Focus Article

Drones and digital photogrammetry: from classifications to continuums for monitoring river habitat and hydromorphology

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Recently, we have gained the opportunity to obtain very high-resolution imagery and topographic data of rivers using drones and novel digital photogrammetric processing techniques. The high-resolution outputs from this method are unprecedented, and provide the opportunity to move beyond river habitat classification systems, and work directly with spatially explicit continuums of data. Traditionally, classification systems have formed the backbone of physical river habitat monitoring for their ease of use, rapidity, cost efficiency, and direct comparability. Yet such classifications fail to characterize the detailed heterogeneity of habitat, especially those features which are small or marginal. Drones and digital photogrammetry now provide an alternative approach for monitoring river habitat and hydromorphology, which we review here using two case studies. First, we demonstrate the classification of river habitat using drone imagery acquired in 2012 of a 120 m section of the San Pedro River in Chile, which was at the technological limits of what could be achieved at that time. Second, we review how continuums of data can be acquired, using drone imagery acquired in 2016 from the River Teme in Herefordshire, England. We investigate the precision and accuracy of these data continuums, highlight key current challenges, and review current best practices of data collection, processing, and management. We encourage further quantitative testing and field applications. If current difficulties can be overcome, these continuums of geomorphic and hydraulic information hold great potential for providing new opportunities for understanding river systems to the benefit of both river science and management. © 2017 The Authors. *WIREs Water* published by Wiley Periodicals, Inc.

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INTRODUCTION

Monitoring the spatial and temporal variation in physical river parameters is important for understanding and improving habitat quality and distribution, especially with respect to the potential impacts of climate change.[1–3] Remote sensing based methods have long played a role in surveying and

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monitoring physical river habitat and hydromorphology.[4,5] A growing body of literature demonstrates the use of digital photogrammetry[6,7] and spectral-depth correlations[8–10] for quantifying fluvial topography and flow depth, the computation of image textural variables and roughness of terrestrial laser scanner point clouds for quantifying fluvial substrate size,[11–15] and the use of multispectral imagery for mapping hydrogeomorphic units.[16] These developments have made important contributions to our abilities to map and measure physical river habitat parameters. However, few of these approaches are capable of quantifying a number of physical habitat parameters simultaneously (e.g., topography, water depth, substrate size, and hydraulic variables) using a single dataset at the spatial resolutions most appropriate for habitat evaluation.

Recent developments in the capabilities and availability of drones [otherwise known as small unmanned aerial systems (sUAS), unmanned aerial vehicles (UAVs), or remotely piloted aircraft systems (RPAS)], alongside parallel advances in digital photogrammetry mean that a relatively new, alternative approach for the remote sensing of rivers is now possible. Interest in drones for image acquisition and associated structure-from-motion (SfM) digital photogrammetric image processing has seen a dramatic expansion over the last few years, within both academic and commercial spheres. Web of Science returns only eight articles featuring the words 'UAV' and 'river' (topic field) between 1950 and 2010, a figure which increases almost eightfold for the period 2011 to present (search conducted September 9, 2016). Published studies suggest that this novel approach is capable of rapid, flexible, bespoke data acquisition, which is relatively inexpensive and capable of exceptionally high spatial resolutions.[17,18] As such, the combined use of drones and digital photogrammetry has been heralded as the route to democratization of data acquisition within the geosciences, and in this capacity might enable the quantification of physical river habitat parameters at the mesoscale.

Within this article, we review the importance of monitoring physical river habitat before describing the key elements of the drone and SfM-based photogrammetry method. We present two case studies to demonstrate the contributions made using drones and SfM in fluvial settings to date. The first represents an early example for replicating traditional habitat classification schemes, which was conducted with a view to characterize habitat rapidly in response to planned channel engineering works on a large river in Chile. The second case study provides a more recent example of the continuums of physical habitat data which were obtained using the drone-SfM method on a highly mobile lowland river in the UK, as informed by best practice at the time of writing. Here, we also provide an assessment of data accuracy and precision. We consider how technological and methodological developments might permit us to move away from classification schemes and toward these data continuums for monitoring and mapping physical habitat in a way which has the potential to precipitate a fundamental shift in our understanding of river science and our management of river systems.

The Importance of Physical River Habitat Monitoring

River systems form important habitats for a range of fauna and flora. To monitor and assess habitat quality, we often collect data on the water quality and energy budget, as well as the physical conditions of the river i.e., the geomorphology and hydrology or 'hydromorphology.'[19–21] These river habitat parameters vary in space and in time with changes in underlying geology and tectonics, climate and weather patterns and as a result of anthropogenic modifications, including channel engineering works (i.e., modification to the geomorphology) and/or regulation of river discharge (i.e., modification to the hydrology). Such alterations modify the basic physical template of rivers and therefore modify the quality and availability of fluvial habitat.[1,21,22] Monitoring this spatial and temporal variation in physical river parameters is important therefore for understanding and improving habitat quality and distribution, especially in light of the potential impacts of climate change.[1–3] Physical habitat monitoring within rivers forms a key aspect of the European Union's Water Framework Directive and a variety of other applications within both science and management, including river restoration works, fisheries development, and environmental flow assessments.[19,23,24]

The methods by which we retrieve physical habitat information vary widely and are often influenced by our prevailing conceptualization of the river as a system. The 'river continuum concept' (RCC) advocates a smoothly changing river system in which the physical environment and its inhabitant biota vary gradually and predictably downstream.[25] Acceptance of this concept has permitted broad scale mapping or quantification of physical habitat parameters at discrete sampling locations, and the subsequent assumption that interpolation between these locations provides an adequate representation of the spatial distribution of physical conditions within the system.[4]

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Alternatively, Ref 26 proposed a spatially nested, hierarchical classification framework for organizing our understanding of the spatial and temporal variation within river systems (Figure 1). This framework allows for greater spatial heterogeneity within river systems than the RCC, and its hierarchical structure facilitates integration of different data types at different resolutions, assisting scientists and managers to choose the level most applicable to their work.[26] More recently, some of these established theories have been questioned,[4,27,28] by those who argue that '… established research and management concepts often fail to fully recognise the crucial roles played by habitat heterogeneity…' (Ref 27, p. 36). Instead, a 'riverscape' type approach has been proposed, which shifts our understanding of rivers from gradually changing longitudinal elements to those characterized by high levels of spatial and temporal diversity. Such a change in our conceptualization of rivers precipitates a need for different ways in which physical habitat can be measured and classified. Broad scale mapping and discrete point or transect sampling are no longer sufficient for characterizing the detailed spatial structure of fluvial habitat heterogeneity.[21]

Ref 4 suggests that a riverscape approach should involve characterization of physical habitat in a spatially continuous (rather than sampling points or lines) and spatially explicit way (i.e., fully georeferenced to absolute or relative co-ordinate systems), to allow precise quantification of physical habitat variables and improve our understanding of the size, distribution, and connectivity of different habitat types.[20] Such an approach should facilitate the integration of multiple spatial datasets, consider spatial scale and context, enable the establishment of baseline conditions, and provide an opportunity for exploring temporal variability within physical habitat parameters, which is currently rarely considered. Ref 29 (p. 199) argues that 'Real contributions from research to sustainable management of river systems… need to match a sophistication of concepts with a direct practicality (without which applications are unlikely).' Thus, an ideal approach for quantifying physical habitat parameters should also be practical, logistically feasible, cost effective as well as objective and repeatable. The challenges associated with an approach which can fulfill all these criteria are not to be underestimated, but it is suggested that studies at the mesohabitat scale have potential '…to act as a fulcrum between scientific detail and applied universality' (Ref 29, p. 199). We typically define the mesoscale as the active channel width, and channel lengths, which are small multiples of channel width.[29] Studies over these extents comprise both meso- and microscale features and typically require data of 'hyperspatial' resolutions (<0.1 m).

Drones (UAVs, UAS, and RPAS)

In recent years, image acquisition from small drones has been demonstrated to provide hyperspatial resolution datasets covering relatively small areas (tens of thousands of square meters). While historically, drones had been used predominantly for military

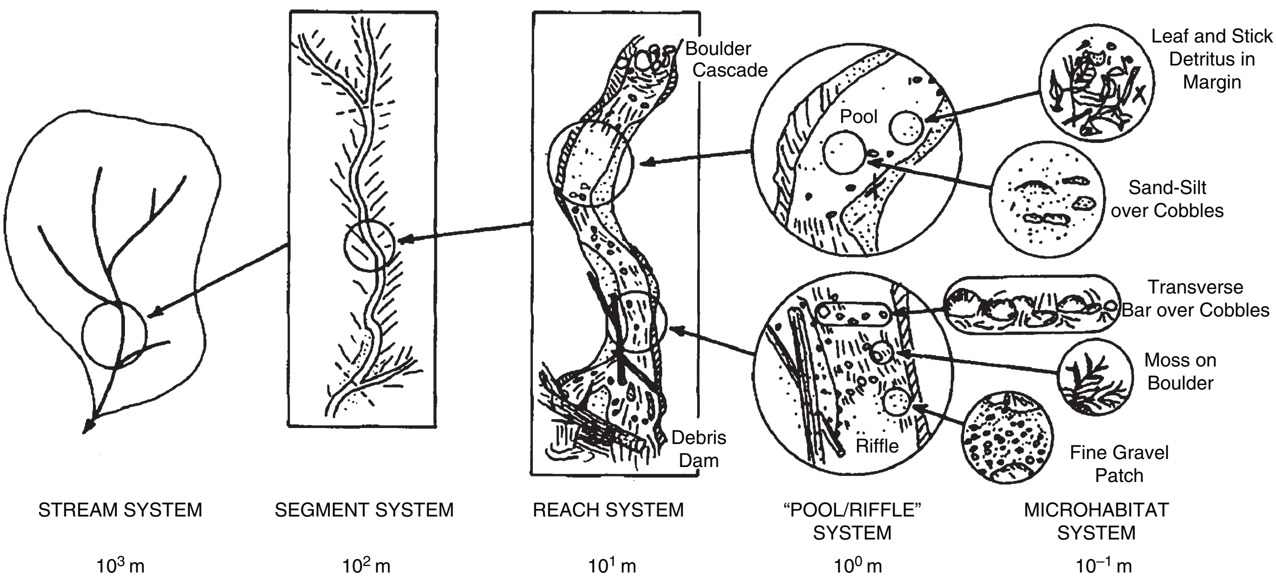

FIGURE 1 | Hierarchical organization of a stream system and its habitat subsystems .Approximate linear scale, appropriate to second- or third-order mountain stream, is indicated.[26] Environmental Management, Vol. 10, 1986, p. 199-214, Frissell et al., ((c) Springer-Verlag New York Inc.) With permission of Springer.

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reconnaissance and target acquisition,[30,31] since the 1990s new application opportunities have opened up within civilian research and the commercial sector. This has included application in fields such as archeology,[32] landslide and hazard mapping,[33] mapping of glacial landforms,[34] monitoring of crops and vegetation,[35–38] geomorphological mapping,[39] and in river science.[17,18,40]

A drone system usually consists of an aircraft platform mounted with one or more sensors combined with a ground-based control station from where it is operated. The sensor typically comprises an inexpensive, nonmetric, consumer-grade digital camera, from which small format, overlapping images are acquired for photogrammetric purposes. However, an increasing variety of drone-mountable sensing systems, including miniaturized laser scanners and multispectral cameras, are now becoming available.[41] Drone platforms themselves are classified into fixed- and rotary-winged systems and by weight and endurance capabilities.[31,42] These classifications vary between countries, but are important in determining the legal regulations for flying and data acquisition for both commercial and research purposes. The market provision of drones for civilian applications is expanding very rapidly, as is platform and sensor technology. Consequently, drones and the reviews which describe them quickly become out-of-date. Within this review, we consider primarily the use of RGB imagery collected from small drones (less than 20 kg).

Digital Photogrammetry (Structure-from-Motion)

In parallel with the rapid development of drones for civilian research, advances in computer vision and image analysis have led to an increased availability of software packages offering image processing chains capable of producing both orthophotos and rasterized digital elevation models (DEMs) from drone imagery. SfM provides an automated method for modeling the relative 3D geometry of a scene by image matching a series of overlapping 2D images, which may then be georeferenced to map co-ordinates.

In contrast to traditional photogrammetry, SfM algorithms allow the reconstruction of the 3D scene without prior knowledge of camera positions or the use of ground control points (GCPs),[43–46] although the latter are usually required for scaling and georeferencing. The process is multistage, starting with the identification of common features across sets of photographs that are overlapping and convergent (i.e., which show the same subject from different angles). The 'scale invariant feature transform' function developed by Ref 47 is one of the image matching algorithms frequently used as part of the SfM process and is a powerful method capable of recognizing conjugate (matching) points in overlapping images, regardless of changes in image scale, view angle, or orientation.[46,48] This is performed using patterns of image brightness and color gradients (i.e., variations in image texture) which can be identified at various different scales. The kernel- or area-based approaches used in traditional photogrammetry require constant image resolution and the acquisition of imagery at nadir, which can be significantly more difficult to obtain using drones than manned aircraft.[44,46,48] As a result, the SfM photogrammetric process, which actually provides optimal results using imagery which has been acquired off-nadir, convergent and from multiple altitudes,[49,50] represents a dramatic step forward for processing drone imagery. Recent research suggests that even smartphone imagery can be used successfully within an SfM workflow.[51]

Following the identification of prominent matching points between the convergent, overlapping images, 'collinearity equations' are computed. These equations describe the geometric relationship between the co-ordinates of each point in the two-dimensional plane of the sensor/camera, to the three-dimensional co-ordinates of the same point on the scene/object below. Successive bundle adjustments are then performed on these equations. This process uses a nonlinear least-squares optimization approach to estimate simultaneously the camera parameters, relative camera positions, and 3D scene geometry based on all input images.[52] The result is an alignment of all the input images and a 3D 'point cloud' which describes the scene geometry as a set of sparse data points at the locations of matched image features.[53,54] During this phase, automated camera lens calibrations are conducted to reduce the impact of lens distortion on the model output. The next step takes the information gained by the bundle adjustment to subject the original images to multiview stereo techniques.[55] This is a computationally intensive process that adds many more 3D coordinates to the scene geometry model to create a 'dense point cloud.'

Finally, the model is georeferenced from an arbitrary co-ordinate system to an absolute co-ordinate system so that it can be used for quantitative measurement and comparison with other spatial datasets.[44,48,54,56] Nondirect georeferencing typically comprises the use of GCPs, at least three of which

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are required to perform a three-dimensional, seven-parameter transformation of the model.[45,56] This transformation is linear and any errors are carried through to the final georeferenced output.[46] Once transformed, the model can be exported as (1) a point cloud, (2) a rasterized DEM, and (3) textured using the original imagery to produce an orthophoto. Textured triangle-mesh outputs are also possible, though these are typically used for visualization rather than analytical purposes. For further detail on the SfM process, readers are referred to recent reviews by Refs 57 and 58.

The SfM-photogrammetry method has been integrated into a number of software packages, including the commercial PhotoScan Pro (Agisoft LLC, St. Petersburg, Russia) and Pix4Dmapper Pro (Pix4D, Lausanne, Switzerland), and the open source VisualSFM.[59] The SfM processing chains are usually largely automated and can be performed easily by nonexperts. In recent years, SfM has seen application in various fields, including archeology,[56] glaciology,[60] and geomorphology,[45,46,51,54,61–63] using various camera and platform setups. Within this review, we focus specifically on the use of SfM for river habitat applications, in conjunction with drone imagery.

CLASSIFICATIONS OF PHYSICAL RIVER HABITAT

Much of the work using drones and digital photogrammetry for mapping and monitoring physical river habitat has focused on replicating the well-used classification systems which are typically implemented during walk-over assessments or large scale remote sensing surveys. Examples can be broadly categorized into those which conduct manual mapping on the drone-SfM outputs, and those which experiment with automated classification procedures for feature detection. Our first case study provides an illustration of the former.

Case Study 1: San Pedro River, Chile

For this case study, we provide an example of traditional geomorphological mapping conducted using outputs from the drone-SfM process. The imagery was collected from a site on the right bank of the San Pedro River in south-central Chile in May 2012, and processed using SfM-photogrammetry. The site is located just downstream of the outlet from Lake Riñihue, where the San Pedro River is deep, gently sinuous with very clear water. Here, the right bank is composed of consolidated clay bedrock, overlain by areas of gravel and cobbles with some boulders and large woody debris. The focus of this case study is this area of clay bedrock, which hugs parts of the bank. Here, water depth is relatively shallow (up to *c.* 2 m).

Background

In order to meet growing energy demands in Chile, this site has been selected for the construction of a large (56 m) hydropower dam and reservoir, as one of a number to be installed on high gradient, powerful Andean rivers. Significant concern has been raised about the impact the dams will have on natural river habitats[64] as channel engineering works will modify the natural hydromorphology.[65] Such changes have significant implications for habitat quality and availability, and subsequent impacts on unique native Chilean fish populations are inevitable.[66] Ongoing research has been aiming to characterize the current physical river habitat, prior to dam construction, in order to better understand the requirements of the little studied native fish.[67–69] It is hoped that this will help inform planning on how to maintain or restore similar habitats in future, in the knowledge that this particular section of the San Pedro River has a high species richness and thus is representative of the physical conditions suitable for many fish species. Drone-based work on the San Pedro in May 2012 was aimed at providing high-resolution remote sensing data about the physical habitat (specifically substrate size), in a way, which is faster, less laborious, more objective, and more spatially continuous than traditional habitat surveying. The need for such data is especially acute given the relative lack of national aerial remote sensing surveys in countries such as Chile.

Application of Drones and Digital Photogrammetry

To obtain the imagery of the San Pedro site, we mounted a small, RGB, consumer-grade, digital camera (Panasonic Lumix DMC-LX3, Osaka, Japan) onto a small, lightweight, rotary-winged drone (Draganflyer X6, Draganfly Innovations Inc., Saskatoon, Canada) and flew over the extensive shelf section on the right bank of the river (*c.* 170 m long × *c.* 20 m wide). A study area of this size was at the technological limits of what could be achieved using drones at the time of survey in 2012, but is relatively small in comparison to the areas which can be surveyed with ease by contemporary drone systems today. We positioned the drone at *c.* 25 m above ground level and set the camera focal length manually to 5 mm, to allow production of hyperspatial

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resolution outputs. We collected images with a high level of overlap (>80%) to allow for subsequent processing using SfM-photogrammetry. We distributed artificial GCPs across the site and recorded their position using a Spectra Precision EPOCH 50 global navigation satellite system (GNSS), capable of subcentimeter accuracy. Using this drone, about a day's work was required in total for site setup and data collection of *c*. 210 images. Significant advances in drone technology since 2012 mean that an equivalent amount of imagery can now be collected by a drone such as the DJI Inspire 1 (Da-Jiang Innovations Science and Technology Co. Ltd., Shenzhen, China) in about 15 min, with some additional time for GCP layout and surveying. We imported the drone images into Agisoft's PhotoScan Pro software for SfM photogrammetric processing to create a 0.01 m resolution orthophoto (Figure 2) and a 0.02 m resolution DEM. As shown in Figure 3, these very high-resolution SfM products permit the following, all of which were achieved by mapping at a scale of 1:100 using the measuring tools available within a GIS environment (ArcMap, ESRI Ltd, Redlands, USA):

1. Detailed mapping of key breaks of slope from the DEM, in accordance with geomorphological classification system presented by Ref 71.
2. Quantitative measurement of slope angles between breaks of slope, using the DEM.
3. Manual measurement and classification of substrate size according to the Wentworth Scale[72] using the orthophoto.
4. Mapping of the position of large woody debris, as shown in the orthophoto.

These outputs allow, for the first time, a spatially continuous and explicit characterization of the physical habitat at this location. Data such as this has the potential to contribute to a wide range of science and management scenarios, including sediment budgeting, enabling the development of conceptual models of habitat distribution and spatial connectivity, aiding decision-making and research designs for further investigation of the effects of engineering works (such as this proposed hydropower facility) and for inferring habitat preferences or information on fish swimming performance when combined with fish sampling surveys.[68,73]

In recent years, other work has demonstrated how a range of physical habitat indicators can be identified and classified using drone imagery and digital photogrammetry. For instance, surface flow types have been mapped manually from tethered balloons and rotary-winged drone imagery,[74,75] hydromorphological mapping has been conducted using supervised classifications of drone images,[76] mesohabitat mapping has been conducted using a combination of drone imagery and side-scan sonar data,[17] locating the presence of intermittent streams has been performed using supervised classifications of fixed-wing imagery,[77] the position of large woody debris has been mapped both manually[78] and using supervised classification techniques,[79] various mapping methods have been used to characterize riparian and in-channel vegetation and algae from drone imagery,[35,80–82] and the impact of species reintroduction has been assessed using DEMs and orthophotos.[83]

As with traditional habitat mapping, decisions are made within all these examples about which classification scheme to use, the scale, coverage, and frequency of sampling, and in some instances, the method of interpolation or extrapolation. These choices are not always explicit or fully justified, but are typically led by the nature of the application, existing practices, or protocols within certain geographic regions or academic disciplines, and the availability of time, funds, and resources. As a result, the habitat classification methods we use, whether traditional or drone-based and including our example on the San Pedro River, can be subjective, scale-dependent, nontransferable, nonquantitative, inconsistent, and/or based on inference. Furthermore, assumptions are made about the accuracy and reliability of these classifications, which are not substantiated by quantitative evidence. However, significant technological advances in drones and associated digital photogrammetric processing techniques now offer us the opportunity to move away from some of these restraints by providing an approach which is objective, rapid, quantitative, spatially continuous, and of exceptionally high spatial and temporal resolutions.[78,84,85] The luxury of such a method has been previously unattainable within physical habitat studies, but now encourages us to move away from broad classifications of river habitat in favor of detailed continuums of quantitative data.

CONTINUUMS OF PHYSICAL RIVER HABITAT

A continuum is defined as 'a coherent whole, characterized as a collection, sequence, or progression of values… varying by minute degrees.'[86] The physical habitat within river systems includes numerous

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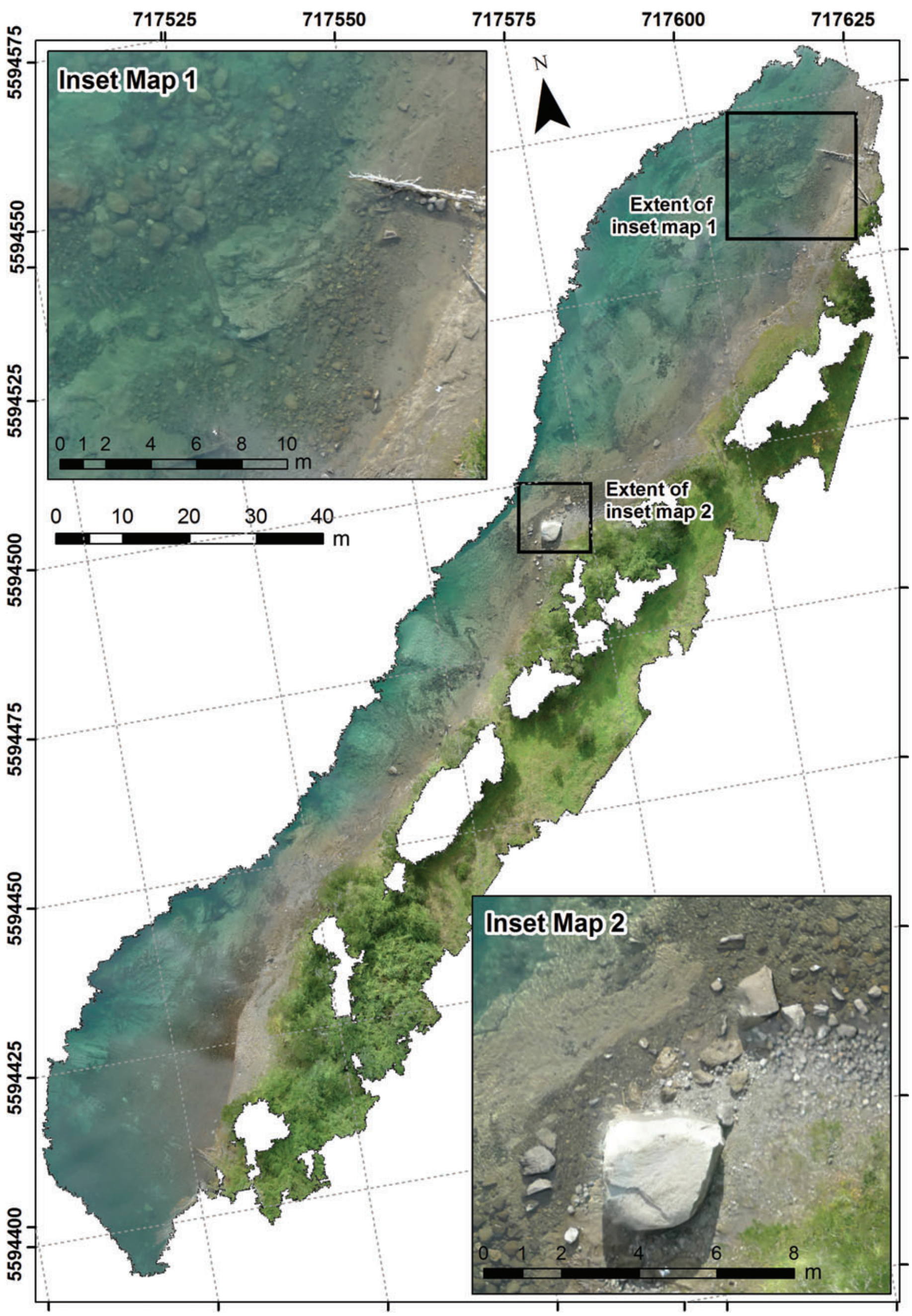

FIGURE 2 | Orthophoto of the Piedra Blanca site on the San Pedro River, Chile, obtained using the drone-structure-from-motion (SfM) method.[70]

continuums, such as grain size, water depth, topographic elevation, and flow velocity. The concept is that if we can capture these continuums, we may then be able to provide two- or three-dimensional, hyperspatial resolution, quantitative measurements of physical river habitat parameters over entire river catchments. In theory, these continuums can then be used over a range of spatial or temporal scales, dependent on the requirements of a given application. In practice, while recent technological developments in drones and digital photogrammetry are beginning to convert this theory into reality, the current challenge is to evaluate fully and realistically the application of this approach to real-world river science and management scenarios. We are faced with a number of key questions (Box 1).

In the last few years, research aimed specifically at answering these questions has started to

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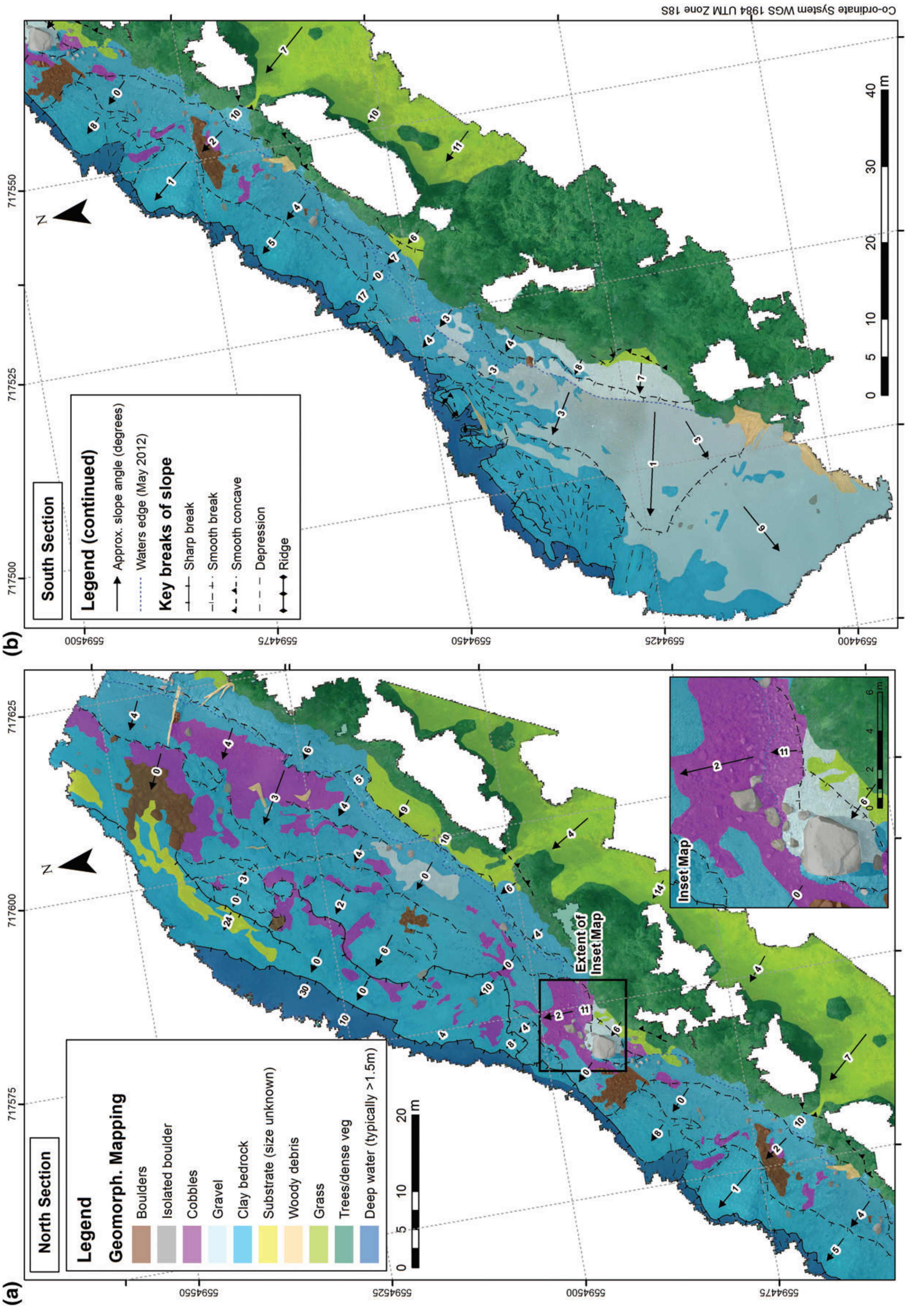

FIGURE 3 | Geomorphological mapping of the Piedra Blanca site on the San Pedro River, Chile.[70]

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BOX 1

FOCUS AREAS FOR CONVERTING TECHNOLOGICAL DEVELOPMENTS INTO VALUABLE METHODS FOR RIVER SCIENCE AND MANAGEMENT

Q1. Can drones and digital photogrammetric approaches actually provide continuums of physical river habitat data in practice? And, if so;

Q2. How accurate and precise are these continuums?

Q3. Do these continuums confirm the validity of (1) our prevailing conceptualizations of the river system, and (2) the practices we use to manage river habitats?

emerge within the academic literature, most frequently addressing Q1. Much of the work within river science has focused on the continuums of topographic data in particular, provided by DEMs derived directly from the drone-SfM method.[18,46,78,85,87] Numerous examples have appeared within the more general geomorphology literature too.[33,34,40,54,58,84,88,89]

Case Study 2: River Teme, UK

Background

The River Teme, at our selected site in Herefordshire (England), is a meandering, highly mobile, gravel bed river with a width of 3–13 m, which is intimately connected to its floodplain. In very recent times (since 2014) it has changed course dramatically in response to major winter storm events, shifting its position by more than 100 m in some places. Clearly such significant geomorphic change will impact heavily on the distribution of river habitat. We are unable to study past change in habitat availability in great detail due to a lack of earlier imagery at hyperspatial resolutions. However, research is ongoing to monitor future changes in channel geomorphology and quantify how accurately we are able to measure these changes using drone and digital photogrammetry based approaches.

Application of Drones and Digital Photogrammetry

Figure 4 provides an example of an orthophoto and DEM generated using drone imagery and SfM for this stretch of the River Teme. These data form our baseline survey, against which future change will be compared. We obtained the imagery using a Panasonic Lumix DMC-LX3 camera mounted on a Draganflyer X6 drone, flown at a height of *c.* 25 m above ground level, in August 2016. We used seven artificial GCPs surveyed using a total station and six fixed markers surveyed using a Trimble R8 RTK GNSS to give scale to our model (British National Grid). The resulting spatial resolution of the DEM and orthophoto were 0.02 and 0.01 m respectively. Given the clear water and low flow levels during our survey we are able to model the submerged topography in most parts of the site, with the exception of some parts of the main channel and an area of turbid, ponded water at the downstream end of the point bar (as shown by the holes in the data in Figure 4(b) and (d)). Figure 4 clearly demonstrates that detailed topographic heterogeneity exists both within the wetted channel itself as well as the surrounding area (Q1—proof of concept).

Data Analysis

Elevation accuracy was computed using 490 validation points collected during a total station topographic survey, also conducted during August 2016 (Figure 5, Table 1). The equation intercept values in Figure 5 indicate a trend toward elevation overestimation within all parts of the site, with a stronger correlation between observed and predicted values for exposed (slope = 0.9878) than submerged areas (slope = 0.6825). Mean elevation error in exposed parts of the site is 0.052 m, but degrades to 0.101 m in submerged areas due to the refraction of light at the air–water interface (Table 1). Large overestimations in elevation in exposed areas (>0.2 m) are associated with notable, vegetated breaks of slope. Here, any small errors in the horizontal dimension result in significant errors in the vertical. Where validation points in these locations are excluded, mean elevation error for exposed areas is improved to 0.037 m. These error assessment results reflect other findings reported to date where a similar approach is used.[18,40,46,54,61,85,87] In submerged areas, overprediction increases with water depth (i.e., with decreasing elevation in Figure 5(b)). A relatively simple refraction correction procedure has been shown to reduce the magnitude of elevation overestimation in submerged areas with clear water.[18] Very recently, a development of this correction procedure, which iteratively corrects the effect of refraction for each image in the SfM process, has been able to reduce elevation error further still, to

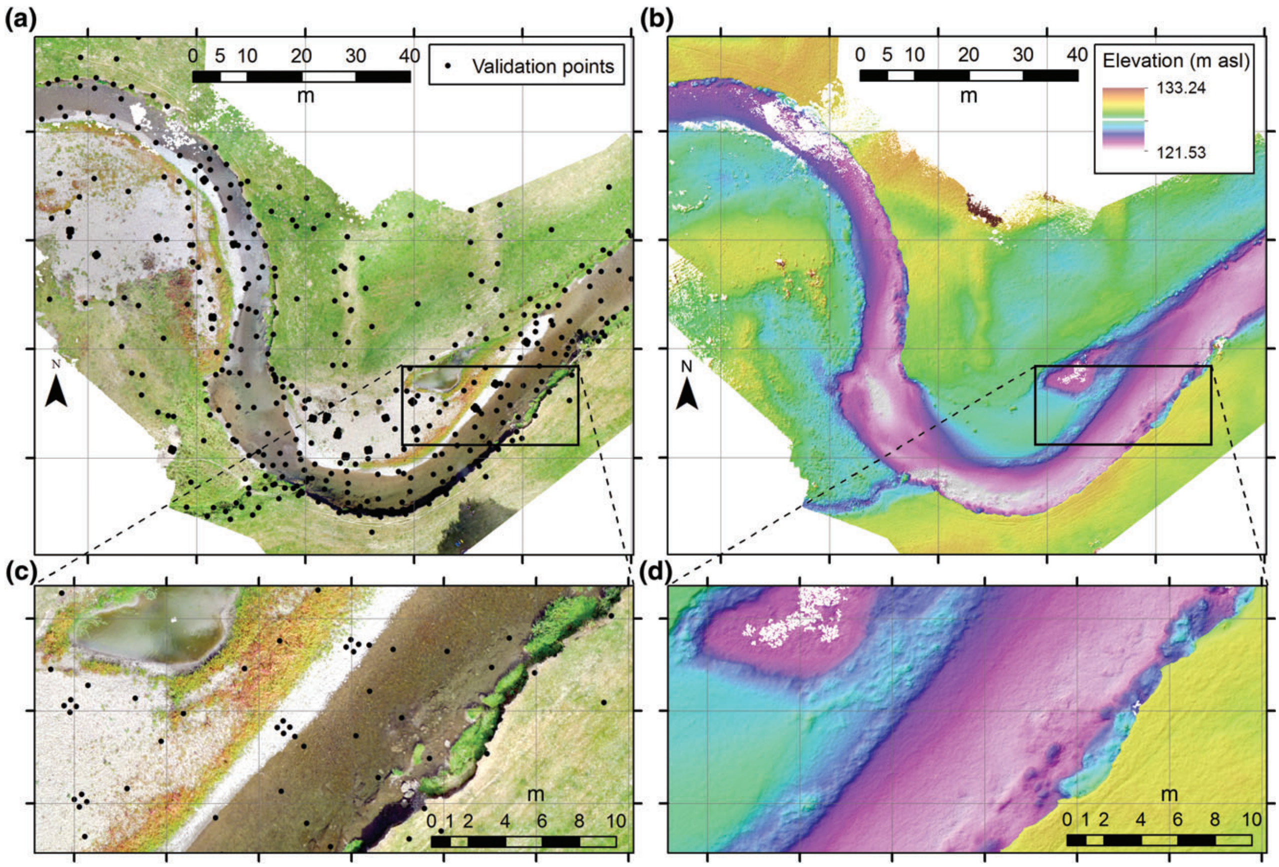

FIGURE 4 | River Teme orthophoto (a and c) and digital elevation model (DEM) (b and d) generated using drone imagery processed using structure-from-motion (SfM)-photogrammetry. Flow is from the left to right side of the image in (a) and (b) and from bottom to top in (c) and (d). The validation points shown in (a) and (c) denote the location of survey points collected with a total station and subsequently used to assess quantitatively the accuracy and precision of the drone-SfM derived DEM.

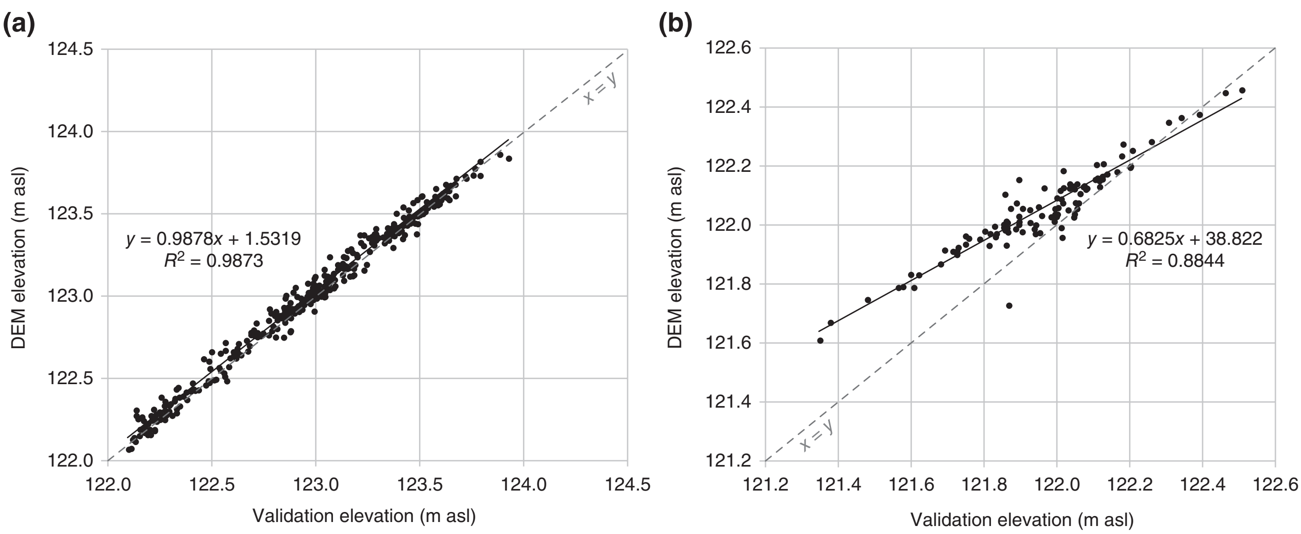

FIGURE 5 | Observed versus predicted elevation data for (a) exposed and (b) submerged parts of the River Teme field site.

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TABLE 1 | Accuracy and Precision Measures for the River Teme Digital Elevation Model

Area of Site	Accuracy Mean Error (m)	Precision Standard Deviation (m)
Exposed areas	0.0515	0.0917
Exposed areas exc. breaks of slope	0.0369	0.0510
Submerged areas	0.1007	0.8170

levels which are commensurate with results typically obtained in dry, exposed terrain.[90]. However, accurate and reliable quantification of submerged bed topography remains challenging in deep (>1.4 m), turbid, and turbulent waters (Q2).[87,90,91] Further research is needed to quantify the exact depths, levels of turbidity and turbulence at which the method begins to fail.

Evidence of our ability to provide spatial continuums of other physical river habitat parameters (Q1) is also beginning to emerge within the academic literature. For example, image texture approaches, previously used with traditional aerial imagery to produce continuous maps of fluvial grain size[11] have recently seen application to drone imagery. Ref 78 generated high-resolution orthophotos (0.05 m) for a 1 km section of the Elbow River in Canada using imagery acquired from an Aeryon Scout quadcopter (Aeryon Labs Inc., Waterloo, Canada) and processed using the EndoMOSAIC digital photogrammetry software (MosaicMill Ltd, Finland). A strong predictive relationship (R^2 = 0.82) was developed between close-range photo-sieved grain size data and a measure of drone image texture, to provide site-wide grain size predictions (Q1). Unfortunately, however, this was not accompanied by any quantitative assessment of error (Q2) and the spatial resolution of grain size predictions (1 m) does not improve on the resolution of earlier work using manned aircraft.[11,78] Recent conference proceedings indicate that other approaches to continuous grain size quantification using drones and digital photogrammetry are also being explored.[92–94] Our ability to measure water depth and quantify the roughness of topographic point clouds within the wetted channel (Q1) also suggests that drone derived products may present an opportunity to assess the hydraulic environment within relatively shallow, clear-flowing rivers.[75] Additional developments have made use of SfM applied to imagery derived from manned aircraft too, including riverscape mapping over longer reaches (e.g., 32 km).[63] While much of this research remains in its infancy, surveying physical river habitat parameters at these fine scales has the potential to provide new opportunities for knowing rivers as continuums, including those smaller and more marginal features, which may be overlooked by broader scale classifications.

EVALUATION

Table 2 offers an overview of how far research into the use of drones and digital photogrammetry for river habitat assessment has progressed to date. Proof of concept work (Q1) which has emerged within the last few years is now beginning to pave the way for detailed assessments of accuracy and precision of these continuums (Q2). Continued research and systematic experimentation for the acquisition of a wider range of physical habitat variables, in a range of contrasting fluvial environments, is clearly critical however if drones and digital photogrammetry are to provide continuums which actually allow us to improve our understanding of the science of river systems and refine our methods of management (Q3). The potential of this method to provide relevant data at the critical scale for habitat assessments means that it may have a key role to play in enabling reliable, quantitative monitoring of river habitats, informing successful and sustainable climate change adaptation strategies and subsequently reducing the risk of species decline and loss in certain settings. At present, this remains an ambition rather than a reality, and further contributions to Q1, Q2, and Q3 are therefore required.

TABLE 2 | An Overview of the State of Drone and Digital Photogrammetry Based Research for Quantifying Physical River Habitat Parameters

	Data Continuums		
Physical Habitat Variable	Q1. Proof of Concept	Q2. Error Assessment	Q3. New Knowledge/Practices
Topography/water depth	Refs 40, 46, 70, 78, and 95	Refs 18, 70, and 87; *Ref* 85	
Grain size	Ref 78; *Ref* 92	Refs 70, 93 and 94	
Flow velocity	*Ref* 96		

Text in roman indicates peer-reviewed publications.
Text in italics indicates conference abstracts and proceedings, and unpublished findings where these are publically available.
Note that this table does not include studies which do not use both drone imagery and digital photogrammetry.

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In terms of the routine operational use of drones and digital photogrammetry, we are able to identify a number of broad challenges, which must be addressed to help realize this ambition. These are given in no particular order:

Data Acquisition

- *Image blur*. The low flying altitude and variable effectiveness of camera gimbals mean that drone imagery can suffer from blur. Image blur increases noise within the SfM point cloud which subsequently degrades the quality of topographic products.[97] Methods to identify, reduce, or prevent blur within UAS imagery[98] require further attention.
- *Need for GCPs*. The use of GCPs providing adequate representation of the survey area in three dimensions has been essential for accurate spatial positioning and scaling of image and topography data to date. However, the distribution and survey of GCPs increases significantly the time needed in the field and necessitates the use of expensive survey equipment. Technological developments in miniaturizing higher grade GNSS and increasing the payload capacity of small drones may reduce the need for GCPs. Initial work suggests that while horizontal positioning can be adequately obtained with the use of an on-board RTK GNSS, that vertical errors are greater than those obtained with the use of GCPs.[99] Other research in this vein suggests that acceptable positioning accuracies can be obtained with relatively small numbers of GCPs[100] and that direct georeferencing using equifinality relationships within the SfM workflow may obviate the need for GCPs altogether.[50]
- *Radiometric and spectral resolution*. The majority of research to date makes use of 8-bit RGB imagery acquired from small-format, consumer-grade digital cameras because they are light enough to be carried by small drones. The limited radiometric resolution of this imagery tends to hinder the restitution of topography in darker parts of the site (including in areas of shadowing and deeper water), due to a reduction in the image texture which is required to identify matching points between images. Future research should give greater consideration to radiometric resolution[41] by making use of cameras capable of acquiring RAW format images, which offer higher bit depths. Multispectral sensors will also benefit habitat mapping in future, especially as the market for drone-mountable sensors continues to expand and diversify.
- *Weather conditions*. Poor scene illumination is thought to hinder the success of SfM image matching processes[101] and windy conditions can result in significant amounts of image blur. Recent research suggests that techniques for reducing the problematic impacts of sun glint on remotely sensed imagery are possible,[102] but to our knowledge these have not yet been specifically applied to imagery acquired using a drone-SfM approach. Careful flight planning is therefore required to ensure high quality image capture.
- *Battery life*. Single flight times vary in accordance with the power supply and demand of different drones. This can mean that multiple flights are necessary to provide adequate coverage of field sites. Combined with the regulatory requirement in many countries to maintain visual line-of-sight at all times and the need for surveying GCPs, battery life is one of the major factors in determining field time and coverage potential. In our experience, the Draganflyer X6 drone used within this article can realistically manage single flight times of *c*. 6 min. Newer drones are capable of longer flight durations though. For example, the DJI Inspire 1 rotary-winged system (Da-Jiang Innovations Science and Technology Co. Ltd., Shenzhen, China) can fly for up to 20 min on a single battery and thus achieve much greater coverage within a single flight. Fixed wing drones are typically capable of even longer flight times of 30 min–1 h, with the Bramor ppX drone (C-Astral Aerospace Ltd, Ajdovscina, Slovenia) advertised to deliver industry-leading flight times of up to 3.5 h. Newer lithium-sulfur (Li-S) batteries are also advocated to increase possible flight times.
- *Flight regulations*. The UK regulatory environment is currently favorable for noncommercial drone-based research, provided that Articles 94-95 and 241 of the Air Navigation Order 2016 are adhered to.[103] Drone use in 'congested areas' of the UK does require Civil Aviation Authority permission however, and should be factored into the use of drones for monitoring habitats within urban waterways. The regulatory landscape for drone flying is rapidly evolving both within the UK and elsewhere (e.g., new Part 107 of Federal Aviation

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Authority regulations in the USA[104] and European Aviation Safety Agency's Prototype Commission Regulation on Unmanned Aircraft Operations[105]), therefore researchers and practitioners should consult the local civil aviation authority guidance for up-to-date advice on flying regulations and for obtaining relevant permissions.

- *Water quality*. In rivers and other aquatic environments, the success of the drone-SfM approach is reliant on good visibility and thus water quality is a critical limiting factor. The method is not applicable in areas of very turbid (i.e., high sediment concentrations) or white water (i.e., high water surface roughness). Investigations by the lead author are currently exploring the thresholds at which turbidity and turbulence prohibit the use of this method in fluvial settings.
- *Spatial coverage*. At present, the areal extent of drone surveys is limited. Coverage of entire river systems is not possible without a notable loss in spatial resolution or a significant increase in survey time and effort. This is a consequence of the well-known trade-off between spatial coverage and spatial resolution, limited drone battery life and widespread regulations concerning maximum flight altitudes, distance from the pilot and line-of-sight flying requirements. While ongoing technological developments may help to improve this situation in future, we suggest that regulatory requirements are unlikely to be relaxed significantly. Therefore, difficulties in covering larger spatial extents may always be a limitation of drone-based surveying methods.

Data Processing

- *Reliance on image texture*. The SfM process is heavily dependent on image texture to successfully match points between overlapping images. Where this is lacking, the approach is compromised.[106,107] As a result, surveys conducted over large expanses of smooth, opaque water surfaces or areas of homogeneous grassland should not be expected to produce useful results for physical river habitat assessments.
- *Geometric restitution is only possible for visible features*. Unlike laser scanning approaches, the SfM technique is only able to reconstruct surfaces that are clearly visible from the position of the drone. As a result, dense or overhanging vegetation will obscure any underlying features of interest and elevation models will either appear to overestimate the true position of the ground surface[45,62] or confuse the image matching process as its appearance varies between view angles.[108] This can make the use of drones for river assessment impossible on narrow streams with dense riparian tree cover. Similarly, for the SfM process to work in submerged areas, a clear view of the channel bed is necessary, thereby excluding rivers with highly turbid and turbulent flows.
- *Processing power*. The SfM process is computationally demanding and time consuming, particularly for large image datasets. The River Teme survey described here is relatively small, comprising 134 nongeotagged images which cover an area of approximately 8800 m^2. These images took approximately one working day to process to completion within Agisoft's PhotoScan Pro v.1.2.4.2399 (Agisoft LLP) using an Intel Core i7-4790 32 GB RAM 64-bit computer with a 2 GB Dual Nvidia Quadro K620 video card. The use of geotagged imagery and the use of higher performance computing will inevitably enable much shorter processing times.
- *Large data volumes*. Drone image datasets and their resultant SfM outputs typically require large digital storage volumes. The River Teme dataset presented here (photographs and processed data) occupies *c.* 3 GB of disk space. While a handful of surveys of this size are relatively manageable, if this approach is to become routine then researchers and management agencies may be faced with difficulties when attempting to share datasets for perhaps hundreds of site surveys. Furthermore, continued research is needed into methods of data processing and analysis, which exploit effectively the high spatial and temporal frequency of this data. Some progress has been made in recent years, including the increase in availability of open source point cloud management software (e.g., CloudCompare) and processing routines.[14,109]
- *Errors within the SfM process*. The black-box nature of SfM software packages, including PhotoScan Pro (Agisoft LLP), means that isolating exact sources of error is challenging. Systematic doming errors have been observed within SfM-generated DEMs[18,62] and are thought to result from inadequate self-calibrations of camera lens models.[110,111]

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Recent research suggests that careful flight planning can reduce these systematic errors by the addition of imagery acquired at convergent view angles.[49] Ref 58 provides a thorough overview of SfM error sources.

Despite these current limitations, drones and digital photogrammetry have undoubtedly and irreversibly revolutionized our data collection toolbox for river habitat surveying. The research reviewed here evidences numerous advantages over traditional methods; namely the hyperspatial resolution, spatially explicit and spatially continuous data which can be obtained more quickly, more easily, more flexibly, and more frequently than using other approaches. These advantages permit new possibilities for surveying quantitatively the heterogeneity of the physical river habitat. Drone platforms capable of the kind of analysis presented here can currently be purchased for *c*. £1000 (e.g., DJI Phantom 4, Da-Jiang Innovations Science and Technology Co. Ltd., Shenzhen, China)), and SfM processing workflows are user-friendly and easily learnt by nonexperts. This democratization of data collection places control with the user, thereby making '…question-driven, high resolution research considerably more feasible than it has been previously' (Ref 112, p. 71). Results of initial publications lend support to the concept of a spatially heterogeneous riverscape[63,75,85] as advocated by Ref 4 and others in the early 2000s.[27,28] Going forward, further examination of this heterogeneity may permit new and valuable insights into the ecological importance of physical habitat, its spatial and temporal significance, and the mechanisms by which it is regulated . In Box 2, we provide some specific guidance for those considering using drones and digital photogrammetry for monitoring physical river habitat and hydromorphology.

CONCLUSION

Within this article, we have reviewed the contribution of drones and digital photogrammetry for monitoring physical river habitat and hydromorphology to date. The monitoring of physical habitat parameters continues to play an important role in how we manage and understand river systems, and traditional methods fall short of providing the mesoscale, spatially continuous and explicit datasets required under the 'riverscape paradigm.'[4] A growing number of proof-of-concept studies indicate that drones and digital photogrammetry provide a promising alternative method, including the ability to produce orthoimagery and

BOX 2

IMPORTANT CONSIDERATIONS FOR THE PRACTICAL APPLICATION OF DRONES AND DIGITAL PHOTOGRAMMETRY FOR PHYSICAL RIVER HABITAT MONITORING

What is your budget?
The budget should be sufficient to cover the acquisition and maintenance of the drone(s), the sensor(s), the digital photogrammetry software, the computer, and video card to be used for SfM processing, the digital storage facility(s), data collection accessories (e.g., GCPs, additional batteries, additional controllers, and surveying equipment), and for insurance (drone cover plus public liability). Additional costs may be incurred for flight training and obtaining permission to conduct 'aerial work' (i.e., commercial work[103]).

What is your application area?
Your intended application will influence the type of drone and sensor you need, and careful consideration should be given to factors such as; the size and accessibility of the area to be surveyed, the required spatial resolution of the output orthophotos and topographic datasets, the required spectral and radiometric resolution of the sensor, the stability and typical flight duration of the drone, the capabilities of SfM-photogrammetry, the need for GCPs, and an awareness of how to minimize output errors.[57]

What are your responsibilities?
Drone pilots are responsible for safe and legal flying, in accordance with the regulations and recommendations, which apply in the location of flight. This should include an awareness of flight limiting factors such as the presence of trees and other substantial vegetation, powerlines, pedestrians not under the pilots' control, and the proximity of urban areas and restricted airspace. This list is not exhaustive and it is the responsibility of the drone pilot to conduct a thorough risk assessment in advance of flights. Special permissions may be required in some countries and therefore it is important to obtain advice from the local aviation authority, and approval from the relevant landowners. Reckless and noncompliant flying poses a danger to life and property and threatens to jeopardize the future use of drones for research and management within our discipline.

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topographic data at exceptionally high spatial (<0.1 m) and temporal resolutions, over mesoscale channel extents, in a way which is often inexpensive and can be implemented by nonexperts. We have described and evaluated this method through the use of two case studies. The first represents an early use of drone imagery for conducting a rapid and spatially continuous classification of fluvial substrate size on the San Pedro River in Chile. Our second case study goes a step further by demonstrating how continuums of data, rather than broad scale classifications, can be obtained. These continuums have potential for describing and analyzing the detailed heterogeneity of physical river habitat at the mesoscale. Existing quantitative error assessments suggest that topographic drone-SfM outputs are accurate and reliable, but rigorous quantitative assessments of other continuums, such as grain size and flow velocity, are currently lacking. The drone-SfM approach faces a number of data collection and data processing challenges, which we have reviewed within this article, and continued systematic experimentation and field application is required to pin down adequately the accuracy and precision of outputs. With continued development however, this method has the potential to inform new approaches to routine physical river habitat monitoring and management, and contribute to new understandings of the riverscape.

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