 1996; Evans and Norris, 1997). The European Union’s Water Framework Directive (European Commission, 2000) recognises the importance of grain size in governing habitat quality. Such data is required to help predict the ability of fluvial organisms to adapt to extremes in flow level, which may result from regulated flow regimes, dam constructions, hydro-peaking operations and changes in climate and weather patterns (Goodwin et al., 2006; Habit et al., 2007; Garcia et al., 2011).

Traditional approaches to grain size mapping typically use visual classification schemes such as the Wentworth Scale (Wentworth, 1922; Table 1). Users of this classification include the UK's River Habitat Survey (Environment Agency 2003) and the 'Physical Habitat Simulation System' (PHABSIM) devised by the United States Fish and Wildlife Service but now used more widely (e.g. Centre for Ecology and Hydrology, 2001). Quantitative methods usually involve in-situ or laboratory based physical measurement of individual grains, including areal, grid, transect or volumetric sampling (Wolman, 1954; Hey and Thorne, 1983; Church et al., 1987; Rice and Church, 1996). Data collection of this type is never spatially continuous, only sometimes spatially referenced, and rarely covers large spatial areas with great detail. Furthermore, traditional approaches can be labour-intensive, time consuming and often make assumptions about the representativeness of the spatially discontinuous samples over larger areas (Leopold, 1970; Verdú et al., 2005). The finer grain material is often under-sampled by a grid-by-number approach (Wolman, 1954; Church et al., 1987) and the removal of samples for volumetric analyses in the laboratory can destroy the local patches of habitat that they are aiming to investigate (e.g. freeze coring; Milan, 1996).

Since the 1970s, alternative methods of grain size quantification have made use of remote sensing technologies, fuelled by the need for less subjective approaches, which are non-invasive, reduce the time and effort spent in the field or laboratory and provide more continuous spatial coverage at a range of scales (Table 2). Ongoing advances in digital photogrammetry, digital image analysis and surveying technologies mean that there is now an evolving body of remote sensing research for grain size quantification, an overview of which is provided in Table 2. These studies evidence the common trade-off between resolution (i.e. level of detail) and coverage (i.e. extent of survey) which often afflicts remote sensing methods. No single technique has yet proved its value for the rapid quantification of grain size at the mesoscale; that is, with centimetric spatial resolution over channel lengths from c. 50m to a few hundred metres. Yet such outputs would be of great value for contributing to scientific understanding of mesohabitats and their applied management (Frissell et al., 1986; Newson and Newson, 2000).

In recent years, dramatic development in the technology and applicability of drones has provided an alternative approach for quantifying fluvial grain size. Drones are sometimes known as 'unmanned aerial systems' (UAS), 'unmanned aerial vehicles' (UAVs) or 'remotely piloted aircraft systems' (RPAS). Within this letter, we focus on the use of small (< 7kg) drones which are often used in conjunction with novel 'structure from motion' digital photogrammetry (henceforth 'SfM') to derive fully orthorectified and georeferenced aerial imagery and topographic data. Readers are referred to Smith et al., (2015) and Eltner et al., (2016) for further detail on these developments.

To date, very few published studies have applied drones and SfM for quantifying fluvial grain size specifically. Those who have made progress in this area have adapted the image texture methods of Carbonneau et al., (2004) used originally on imagery acquired from manned aircraft. For instance, Tamminga et al., (2015) acquired 5cm resolution imagery from a small, rotary-winged drone over a 1km stretch of the Elbow River in Canada. Imagery was processed using digital photogrammetry software EnsoMOSAIC (MosaicMill Ltd, Finland) to create an orthophoto. Image texture, in the form of standard deviation of spectral values, was computed from this imagery, using a 1m^2 moving window. Grain size calibration data were acquired using close-range photo-sieving for 30 small sample plots (1m^2), where the B axes of 50 clasts were measured automatically using a Matlab routine. The resulting relationship between image texture and grain size gave a strong empirical correlation (R^2 = 0.82), which was subsequently used to estimate grain size over the entire area of interest. Whilst the drone imagery itself was of hyperspatial resolution (5cm), the nature of their approach means that Tamminga et al., (2015) were only able to produce grain size predictions at a much coarser 1m spatial resolution. Furthermore, they present no associated quantitative error assessment of their predictions.

A similar approach was taken by de Haas et al., (2014) as part of a study exploring the evolution of alluvial fan surfaces. Drone imagery was collected at a resolution of 4-6cm and processed using SfM and the texture approach of Carbonneau et al., (2012) to produce grain size outputs at 0.7m resolution of an area covering 0.745km^2. Relative motion blur was found to affect drone image quality, and was attributed to a combination of cloudy conditions (which reduced light levels and therefore necessitated increased exposure times) and wind gusts. Blurred parts of the resulting orthophoto artificially reduced image texture outputs and adversely affected the calibration with grain size. As a result, such areas were excluded from the calibration. Validation of the model using independent grain size data is not presented by de Haas et al., (2014) which again prohibits an understanding of the accuracy of this texture approach and limits any real comparison against existing techniques.

These papers highlight a need for robust and quantitative testing of grain size estimations produced using drones and SfM. In addition, the development and evaluation of alternative approaches which are less affected by spectral issues may be of value. For example, 3D point cloud analysis methods developed for grain size estimation using terrestrial laser scanner data (e.g. Heritage and Milan, 2009; Brasington et al., 2012) may be applicable to drone imagery, as dense point clouds are one of the outputs from SfM. Westoby et al., (2015) applied a drone and SfM derived point cloud roughness approach to grain size quantification of an Antarctic moraine, but were unable to obtain a strong calibration relationship (R^2 = 0.225) between the standard deviation of elevation (i.e. roughness) and patch-scale D_{50} measures (i.e. grain size). They report a mean grain size estimation error of -2.90mm based on only five validation points, and do not report the precision of their results. Woodget et al., (2016) provide an initial pilot study in a fluvial setting, where point cloud roughness data were successfully used for grain size prediction (R^2 = 0.7712, mean error = -0.01mm, precision = 16.4mm). We build on these results within this letter, using different and more comprehensive ground validation data. Our aim is to provide a quantitative assessment of the accuracy and precision of grain size predictions made using (a) an image texture approach and (b) a point cloud roughness approach, based on imagery acquired using a small drone and processed using SfM.

Site location

We selected a c.120m long reach of Coledale Beck, a gravel-bed river located in Cumbria for this research. The chosen reach comprises a meandering pool-riffle system, with a bed composed predominantly of cobbles and boulders. The channel features a number of large unvegetated point bars and opposing steep, undercut banks. Variable grain sizes and a safe and accessible location for drone flying made this a suitable site. Furthermore, the sediment dynamics of Coledale Beck are of interest due to their downstream impacts on Bassenthwaite Lake. The lake is designated as a National Nature Reserve and a Site of Special Scientific Interest, partly due to its rare vendace (*Coregonus vandesius*) fish population. The spawning grounds of this species are particularly sensitive to changes in the quantity and quality of sediment within the lake. Increasing siltation of the lake is thought to be partially responsible for the significant decline and subsequent extinction of the vendace population (Orr and Brown, 2004). As a result, methods capable of mapping and monitoring the evolution of sediment distribution within inflowing streams hold potential for habitat evaluation and informing management strategies.

Data acquisition and processing

Site set-up

Prior to data collection at Coledale, we established four permanent markers at the outer extents of the area of interest, using wooden stakes and circular survey markers. All subsequent data collected using a Leica Builder 500 total station (expected accuracy c. 1.5mm) were referenced to these markers using an arbitrary local co-ordinate system.

Drone survey

We flew a Draganflyer X6 rotary-winged drone over the site at an altitude of c. 30m above ground level. Flight control was entirely manual due to the lack of an autopilot function. The drone was mounted with a small, consumer grade digital camera (Panasonic Lumix DMC-LX3) held in a 1-axis brushless gimbal. The survey was conducted in July 2013 during dry, bright and calm weather conditions. We distributed 25 ground control points (GCPs) prior to the drone survey, ensuring they were positioned to represent adequately the variation in topography across the site. The GCPs were constructed from thin, black PVC sheeting, marked in a cross pattern with white paint and, once positioned, were surveyed using the total station relative to the local co-ordinate system (using the permanent markers). The relatively short battery life on the drone (c. 6 minutes) meant that three flights were required to cover the site with sufficient redundancy for subsequent processing using SfM. We acquired a total of 88 images from the drone, of which we discarded 24 due to blurring or unsuitable coverage.

Structure from motion digital photogrammetry

We imported the remaining 64 images into Agisoft's PhotoScan Professional digital photogrammetry software, and processed them to create a c. 1cm resolution orthophoto, a c. 2cm resolution digital elevation model (DEM), and dense 3D point cloud, all referenced to the local co-ordinate system using the GCPs and permanent markers. For further detail on the SfM process, readers are referred to Fonstad et al., (2013), Smith et al., (2015) and Eltner et al., (2016).

Ground truth data

For ground truthing purposes, we established 23 grain size sample plots along four exposed bars at Coledale Beck (Figure 1). Each plot measured 40cm x 40cm. This plot size was sufficiently large as to encompass the largest clasts within the field site, but sufficiently small to ensure substrate size was as uniform as possible within the plot itself. For each plot, a scaled, close-range photograph (e.g. Figure 1c) was acquired using a handheld camera. These photographs were then georeferenced in GIS to the site coordinate system, using a total station survey of each plot's four corners. Within these plots, a sample of clasts were selected for measurement using a 5cm x 5cm regular grid. Clasts falling beneath each grid node had their A- and B-axis dimensions measured from the scaled photograph, unless they were deemed unsuitable for measurement. Unsuitable clasts were those which were too small to measure at a scale of 1:1, those which were largely obscured by other clasts, and those which were not included fully within the photograph. Based on these data, we computed grain size statistics for each plot, including the mean, D_{50} (grain size of the 50th percentile, or the median) and the D_{84} (grain size of the 84th percentile).

Data analysis

Image texture

We used the technique developed by Carbonneau et al., (2004) to compute image texture from the orthophoto output. This empirical approach aims to establish a statistical correlation between a given measure of image texture and grain size. We computed image texture using a Matlab (Mathworks Inc.) routine on the red band of the imagery (this is an arbitrary choice and the method would also work on other bands). A square moving window with a kernel size of 41 pixels was passed over the image at intervals of five pixels (the routine requires a kernel size of an uneven number). A kernel size of 41 pixels is roughly equivalent to a kernel width of 41cm and was selected based on *a priori* knowledge that maximum clast sizes at Coledale Beck rarely exceed 40cm. We chose the interval size of five pixels as a compromise between detail and processing time. As a result, texture outputs are produced at 5cm resolution, but this could be altered as necessary. Within each kernel step, a measure of image texture is calculated and assigned to the central pixel. Image texture can be measured using a number of different metrics; in this case, we calculated the 'negative image entropy'. This is a measure of image texture calculated using a grey level co-occurrence matrix (GLCM), i.e. a grey-tone spatial dependence probability distribution matrix first advocated by Haralick et al., (1973). The matrix provides the probabilities of all pairwise (*i, j*) combinations of pixel grey levels occurring within the specified moving window. The outputs are a function of the angular relationship between a single pixel and its neighbours (*V*), and the distance between them (the inter-pixel sampling distance, *D*). We chose to use negative image entropy to compute image texture based on the work of Carbonneau et al., (2004), however other measures are available and should be explored in future. Negative image entropy provides a measure of randomness or the disorder of pixel values and is calculated according to Equation 1;

$$Negative\ Entropy = \sum_{i,j} P_{i,j}\,(-\log P_{i,j})$$

Equation 1

(after Haralick 1979)

Where *P* is the co-occurrence matrix of the image within each step of the moving window, based on the number of times that cells with grey levels *i* and *j* occur in two pixels separated by set distance *D* and direction *V*, divided by the total number of pixel pairs. The output is a map of negative image entropy, where higher values are returned for more textured or heterogeneous parts of the image and lower values for smoother or more homogeneous areas (Figure 2a). This image texture map was then imported into GIS to permit statistical comparison with the ground-truthing sample plots using linear regression.

Point cloud roughness

We exported the dense point cloud of the Coledale site from PhotoScan Pro (Agisoft LLC) to the open source CloudCompare software (www.danielgm.net/cc/), and assessed the need for detrending, filtering and smoothing of the cloud. Detrending was found to be unnecessary but filtering and smoothing were required to reduce noise within the cloud. This noise can introduce roughness to the point cloud which does not result directly from grain size and therefore must be removed. A filtering and smoothing procedure was written in-house. We filtered the cloud by taking the mean of the interquartile range in elevation within 6mm x 6mm cells and smoothed the cloud by averaging elevation values within a 2.5cm radius moving window. We performed a visual sensitivity check on the filtering cell size and smoothing window size, to ensure that sufficient noise was removed whilst preserving as much of the topographic detail within the cloud as possible.

Next we used CloudCompare's inbuilt roughness tool to compute roughness values for each point in the smoothed and filtered cloud. Roughness is defined as the distance between each point in the cloud and the least squares best fitting plane computed on its nearest neighbours within a spherical kernel of a specified size.

Roughness was computed for a kernel radius size of 20cm, again based on *a priori* knowledge of typical grain sizes at Coledale Beck. Lastly, we rasterised roughness outputs at 3cm resolution (Figure 2b), exported them to ArcGIS and computed roughness statistics on a plot by plot basis for subsequent linear regression against the ground truth data.

Jack knife analysis

Linear regressions of image texture and roughness with grain size for each of our sample plots provide calibration relationships for predicting grain size over the wider area of interest. Validation is also required to assess the accuracy and precision of grain size estimates. We validated our calibration relationships using a jack knife approach (Quenouille 1949, Tukey 1958), an iterative method which excludes one ground truth plot at a time, and uses the linear regression equation based on the remaining plots to predict grain size for the excluded plot. We compared the measured grain size for each plot to the equivalent predicted grain size, to assess the strength of the predictive relationship. Measured grain sizes were also subtracted from the predicted grain sizes on a plot by plot basis to obtain residual error values. The average and standard deviation of the residuals for all plots are taken to represent the overall accuracy and precision of grain size estimates.

Results

Calibration and validation relationships for grain size predictions using image texture and roughness approaches are presented in Table 3 and Figures 3-4. We found that maximum negative entropy and average roughness values correlated against D_{84} of the B axes produced the strongest calibration relationships (Table 3). Our results demonstrate that for this site, the point cloud roughness approach to grain size estimation gives both stronger calibration and validation relationships, as indicated by the slope and R^2 values. Furthermore, grain sizes predicted using the roughness method are almost two orders of magnitude more accurate than those predicted using the image texture method, as indicated by the mean of residual errors. Precision, represented by the standard deviation of residual errors, is greater than 1cm for both approaches.

Discussion

Within this paper we have, for the first time, quantified the accuracy and reliability of an image texture and a point cloud roughness approach to grain size quantification using drone imagery and digital photogrammetry. The high resolution, quantitative, objective, spatially continuous, spatially explicit results are easily computed and have potential to aid our understanding of sediment dynamics and habitat heterogeneity at the mesoscale within a riverscape style framework (Fausch et al., 2002). However, our results raise three important and interlinked questions;

(1) Why does our image texture approach not produce calibration relationships of similar strength to those reported by others (de Haas et al., 2014, Tamminga et al., 2015)?

Weak calibration and validation relationships between image texture and grain size, and poor residual errors, will occur when image texture is influenced by factors other than grain size. These factors might include the use of blurred imagery, the effects of local topographic shadowing, the presence of vegetation or water, and notable variations in grain colour (i.e. lithology). Relative motion blur, a consequence of (a) increased exposure times resulting from cloudy conditions and (b) wind gusts, are noted by de Haas et al., (2014) as a significant problem in predicting grain sizes using image texture. They note that quantitative correction of relative motion blur could not be conducted because their fixed-wing drone was not equipped with the accelerometers necessary to provide correction data. The specification of the gimbal used is not presented by de Haas et al., (2014), however, given the age of the drone model they use, we anticipate a gimbal which is rather more rudimentary than the 3-axis stabilisation mounts often available today. As a result, the approach of de Haas et al., (2014) is to side-step the issue by excluding any blurred sections of the orthophoto from further analysis, to achieve strong calibrations with grain size (R^2 = 0.82). However, such manual interventions can be time consuming and may result in inadequate site coverage or necessitate extra field time. Furthermore, the issue of image blurring remains unaddressed. Tamminga et al., (2015) find that shadows also disrupt calibration relationships by introducing high texture values in areas of pronounced topographic relief and vegetation, which in turn result in erroneously high grain size predictions. However, the 3-axis stabilised gimbal used on their Aeryon Scout drone helps to reduce image blur, permitting another strong calibration with grain size (R^2 = 0.82). In this paper, we use a basic 1-axis camera gimbal on our drone, which was flown in calm wind conditions. Whilst efforts were made to remove blurred images before photogrammetric processing, areas of blurring are evident on the resulting orthophoto which is then used to develop the empirical calibration with grain size. Alongside the minor influence of vegetation presence and minor variations in grain colour within some of the ground truth plots, we expect that this gimbal is the main reason for the poorer calibration with grain size than reported elsewhere. However, further dedicated testing is required to prove this, and subsequently to reduce the incidence of blurring or improve our ability to detect and eliminate it from images. Some initial work on blur detection and removal is provided by Sieberth et al., 2013 and Sieberth et al., 2016. Future work might also explore the use of texture metrics other than negative entropy for improving a calibration with grain size.

(2) Why does our point cloud roughness approach perform so much better than our image texture approach (Table 3)?

Our point cloud roughness method was conceived out of a need to move away from the adverse effects of blurred drone imagery. Given that exactly the same drone imagery is used as input for both texture and roughness approaches though, we might expect the roughness approach to be adversely affected by blur too. The SfM-photogrammetry process computes indirect measures of elevations using drone image parallax, to create a point cloud. Thus where image quality is poor (e.g. due to blurring) or lacking in texture (e.g. spectrally homogeneous areas) then greater amounts of noise (i.e. erroneous point matches) are likely to be observed. More generally, we would expect other factors to influence the point cloud roughness-grain size relationship, including;

- Presence of vegetation – where topographic variation in the point cloud is not a result of variation in grain size.
- Interstitial spaces between large clasts which are occupied by smaller clasts - where topographic variation is high within the extent of the kernel but grain size is low.

- Complex levels of topographic variation over short distances – where features such as footprints introduce variation which does not result from grain size and cannot be removed easily by detrending.
- Packing and imbrication of clasts – where partially buried clasts do not produce the same topographic signature as exposed clasts of equivalent size, a well-known issue for a number of grain size quantification methods (e.g. Church et al., 1987; Sime and Ferguson, 2003; Heritage and Milan, 2009; Picco et al., 2013).

Despite these complicating factors, we are still able to predict grain sizes with exceptionally low mean residual errors (<1mm). We suggest that it is only by implementing the smoothing and filtering procedures described earlier that this has been possible. We also note that the standard deviation of residual errors is much higher (>1cm), indicating a lack of precision and reliability of our roughness grain size predictions, which probably results from point cloud noise. As a result, further systematic research is required to improve precision, regardless of such low mean errors.

(3) Which remote sensing approach is "best" for quantifying fluvial grain size?

The accuracy and precision of our results for a point cloud roughness method indicates that they are roughly in line with or better than other remote sensing approaches for grain size quantification (Table 2), including other drone based approaches (e.g. Westoby et al., 2015). The spatial resolution of our outputs is also finer than those approaches with similar mean accuracy levels (Table 2). However, we note that the slope of the observed versus predicted relationship for point cloud roughness (0.7752, Figure 4) is lower than those reported by Carbonneau et al.,

(2004) and Carbonneau et al., (2005b) for the use of an image texture approach of imagery acquired from a manned aircraft (Table 2). Again, we anticipate platform stability and image clarity to be responsible for this difference. Ultimately, the choice of the "best" method for quantifying fluvial substrate size will be determined by the specific requirements of a given application, including the required scale, spatial coverage, accuracy, precision, data acquisition and processing times and costs. At present, our point cloud roughness approach is best suited to studies requiring coverage of up to c. 1km channel length with spatial resolutions of a few centimetres. However, with rapid and on-going developments in drone, gimbal, sensor and software technology as well as associated processing algorithms, we anticipate that covering larger areas with greater detail and at lower costs will only become more practicable with time.

Future work

Future research should aim to reduce the impact of image blur on both image texture and point cloud roughness approaches. For example, we intend to compare the results obtained using different camera gimbals and conduct sensitivity analysis to determine the most appropriate kernel sizes for calculating image texture and point cloud roughness. Further consideration of scale and quantification of the range of grain sizes which can be predicted accurately and reliably is also of importance. For instance, the use of the 2.5cm radius smoothing kernel means that reliable prediction of grain sizes smaller than 5cm is compromised at present. A reduction of image blur should reduce point cloud noise and thereby permit a smaller smoothing kernel size to be used and enable prediction of smaller grain sizes. Such enhanced research is necessary to help us fully understand the potential for upscaling and transferability of this method to different fluvial settings and other environments, including submerged areas.

Conclusion

Within this letter we have provided an initial quantitative assessment of two approaches to fluvial grain size measurement using drone imagery processed with SfM digital photogrammetry. We flew a rotary-winged drone over a gravel bed river in the English Lake District and processed the resultant imagery into an orthophoto, DEM and point cloud. An empirical relationship was developed between validation grain size data and grain sizes predicted using (a) an image texture approach on the orthophotos and (b) a roughness approach on the point cloud. Our error assessment reveals poor calibration and validation results for the texture approach, as well as poor accuracy and precision of grain size estimates. We suspect this is due to blurred imagery caused by an inadequate camera gimbal. Point cloud roughness is much better correlated with grain size and produces much lower mean errors. Whilst smoothing and filtering of the point cloud has permitted very accurate grain size estimations on a plot by plot basis, precision is weaker, highlighting the need for improvements to the reliability of this roughness method. The use of either technique requires careful consideration of potential error sources and, crucially, the effects of any degradation in image clarity. With further work, these methods have potential to be of value to a range of river habitat research and management applications. Direct measurements of surface roughness using the point cloud may also provide input to applications beyond habitat assessment, including studies of flow resistance and hydraulic modelling.

Acknowledgments

We are very grateful to Patrice Carbonneau for the image texture processing, to Fleur Visser, Richard Johnson, James Atkins, Andy Skellern, Jeff Warburton, Carl Greenman and Milo Creasey for field assistance, and to the landowners for permitting us access to the site. This research was funded by the University of Worcester (PhD studentship for Amy Woodget) and a student research award from the Geological Remote Sensing Group, a special interest group of The Geological Society of London and the Remote Sensing and Photogrammetry Society.

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Table 1. The Wentworth Scale of particle size definitions (after Wentworth, 1922).

Size range		Wentworth Class
Phi (φ)	Metric (mm)	
<-8	>256	Boulder
-6 to -8	64-256	Cobble
-5 to -6	32-64	Very coarse gravel
-4 to -5	16-32	Coarse gravel
-3 to -4	8-16	Medium gravel
-2 to -3	4-8	Fine gravel
-1 to -2	2-4	Very fine gravel
0 to -1	1-2	Very coarse sand
1 to 0	0.5-1	Coarse sand
2 to 1	0.25-0.5	Medium sand
3 to 2	0.125-0.25	Fine sand
4 to 3	0.0625-0.125	Very fine sand
8 to 4	0.0039-0.0625	Silt
>8	<0.0039	Clay

Table 2. An overview of remote sensing methods for quantifying fluvial grain sizes.

Method	Theory	Extent	Typical Resolution	Typical Accuracy	Typical Precision	Slope (Obs v. Pred)	Limitations	References
Close-range photo-sieving	Manual or automated analyses of photos acquired from tripod-mounted cameras to measure individual grains	Patch level (microscale)	< 1cm	<0.25 phi	?	?	Under- and over-estimations of grain sizes reported by different papers	Adams, 1979; Ibbeken and Schleyer, 1986; Butler et al., 2001; Sime and Ferguson, 2003; Graham et al., 2005a; Graham et al., 2005b
Statistical image analysis	Decomposition of the 2D spectral signatures of images to quantify grain sizes	Patch level (microscale)	<1mm	<3mm	?	?	Extensive site-specific look-up data typically required	Rubin, 2004; Buscombe, 2008; Buscombe and Masselink, 2009; Buscombe et al., 2010; Buscombe 2013
Image textural analysis	Computed image textural variables are correlated with field measures from small patches	Reach to catchment level	c. 1m	3-8mm	13.9-29mm	1.03-1.23	Labour intensive and time consuming collection of field data required for calibration purposes	Carbonneau et al., 2004; Carbonneau et al., 2005a; Carbonneau et al., 2005b; Verdú et al., 2005
Terrestrial laser	Variations of roughness	Patch (microscal	c. 5cm	c. 1mm	2.34cm	0.5261	Requires significant field	Entwistle and Fuller, 2009;

scanning	(standard deviation) in laser-derived point clouds to estimate grain sizes	e) to reach level					and processing efforts to cover large areas (including de-trending)	Heritage and Milan, 2009; Hodge et al., 2009; Brasington et al., 2012; Milan and Heritage, 2012; Rychov et al., 2012

Table 3. Comparison of calibration, validation and residual errors between the image texture and point cloud roughness approaches to grain size quantification.

		Image texture	Point cloud roughness
Calibration	R^2	0.2987	0.7983
	Slope	0.0006	12.347
	Intercept	-0.3479	-0.0028
Validation	R^2	0.1601	0.7551
	Slope	0.2051	0.7752
	Intercept	0.0605	0.0121
Residual errors	Mean (m)	0.0186	0.0002
	Standard deviation (m)	0.0343	0.0184

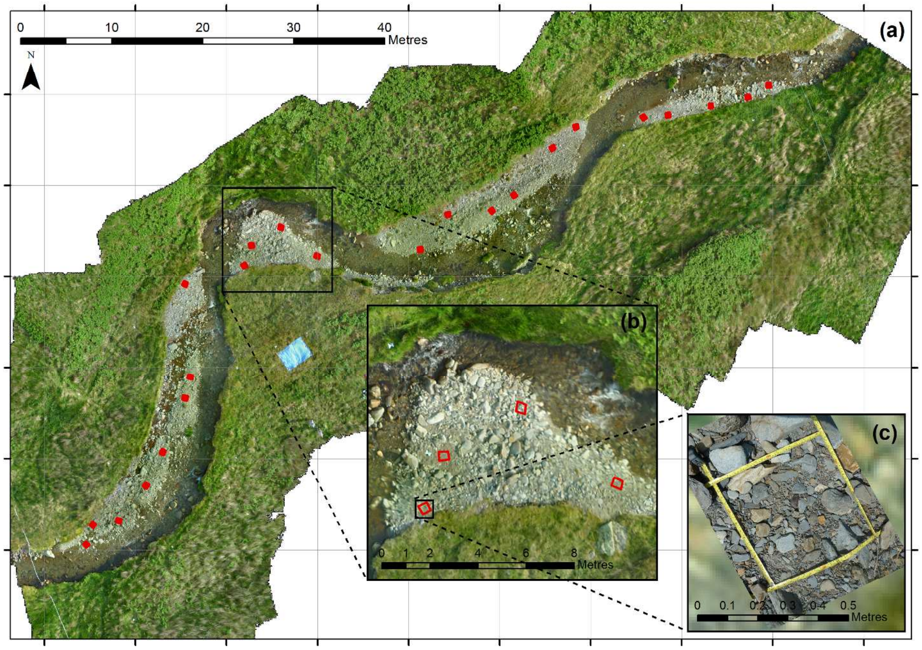

Figure 1. (a) Location of the ground truth validation plots at Coledale Beck, shown over the orthophotos, with close-up views shown in inset maps (b) and (c). Close-range georeferenced photo example for one of the ground truth sample plots is given in (c).

296x210mm (300 x 300 DPI)

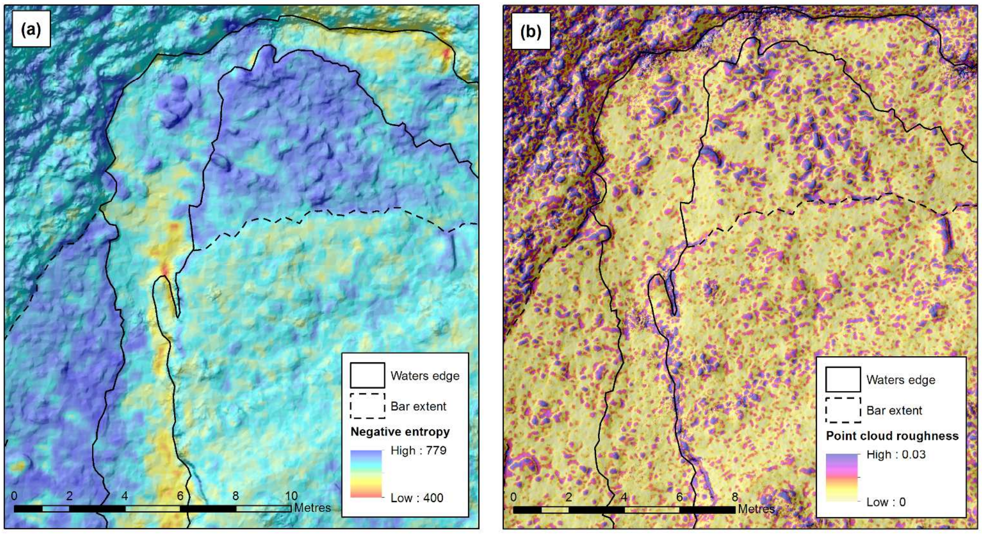

Figure 2. Examples outputs of (a) negative image entropy and (b) point cloud roughness for a subsection of the Coledale Beck site.

289x161mm (300 x 300 DPI)

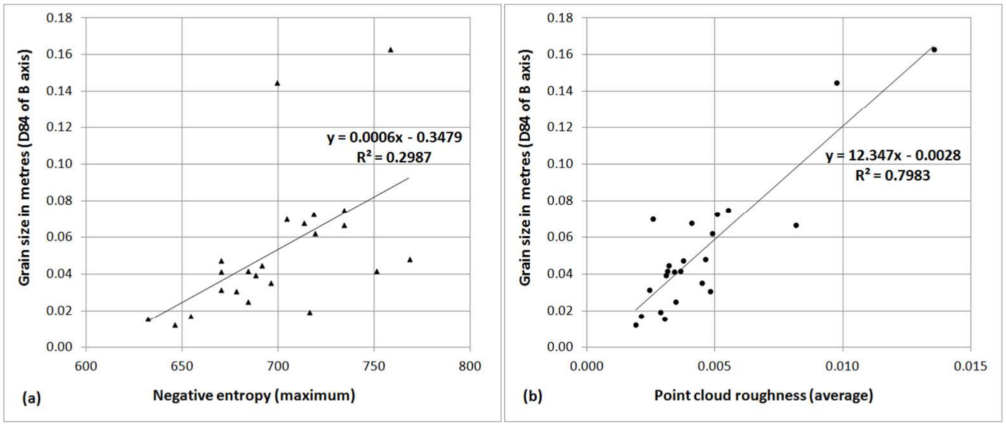

Figure 3. Calibration relationships between (a) negative image entropy (texture) and (b) point cloud roughness, with grain size.

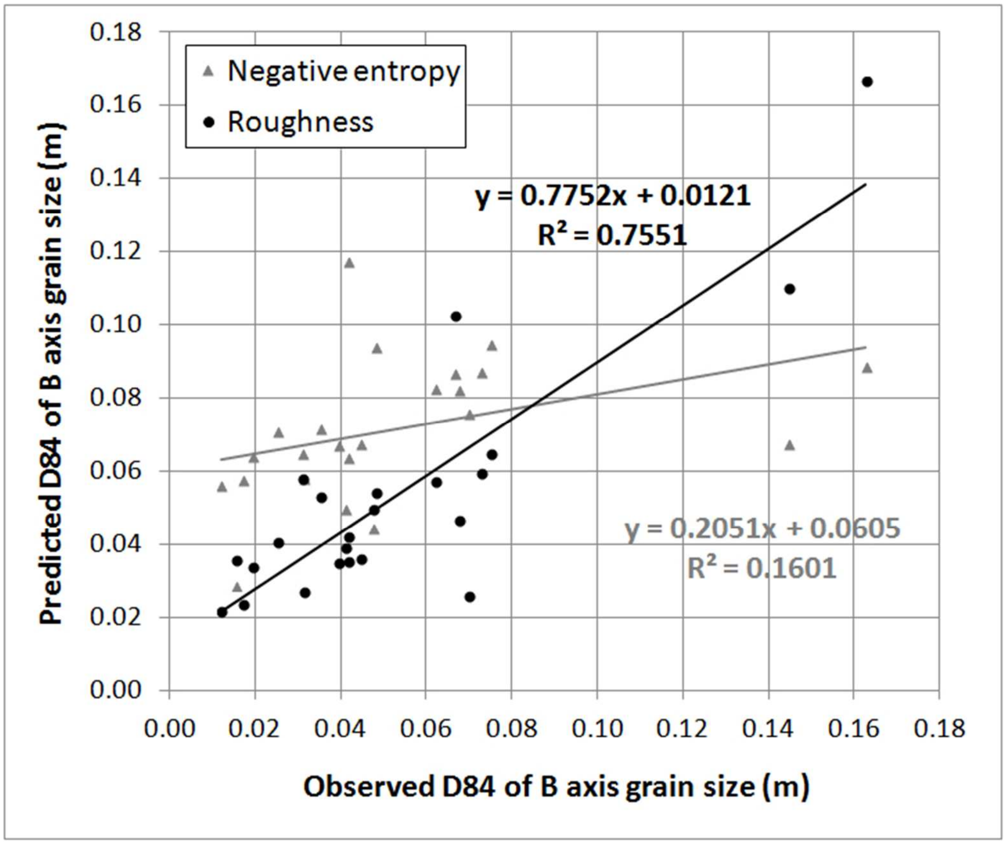

Figure 4. Grain size predicted from negative image entropy and point cloud roughness methods, versus observed grain size (D84 of B axes). N = 23, $p < 0.01$ for both regressions.