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REVIEW PAPER

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Remote sensing of river corridors: A review of current trends and future directions

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Abstract

River corridors play a crucial environmental, economic, and societal role yet also represent one of the world's most dangerous natural hazards, making monitoring imperative to improve our understanding and to protect people. Remote sensing offers a rapidly growing suite of methods by which river corridor monitoring can be performed efficiently, at a range of scales and in difficult environmental conditions. This paper aims to evaluate the current state and assess the potential future of river corridor monitoring, whilst highlighting areas that require further investigation. We initially review established methods that are used to undertake river corridor monitoring, framed by the context and scales upon which they are applied. Subsequently, we review cutting edge technologies that are being developed and focussed around unmanned aerial vehicle and multisensor system advances. We also "horizon scan" for future methods that may become increasingly prominent in research and management, citing examples from within and outside of the fluvial domain. Through review of the literature, it has become apparent that the main gap in fluvial remote sensing lies in the trade-off between resolution and scales. However, prioritising process measurements and simultaneous multisensor data collection is likely to offer a bigger advance in understanding than purely from better surveying methods alone. Challenges regarding the legal deployment of more complex systems, as well as effectively disseminating data into the science community, are amongst those that we propose need addressing. However, the plethora of methods currently available means that researchers and monitoring agencies will be able to identify suitable techniques for their needs.

KEYWORDS

autonomy, hazard monitoring, laser scanning, morphology, remote sensing, river monitoring, SfM, UAVs

Abbreviations: AUV, autonomous underwater vehicle; ADCP, acoustic Doppler current profiler; ADV, acoustic doppler velocimeter; ALS, airborne laser scanning; DEM, digital elevation model; GCP, ground control point; GNSS, global navigation satellite system; IMU, inertial motion unit; IoT, internet of things; LiDAR, light detection and ranging; MBES, multibeam echo sounder; MLS, mobile laser scanning; PIV, particle image velocimetry; SAR, synthetic aperture radar; SfM, structure from motion; SSC, suspended sediment concentration; TLS, terrestrial laser scanner; UAV, unmanned aerial vehicle; USV, unmanned surface vehicle; ULS, UAV laser scanning

1 | INTRODUCTION

Rivers play a crucial environmental and societal role, providing food, water, nutrients, flood and drought mitigation, transport, and potential energy, as well as providing habitats and supporting biodiversity that encourage recreational use (Postel & Richter, 2012). These ecosystem services are incredibly valuable, with freshwater resources contributing a significant component of the global natural capital (Costanza et al., 1997). This explains why 82% of the world's population live on previously flooded land (Dilley, Chen, Deichmann, Lerner-Lam, & Arnold, 2005), whereas 87% have a river as their closest water body (Kummu, de Moel, Ward, & Varis, 2011). Conversely, rivers can present a considerable hazard to those in their vicinity, primarily through flooding (Hirabayashi et al., 2013). Flooding is identified as the most dangerous natural hazard, accounting for 43% of all disasters between 1995 and 2015, with flood events likely to become more severe as a result of climate change (UNISDR & CRED, 2015). Alongside flooding, bank erosion represents a hazard to those communities who reside near river banks (Islam & Guchhait, 2017; Thakur, Laha, & Aggarwal, 2012). However, world rivers are degrading in terms of water quality, sediment loads, and overall ecological diversity (Vörösmarty et al., 2010). Simultaneously, increasing rates of change in land cover across floodplains are affecting the hydrological regime, impacting on ecology, erosion, and flooding (Gregory, 2006; Remondi, Burlando, & Vollmer, 2016; Wasson et al., 2010). It is therefore imperative to monitor river corridors to (a) understand associated processes, (b) evaluate the nature of evolving hazards, (c) maintain ecological sustainability, and (d) preserve their integrity as a resource for future generations.

For the purposes of this review, "river corridors" can be defined broadly to include river channels, riparian zones, floodplains, and associated fluvial deposits, forming an overall classification framework, which can be used to aid research and management (Harvey & Gooseff, 2015). The dynamic interactions across the river corridor are especially important in the context of applied river management, whereby a holistic approach is necessary. River corridor units feed into management strategies and applied research, covering areas including hydrological exchange (Harvey & Gooseff, 2015; Malard, Tockner, Dole-Olivier, & Ward, 2002; Smith et al., 2008), ecosystem functionality (Brunke & Gonser, 1997; Poole, 2002; Stanford & Ward, 1993), monitoring of restored reaches (Bernhardt et al., 2007; Kail, Hering, Muhar, Gerhard, & Preis, 2007; Schneider et al., 2011), and geomorphic evolution (Magdaleno & Fernandez-Yuste, 2011; Ollero, 2010; Richards, Brasington, & Hughes, 2002).

Ultimately, we cannot view rivers as points or lines but as spatially continuous mosaics of information (Fausch, Torgersen, Baxter, & Li, 2002). Remote sensing techniques provide the ideal solution for river corridor monitoring due to their nonintrusive nature, wide ranging spatial coverage, and repeatability. In order to fully understand the river corridor, we need data that are continuous over various scales, with remote sensing being the ideal solution to achieve this, allowing us to test the theory that has been presented, and provide a basis for our understanding of the fluvial form. Over time, river corridor research has been transformed through technological advances making surveys more accurate, efficient, and resolute both spatially and temporally (Entwistle, Heritage, & Milan, 2018; Marcus & Fonstad, 2010). Each advance in remote sensing allows subsequent progression in understanding. This enables novel research into the processes that are shaping river corridors, across scales ranging from grain dynamics to landform hydrological analysis. Herein, we define remote sensing in the broadest sense as any relevant noninvasive form of data collection.

1.1 | Review structure

This review aims to outline both current and future methods that are employed to aid our understanding of the river corridor. Remote sensing offers multiple techniques for monitoring various components of the river corridor (Figure 1a). There are two key distinguishing factors that determine appropriate data collection techniques: (a) the domain to which they are applied and (b) the spatial scale and resolution over which they are applicable. Herein, we have structured the review around these key considerations, first, revisiting the developments in river corridor remote sensing since the mid-20th century, before reviewing techniques across various domains, focussing within these on the scales over which methods are deployed. For the purposes of this review, we define the scales of monitoring based around the morphological units outlined in Figure 1b to provide a structure for the review and context for the following discussion. We also seek to highlight studies that combine multiple remote sensing techniques, such that they are developing new insight into river corridors before "horizon scanning" to try and suggest a future agenda for the remote sensing of river corridors. Finally, we outline the key challenges that will need to be addressed in order for the techniques and methods identified to progress to a point where they can be broadly applied.

2 | RIVER CORRIDOR REMOTE SENSING

2.1 | A brief history of remote sensing of river corridors

In order to provide context for where we are, and where we may be heading, it is useful to know where we started in terms of remote sensing in the fluvial domain. During the 20th century, researchers began using early forms of remote sensing by studying aerial photos to investigate fluvial morphology and the driving processes involved (Coleman, 1969; Fairbairn, 1967; Kinoshita, 1967; Leopold & Langbein, 1966). The launch of the Landsat programme in 1972 led to a rapid uptake in remote sensing for fluvial research (Mertes, 2002), for example, to identify former river channels (Ghose, Kar, & Husain, 1979), investigate water quality and suspended sediment (Aranuvachapun & Walling, 1988), map flood hazards (Rango & Anderson, 1974), and understand the interactions between rivers and vegetation (Salo et al., 1986). By the turn of the century, it was considered that data with a resolution of 1 m were classed as high resolution (Mertes, 2002); however, this is no longer the case. Developments in airborne laser scanning (ALS) facilitated high-resolution collection of topographic data over large areas, allowing an improvement in the

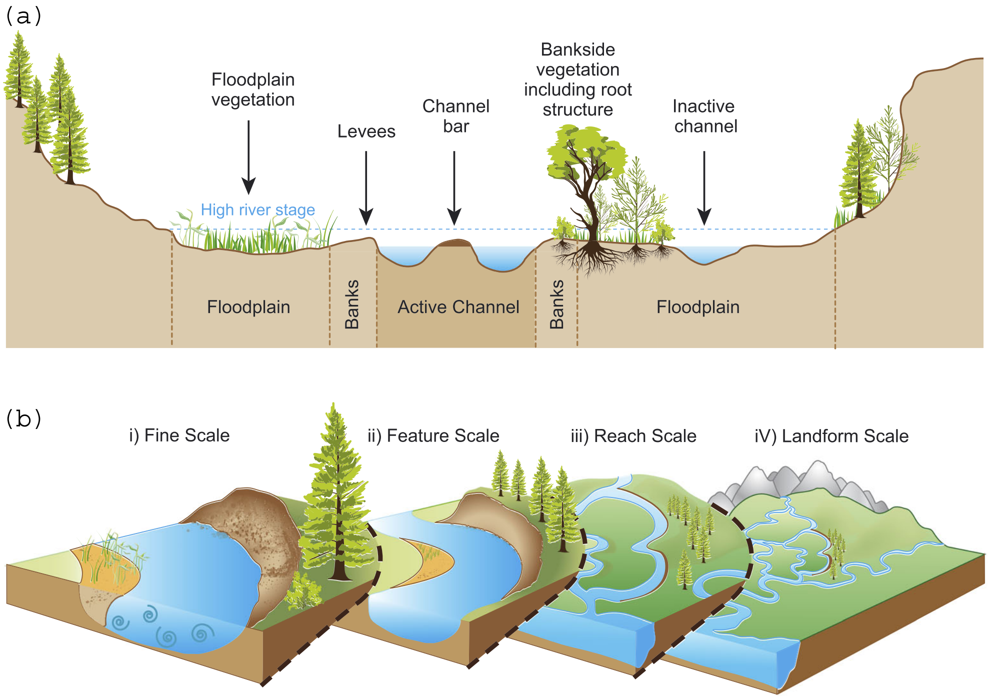

FIGURE 1 (a) The key natural features of a river corridor, including an active channel, floodplains, sediment deposits, relic channels, and vegetation components. (b) A conceptual framework of river corridor scales across which we review research and applications herein, ranging from the (i) fine scale, (ii) feature scale, (iii) reach scale to the (iv) landform scale [Colour figure can be viewed at wileyonlinelibrary.com]

accuracy of data collected for applications such as flood modelling (Bowen & Waltermire, 2002; Cobby, Mason, & Davenport, 2001; Ruiz, González, Herms, & Bastianelli, 2002). The decision to stop degrading GPS data in 2000 facilitated more widespread use of remote sensing. Subsurface techniques more traditionally reserved for oceanic studies began to be used on fluvial systems for research in the early 2000's, with the deployment of acoustic doppler current profiling (ADCP) and multibeam echo sounding (MBES) methods (Muste, Yu, & Spasojevic, 2004; Parsons et al., 2005; Shields, Knight, Testa, & Cooper, 2003). Further improvements in resolution, but with limiting spatial extent, came through the use of terrestrial laser scanning (TLS) in the late 2000's (Heritage & Hetherington, 2007; Milan, Heritage, & Hetherington, 2007), breaking through the previous limits of spatial resolution offered by ALS and that were alluded to by Mertes (2002). Finally, a proliferation in the use of unmanned aerial vehicles (UAVs) in recent years has allowed the collection of high-resolution imagery from which dense models of the earth's surface are created over areas greater than achieved by TLS (Fonstad, Dietrich, Courville, Jensen, & Carbonneau, 2013; Lejot et al., 2007; Westoby, Brasington, Glasser, Hambrey, & Reynolds, 2012).

Whether or not there has been the genuine emergence of a sub-discipline in river sciences devoted to remote sensing, as proposed by Marcus and Fonstad (2010), is perhaps open for debate. We would argue that the remote sensing tools reviewed herein and the associated technical developments that we highlight are used across many disciplines of river science, driven by a desire to better understand the physical processes at work and effectively manage these systems.

2.2 | Current monitoring methods

One of the strengths of remote sensing lies in the broad range of temporal and spatial extents over which methods can be applied (Figure 2). However, there is no "perfect technique," with factors such as cost, scale, and repeatability all playing an important role in determining the most appropriate method for a user (Figure 2). Many of the methods used have been thoroughly reviewed and can be used to inform researchers for deployment and processing, for example, UAV imagery (Westoby et al., 2012), TLS (Telling, Lyda, Hartzell, & Glennie, 2017), ALS (Hofle & Rutzinger, 2011), ADCP (Muste et al., 2004), and MBES (Jha, Mariethoz, & Kelly, 2013), as well as comparing between methods for bathymetric modelling (Kasvi, Salmela, Lotsari, Kumpula, & Lane, 2019). However, the aim of this review is not to provide a methodological overview but rather to evaluate the range of applications and how each approach can enhance our understanding of the river corridor.

2.2.1 | Roughness and grain size

Bed and bank studies have predominantly utilised statistical analysis of dense point clouds to extract roughness metrics. TLS has primarily been used to examine fine-scale roughness due to the high point density, for example, in exploring gravel bars (Heritage & Milan, 2009), variations in roughness preflood and postflood (Picco et al., 2013), roughness across differing climatic drivers (Storz-Peretz, Laronne Jonathan, Surian, & Lucía, 2016), and bank skin drag coefficients (Leyland, Darby, Teruggi, Rinaldi, & Ostuni, 2015). Importantly,

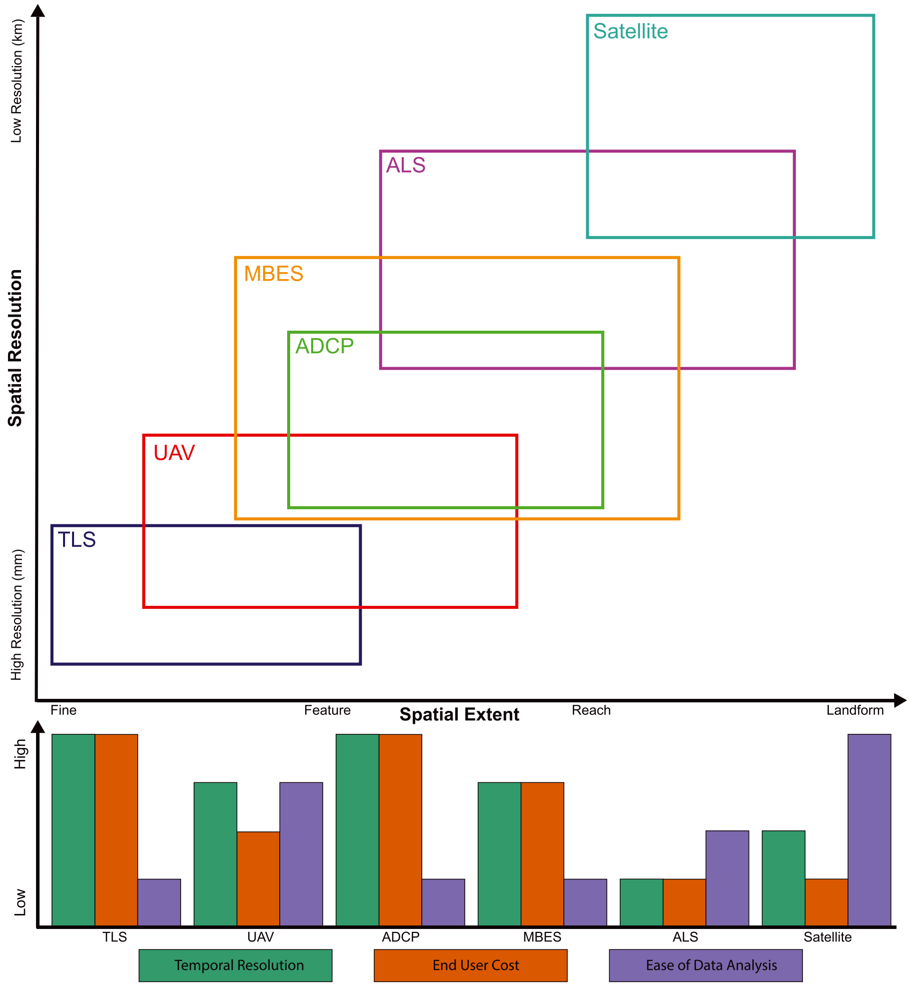

FIGURE 2 A comparison of the spatial resolution and extent of various common survey methods along with temporal resolution, end user cost, and ease of data analysis in the subsequent bar graphs. It should be noted that end user cost is based on typical examples, for example, purchasing TLS equipment is expensive, whereas despite satellite data being expensive to produce, they are freely available in most circumstances. Despite ALS data being free in many circumstances to end users, it is limited in terms of temporal resolution and coverage, with further data collection being very expensive. The top panel was inspired by a similar concept developed in figure 12 of Bangen, Wheaton, Bouwes, Bouwes, and Jordan (2014) [Colour figure can be viewed at wileyonlinelibrary.com]

research into how scan locations and grid cell size impacts roughness calculations has been undertaken to improve deployment (Baewert et al., 2014), and examining the potential for bed roughness extraction with through-water laser scanning has expanded the versatility of TLS (Smith, Vericat, & Gibbins, 2011).

Over larger spatial domains, roughness tends to be derived from overhead imagery. Structure from motion (SfM) techniques have been used for roughness calculations in flume experiments (Morgan, Brogan, & Nelson, 2017; Pearson, Smith, Klaar, & Brown, 2017) as well as field studies (Piton et al., 2018; Smith & Vericat, 2015; Woodget & Austrums, 2017) and river restoration analysis (see Figure 3; Marteau et al., 2017). UAV SfM therefore provides the ability to upscale the spatially limited static terrestrial based methods to feature and reach scales. Currently, calculating roughness over large areas is time consuming and further compounded by SfM data suffering from smoothing effects (Cook, 2017; Smith & Vericat, 2015). Yet ever increasing computer power may help extensive, high-resolution, roughness models become more feasible.

Below water, MBES techniques are predominantly used for bathymetric topography, although research by both Guerrero and Lamberti (2011) and Konsoer et al. (2017) utilised MBES data to investigate bed roughness across a range of study sites. Despite the methods not being fully explored, MBES data may provide insight in to bed and bank roughness across reach scales and greater.

Grain size is somewhat harder to extract. Traditional image-based methods relate image texture to grain size (Carbonneau, Bergeron, & Lane, 2005; Graham, Rice, & Reid, 2005). More recent methods exploit SfM topography with high-resolution imagery (0.0015-m pixel size) from low flight heights (Langhammer, Lendzioch, Miřijovský, & Hartvich, 2017) and through relationships between roughness and in field grain-size measurements (Carbonneau, Bizzi, & Marchetti, 2018; Woodget & Austrums, 2017). Work by Woodget, Fyffe, and

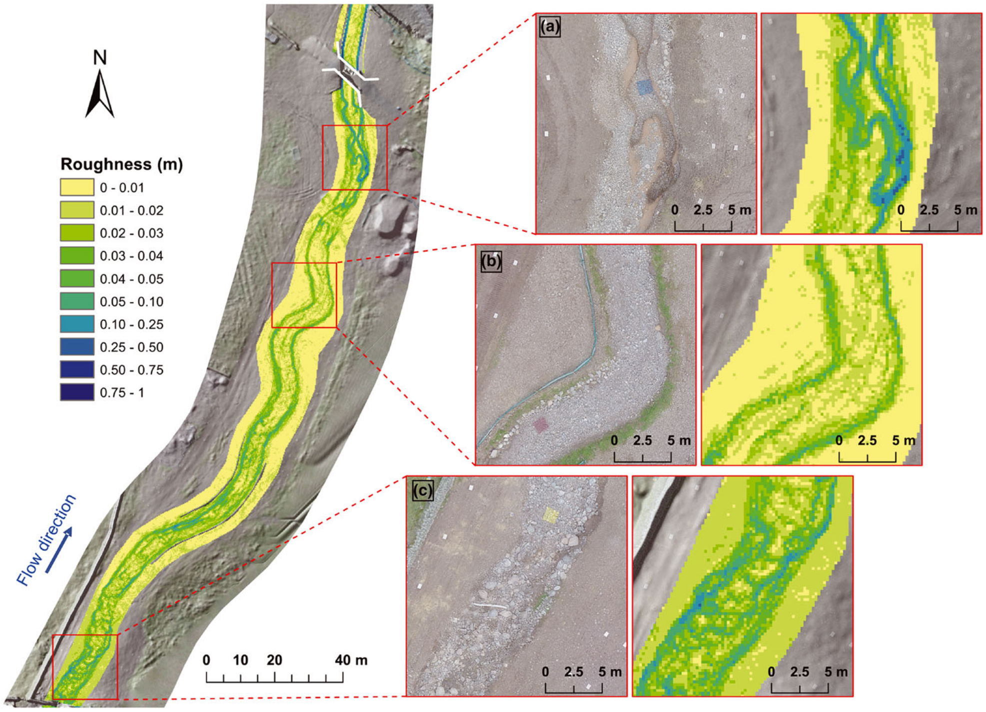

FIGURE 3 An example of roughness calculations performed across a restored channel. SfM methods were used to obtain a DEM before using detrended standard deviation values to obtain surface roughness. Repeat surveys allow the change in roughness to be monitored through time as the channel adjusts. Such results can be used to highlight processes such as channel margin sorting, as well as be fed back in to hydrodynamic modelling. This presents an example of how high-resolution roughness can be scaled up to analyse reach scale process and form interaction. Reprinted from Marteau, Vericat, Gibbins, Batalla, and Green (2017) [Colour figure can be viewed at wileyonlinelibrary.com]

Carbonneau (2018) demonstrated how image texture on a series of individual images outperformed orthomosaics and SfM roughness measures. However, derived relationships may struggle in poorly sorted reaches (Pearson et al., 2017) and where sediment placement is irregular, causing the axis of measurement to be inconsistent.

TLS produces data volumes similar to those from SfM and thus is hampered by similar processing constraints. The technique has been successfully used to investigate grain-size packing distribution (Hodge, Brasington, & Richards, 2009), variations between systems (Storz-Peretz et al., 2016), submerged grain size (Smith et al., 2011), and grain size on large, complex gravel systems using mobile laser scanning (MLS; Wang, Wu, Huang, & Lee, 2011). Through-water TLS is ineffective for deeper channels, where instead, MBES data have been used to infer grain size using statistical inference techniques (Eleftherakis, Snellen, Amiri-Simkooei, Simons, & Siemes, 2014; Snellen, Eleftherakis, Amiri-Simkooei, Koomans, & Simons, 2013). However, the extensive calibration involved and limited spatial applicability restrict the scale of application over which the methods can be used.

2.2.2 | Flow characteristics

Both acoustic doppler velocimeters (ADVs) and ADCPs are used to investigate flow dynamics. The former is used to primarily investigate flow characteristics such as velocity and turbulence in both flume (Abad & Garcia, 2009; Buffin-Belanger, Rice, Reid, & Lancaster, 2006; Lawless & Robert, 2001; Schindler & Robert, 2005) and field set-ups (Buffin-Belanger & Roy, 2005; Lane et al., 1998; Strom & Papanicolaou, 2007; Wilcox & Wohl, 2007). Likewise, ADVs have also been used to investigate applied management problems such as weir construction (Bhuiyan, Hey, & Wormleaton, 2007) and the effects of ship wakes on near bank flow (Fleit et al., 2016). However, the requirement for a static deployment somewhat limits their application beyond fine scales.

Across feature and reach scales, ADCP sensors can be used to better understand flow dynamics, such as investigating the influence of surface ice on vertical separation and helical flow structures (Lotsari et al., 2015), the complex flow properties in the Mekong (Hackney et al., 2015), better calibration of a Delft3D flow model (Parsapour-Moghaddam & Rennie, 2018), and river confluence mixing processes (Gualtieri, Filizola, de Oliveira, Santos, & Ianniruberto, 2018). At the reach scale, ADCPs have been used to investigate flow variation through dynamic morphological systems (Guerrero & Lamberti, 2011), flow interaction with dune bed morphology (Parsons et al., 2005), and flow patterns through a variety of meandering, straight, and abandoned channels (Shields et al., 2003). With increasing portability and potential platform autonomy (Flener et al., 2015), the deployment versatility of such sensors is likely to improve further beyond their already extensive range of deployment opportunities.

Field-based particle image velocimetry (PIV) operates over smaller spatial extents, tracking tracer particles in a fluid over interrogation windows using pattern recognition (Adrian, 1991; Detert & Weitbrecht, 2015). Most systems are static for continual monitoring (Creutin, Muste, Bradley, Kim, & Kruger, 2003; Gunawan et al., 2012; Jodeau, Hauet, Paquier, Le Coz, & Dramais, 2008), yet advances in positional and attitudinal data have allowed helicopters (Fujita & Hino, 2003; Fujita & Kunita, 2011) and more recently UAVs (Bolognesi et al., 2017; Detert & Weitbrecht, 2015; Tauro, Pagano, Phamduy, Grimaldi, & Porfiri, 2015; Thumser, Haas, Tuhtan, Fuentes-Perez, & Toming, 2017) to improve spatial coverage. The method shows promise, producing velocity measurements within 5–8% of those measured from total station tracking (Bolognesi et al., 2017). Future work is looking to eliminate the need for artificial tracers and create a more versatile methodology (Charogiannis, Zadrazil, & Markides, 2016; Legleiter, Kinzel, & Nelson, 2017; Thumser et al., 2017), which would likely result in more widespread use of PIV as a field-based method.

Over larger spatial scales, calibrating against river width has allowed satellite sensors to provide discharge to within 10% of observed values (Bjerklie, Moller, Smith, & Dingman, 2005). To overcome issues with box channels, whereby river width does not increase with discharge, it is possible to use river island size for calibration (Feng et al., 2012). However, the sensitivity of the method is limited by the pixel resolution of the satellite image.

2.2.3 | Water quality

Static ADV and ADCP deployments are able to be used to estimate suspended sediment concentrations (SSC) in the water column through use of acoustic backscatter under laboratory (Ha, Hsu, Maa, Shao, & Holland, 2009; Schindler & Robert, 2004) and field conditions (Chanson, Reungoat, Simon, & Lubin, 2011; Elci, Aydin, & Work, 2009; Leyland et al., 2017). Likewise, the acoustic backscatter from MBES sensors can be used to infer SSC, having been tested in controlled and field conditions (Simmons et al., 2010; Simmons et al., 2017), providing the opportunity to collect SSC data across feature and reach scales, yet their use is not currently widespread.

At the reach scale and beyond, estimates of SSC require the use of satellite imagery. Medium resolution imagery (20–30 m) has been used to investigate SSC at the confluence of the Mississippi and Missouri Rivers, both of which have differing sediment regimes (Umar, Rhoads, & Greenberg, 2018), as well as along the Yangtze (Wang, Lu, Liew, & Zhou, 2009). However, the majority of studies tend to use coarser (250 m) MODIS data focussing on large, well-gauged rivers such as the Yangtze (Wang & Lu, 2010), the Amazon (Mangiarotti et al., 2013; Santos, Martinez, Filizola, Armijos, & Alves, 2018), the Changjiang (Lu, He, Li, & Ren, 2006), and the Solimoes (Espinoza-Villar et al., 2018), utilising statistical relationships between observed SSC values with red and infrared spectral bands. However, this method is limited to those rivers with continual monitoring of discharge and suspended sediment and large enough to be observed from satellites; therefore, alternative methods are required across smaller extents.

Despite water quality estimates derived from remote sensing being well established in estuarine and coastal zones (Brando & Dekker, 2003; Chen, Hu, & Muller-Karger, 2007; Hellweger, Schlosser, Lall, & Weissel, 2004), it is less well developed in the fluvial domain. However, efforts have been made to obtain fluvial water quality data from UAV imagery, such as pollution detection (Lega et al., 2012; Lega & Napoli, 2010). Attempts to replicate satellite data procedures relating spectral data to chlorophyll *a*, Secchi disc depth, and turbidity with UAV imagery have been limited in success (Larson, Milas, Vincent, & Evans, 2018; Su, 2017). Regardless, the increasing use of UAVs in river corridor monitoring will likely improve methods for water quality monitoring.

2.2.4 | Morphology

By far the largest volume of research in river corridor monitoring relates to the measurement and monitoring of morphology through the production of digital elevation models (DEMs). Applications of modern data collection techniques such as TLS and SfM now outweigh traditional point-based survey techniques in the literature. These new techniques are particularly well suited for surveying of small features, which typically demand high-accuracy, high-resolution data, to detect small changes between surveys.

TLS enables users to overcome the spatial limitations of cross-sectional surveys, especially in the downstream direction, through increased point density (O'Neal & Pizzuto, 2011; Resop & Hession, 2010). Analyses such as creating DEMs of difference, comparing voxel models, and point cloud analysis have all utilised TLS data for investigating morphological evolution (Heritage & Milan, 2009; Leyland et al., 2015; Milan et al., 2007; O'Neal & Pizzuto, 2011; Resop & Hession, 2010; Starek, Mitasova, Wegmann, & Lyons, 2013). The advent of MLS has enabled these studies to expand beyond the typical spatial constraints of TLS, producing high-resolution datasets across reach scales (Alho et al., 2009; Leyland et al., 2017; Lotsari et al., 2015).

UAV imagery produces data at similar resolutions to TLS, usually with lower accuracy (see Figure 4) but covering larger areas. The ease of set-up and data collection makes it an ideal tool for repeat surveying, which allows work to be carried out over specific time intervals such as on seasonal or annual cycles (Brunier et al., 2016; Cook, 2017; Flener et al., 2013; Marteau et al., 2017; Miřijovský & Langhammer, 2015; Mirijovsky & Vavra, 2012; Smith & Vericat, 2015), as well as targeting specific high-discharge events (Tamminga, Eaton, & Hugenholtz, 2015; Watanabe & Kawahara, 2016). It is also possible to use UAV-derived topographic models to classify geomorphic features such as new versus old gravel accumulations (Langhammer & Vackova, 2018), showing some potential beyond morphological change detection that future work might pursue.

To capture larger reach and landform scale, morphology currently requires the use of ALS or satellite imagery. At the reach scale, ALS has been combined with historical topographic data (De Rose & Basher, 2011; James, Hodgson, Ghoshal, & Latiolais, 2012), used to monitor planform shift (Lallias-Tacon, Liebault, & Piegay, 2014), and assessed the potential for gully erosion (Perroy, Bookhagen, Asner, & Chadwick, 2010). Likewise, these data can also be used to classify channel characteristics such as riffle, pool, and step sequences (Cavalli, Tarolli, Marchi, & Dalla Fontana, 2008; Marchamalo, Bejarano, Jalon, &

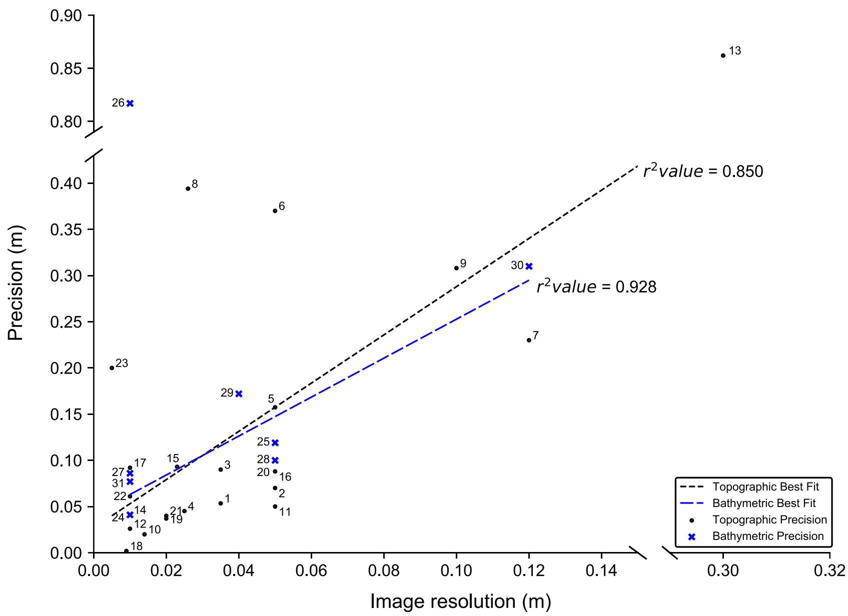

FIGURE 4 The relationships between survey imagery resolution from UAV aircraft and the geospatial precision (based off of RMSE and standard deviation values) for both topographic and bathymetric surveys. Note the higher r^2 value for bathymetric data is due to the exclusion of outlier point number 26 and the relatively fewer number of studies in this area. The *X* and *Y* axes are broken in order to focus on where the data points are clustered. The numbers alongside data points refer to the publications from which data were extracted for the plot, with some papers citing both topographic and bathymetric precisions as well as multiple test sites, and are therefore included twice: 1. Brunier et al. (2016); 2. Vericat, Brasington, Wheaton, and Cowie (2009); 3. Coveney and Roberts (2017); 4. Casado, Gonzalez, Wright, and Bellamy (2016); 5. Lejot et al. (2007); 6. Dietrich (2016); 7. Javernick, Brasington, and Caruso (2014); 8. Cook (2017); 9. Smith and Vericat (2015); 10. Watanabe and Kawahara (2016); 11. Van Iersel, Straatsma, Addink, and Middelkoop (2016); 12. Tournadre, Pierrot-Deseilligny, and Faure (2014); 13. Young, Peschel, Penny, Thompson, and Srinivasan (2017); 14. Bagheri, Ghodsian, and Saadatseresht (2015); 15. (Mirijovsky, Michalkova, Petyniak, Macka, & Trizna, 2015); 16. Tamminga, Eaton, and Hugenholtz (2015); 17. Woodget, Austrums, Maddock, and Habit (2017); 18. Woodget, Carbonneau, Visser, and Maddock (2015); 19. Miřijovský and Langhammer (2015); 20. Tamminga, Hugenholtz, Eaton, and Lapointe (2015); 21. Jaud et al. (2016); 22. Dietrich (2017); 23. Clapuyt, Vanacker, and Van Oost (2016); 24. Bagheri et al. (2015); 25. Tamminga, Hugenholtz, et al. (2015); 26. Woodget et al. (2017); 27. Woodget et al. (2015); 28. Tamminga, Eaton, and Hugenholtz (2015); 29. Shintani and Fonstad (2017); 30. Javernick et al. (2014); 31. Dietrich (2017) [Colour figure can be viewed at wileyonlinelibrary.com]

Marin, 2007), identify features such as alluvial fans and river terraces (Jones, Brewer, Johnstone, & Macklin, 2007), and automate channel network and geometry extraction (Passalacqua, Do Trung, Foufoula-Georgiou, Sapiro, & Dietrich, 2010). Landform scale studies do exist, with studies on the Mississippi River (Kessler, Gupta, Dolliver, & Thoma, 2012), the Lockyer Creek (Croke et al., 2013), and the Blue Earth River (Thoma, Gupta, Bauer, & Kirchoff, 2005), all utilising readily available LiDAR data to analyse morphological evolution, but they are often limited to regions with the financial capabilities to collect ALS data.

Satellite data analysis and application have typically been limited to large rivers such as the Ganges and Brahmaputra (Baki & Gan, 2012; Hossain, Gan, & Baki, 2013), the Mekong (Kummu, Lu, Rasphone, Sarkkula, & Koponen, 2008), the Jamuna (Baki & Gan, 2012), the Yellow River (Chu, Sun, Zhai, & Xu, 2006), and the Selawik and Yukon (Rowland et al., 2016) due to limited pixel resolution. Uses of satellite imagery include automatic calculation of river widths based on classified centrelines (Pavelsky & Smith, 2008; Yamazaki et al., 2014) as well as analysing the relationship between river width and multiple variables across a range of rivers wider than 90 m with discharge values between 100 and 50,000 $m^3 s^{-1}$ using Landsat imagery (Frasson et al., 2019). Satellite data can also be used to identify channel networks much like ALS (Isikdogan, Bovik, & Passalacqua, 2015) and also monitor channel reactivation through the use of synthetic aperture radar (SAR; Jung et al., 2010; Oyen et al., 2012). However, recent and future improvements in satellite image resolution will expand the potential of this method to smaller systems (Khorram, van der Wiele, Koch, Nelson, & Potts, 2016).

The methods above focus on subaerial analysis, as despite the subsurface being equally important, it is considerably more challenging to measure. At fine scales, through-water laser scanning shows potential in acquiring bed morphological data, requiring careful calibration for optimal results (Deruyter et al., 2015). However, there is evidence to suggest that increasing depths reduce accuracy due to laser attenuation (Smith et al., 2011). Similarly, surface instability and sediment concentration have been shown to have an even greater impact on accuracy (Smith & Vericat, 2014).

Similarly, both spectral depth techniques (Javernick et al., 2014; Legleiter, 2012; Lejot et al., 2007; Shintani & Fonstad, 2017; Tamminga, Hugenholtz, et al., 2015) and through-water SfM (Bagheri et al., 2015; Dietrich, 2017; Javernick et al., 2014; Shintani & Fonstad, 2017; Woodget et al., 2015) from UAV imagery can be used to collate high-resolution bathymetric datasets. The latter relies on clear water for optimal results, whereas the former relies on higher SSC to produce variations in spectral reflectance. Although no method clearly outperforms the other, it is apparent that choosing an appropriate technique is site and condition dependent.

Currently, reach-scale and larger scale bathymetric surveying relies heavily on boat-based MBES systems that can operate in a wide range of water conditions, being used extensively for research into the morphology of river beds and their interactions with flow dynamics (Best et al., 2010; Carling, Golz, Orr, & Radecki-Pawlik, 2000; de Almeida et al., 2016; Guerrero & Lamberti, 2011; Hackney et al., 2015; Leyland et al., 2017; Parsons et al., 2005).

Alternatively, green wavelength ALS can collect bathymetry over lengths from one to tens of kilometres (Hilldale & Raff, 2008; Kinzel, Legleiter, & Nelson, 2013; Kinzel, Wright, Nelson, & Burman, 2007), yet footprint size that reduces accuracy and point density are limiting factors (Tonina et al., 2019). Despite these methods being available, the extra challenge in obtaining them makes bathymetric analysis less prominent in the literature. There has also been promise in using light aircraft to fly imaging sensors such as the compact airborne spectrographic imager, which are capable of collecting bathymetric data up to depths of 10 m in clear waters with errors in the region of 0.2 m (Legleiter et al., 2016; Legleiter & Fosness, 2019)

2.2.5 | Vegetation

Vegetation is present across nearly all river corridor domains, whether interacting with flow, influencing bank stability, or contributing to floodplain roughness. At fine scales, resolving the spatial extent of vegetation and discretising vegetation structure are crucial for establishing hydraulic roughness. The reasonable canopy penetration and high spatial resolution make TLS methods favourable. TLS-based voxel models in combination with flume tests are used to analyse plant drag and motion, highlighting differential flows in the canopy and subcanopy layers (Boothroyd, Hardy, Warburton, & Marjoribanks, 2017; Vasilopoulos, 2017). TLS has also been used to identify leafless Manning's *n* values for different species across various flow scenarios (Antonarakis, Richards, Brasington, & Bithell, 2009), investigate spatially variable flow dynamics at differing depths due to submerged riparian vegetation (see Figure 5; Manners et al., 2013), and provide a link between vegetation roughness and subsequent trailing bar morphology (Bywater-Reyes, Wilcox, & Diehl, 2017). Identifying and quantifying areas of vegetation at the fine scale are important for applying drag coefficients, with Brodu and Lague (2012) successfully classifying TLS scans, whereas Jalonen et al. (2015) identified and calculated woody area from voxel models. For larger areas, boat-based MLS may provide opportunities

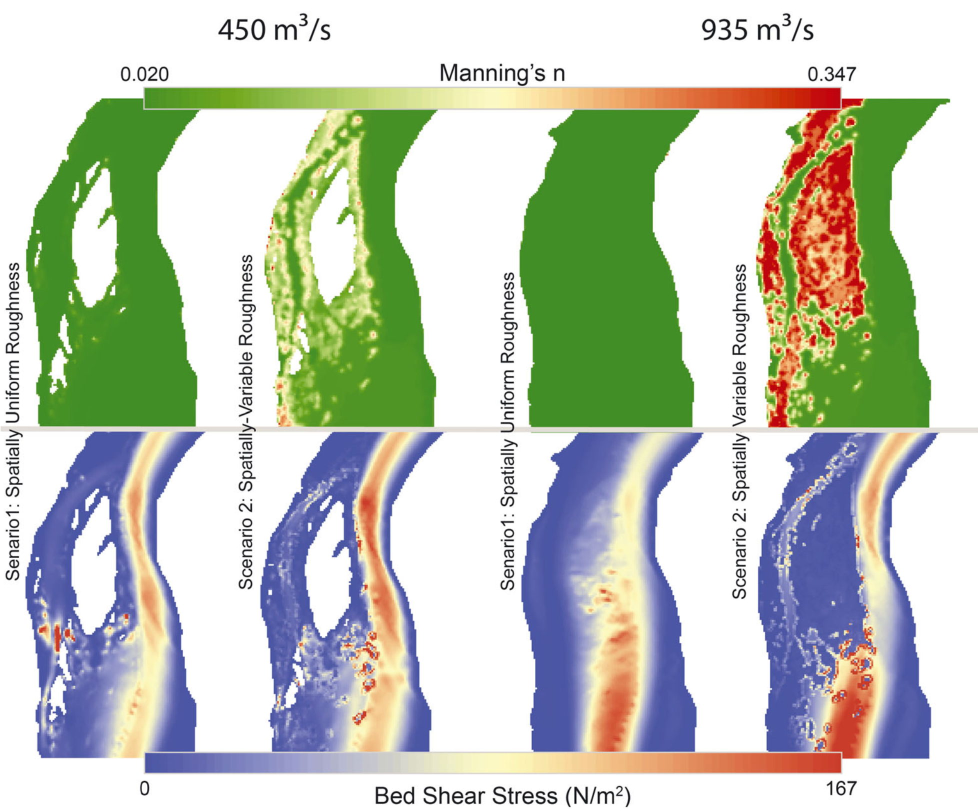

FIGURE 5 The effects of including spatially variable roughness across two discharge magnitudes on bed shear stress. Roughness variation was derived from using plant-scale TLS scans that were upscaled to LiDAR datasets to provide better informed roughness parameterisation when compared with spatially uniform measures. The differences in bed shear stress as a result of using spatially variable roughness highlights the importance of accounting for individual vegetation form and the subsequent impacts this can have on river morphology. Reprinted from Manners, Schmidt, and Wheaton (2013) [Colour figure can be viewed at wileyonlinelibrary.com]

for improved bank vegetation models (Alho et al., 2009; Saarinen et al., 2013).

UAV imagery has been used to monitor changes in vegetation preflood and postflood (Watanabe & Kawahara, 2016), for investigating floodplain grassland phenology (Van Iersel et al., 2016), and to improve habitat classification (Casado et al., 2016; Rapple, Piegay, Stella, & Mercier, 2017; Woodget et al., 2017). However, it is less useful for characterising individual vegetation structure, requiring multiple surveys in leaf on and off conditions (Dandois, Baker, Olano, Parker, & Ellis, 2017).

ALS shows the greatest utility in river corridor vegetation monitoring. At reach scales, ALS has been used for riparian zone classification (Antonarakis, Richards, & Brasington, 2008; Gilvear, Tyler, & Davids, 2004; Michez et al., 2013), assessment of wood and debris retention (Abalharth, Hassan, Klinkenberg, Leung, & McCleary, 2015; Bertoldi, Gurnell, & Welber, 2013), upscaling from TLS models (Manners et al., 2013), creating rainfall interception models (Berezowski, Chormanski, Kleniewska, & Szporak-Wasilewska, 2015), and for linking vegetation to morphological and anthropogenic contexts and needs (Bertoldi, Gurnell, & Drake, 2011; Cartisano et al., 2013; Picco, Comiti, Mao, Tonon, & Lenzi, 2017). At landform scales, ALS has been used to identify sources and volumes of woody debris (Kasprak, Magilligan, Nislow, & Snyder, 2012), the health of riparian ecosystems (Michez et al., 2013), the influence of vegetation on groundwater connectivity (Emanuel, Hazen, McGlynn, & Jencso, 2014), bank stability (McMahon et al., 2017), and water temperature through shading (Greenberg, Hestir, Riano, Scheer, & Ustin, 2012; Loicq, Moatar, Jullian, Dugdale, & Hannah, 2018; Wawrzyniak, Allemand, Bailly, Lejot, & Piegay, 2017). ALS therefore contributes heavily to our understanding of riparian vegetation and, despite potential drawbacks such as cost and mobilisation, is a key method to consider for monitoring activities.

Most studies utilising satellite data create classifications (e.g., Yang, 2007) before investigating the temporal dynamics of vegetation and studying agricultural pressures (Apan, Raine, & Paterson, 2002; Jupiter & Marion, 2008), differing seasons (Makkeasorn, Chang, & Li, 2009; Wang et al., 2011), and deforestation (Macedo et al., 2013) for example. Moreover, vegetation indices can be used to construct relationships between plant traits and spectral imagery. The enhanced vegetation index has been used to quantify evapotranspiration for mixed structure riparian forests (Nagler et al., 2005), the normalised difference vegetation index can be related to surface and groundwater (Fu & Burgher, 2015) or floodplain vegetation health and heterogeneity (Wen, Yang, & Saintilan, 2012), and the vegetation disturbance index can identify areas prone to gully rejuvenation after wildfires (Hyde, Jencso, Wilcox, & Woods, 2016).

By combining datasets, ALS and airborne imagery aided understanding of the ecological health of riparian vegetation over 12,000 km^2, identifying key areas that required ecosystem health management (Michez, Piégay, Lejeune, & Claessens, 2017). Likewise, high-resolution (2.4 m) Quickbird imagery and ALS data have contributed towards the production of hydrodynamic roughness models that are comparable with those obtained through traditional methods (Forzieri, Guarnieri, Vivoni, Castelli, & Preti, 2011; Forzieri, Moser, Vivoni, Castelli, & Canovaro, 2010), as well as to improving riparian vegetation classification across landform scales (Arroyo, Johansen, Armston, & Phinn, 2010). The structural and intensity data provided by ALS provide a good trade-off between requisite detail and spatial coverage (Johansen, Phinn, & Witte, 2010), despite the low temporal resolution that limits such studies to specific time intervals (Figure 2).

2.2.6 | Flooding

Flooding is an important physical process that facilitates channel–floodplain connectivity as well as posing an environmental hazard. Remote sensing provides data through which we can better understand, predict, and monitor flood events, across a range of scales.

Perhaps the most common flood relevant dataset that is produced is the DEM. Despite DEMs commonly being created for reach-scale (and larger) flood models, high-resolution DEMs have helped to improve local flood modelling in Glasgow compared with historical datasets (Coveney & Roberts, 2017) and local flood models produced for a rural village in the Apuseni Mountains, Transylvania, using a low-cost set-up to assess risk to a local school (Şerban et al., 2016). Despite no model validation in the latter case, it demonstrates the potential to improve understanding in typically low-priority locations.

Despite small-scale studies existing (e.g., Caviedes-Voullième, Morales-Hernández, López-Marijuan, Lacasta, & García-Navarro, 2013), it is more common for flood models to use ALS data over large areas to provide topographic information (Castellarin, Di Baldassarre, & Brath, 2011; Fang et al., 2010; Heritage, Entwistle, Milan, & Tooth, 2019; Karim, Kinsey-Henderson, Wallace, Arthington, & Pearson, 2012), providing the optimum trade-off between detail and coverage. Improvements in satellite-derived elevation models such as those from TanDEM-X (12-m resolution) also open the possibility for larger scale DEMs for flood modelling (Krieger et al., 2007). ALS can be utilised to parameterise floodplain roughness in conjunction with satellite imagery (Straatsma & Baptist, 2008) and importantly allow for better mesh discretisation to account for local variations in roughness (Cobby, Mason, Horritt, & Bates, 2003). Satellite imagery is also typically used as a calibration and validation methods (Di Baldassarre, Schumann, & Bates, 2009) as well as for flood boundary delineation, which often utilises SAR interferometry to overcome cloud cover (Frappart, Seyler, Martinez, León, & Cazenave, 2005; Horritt, Mason, & Luckman, 2001; Kuenzer et al., 2013; Martinez & Le Toan, 2007; Martinis, Kersten, & Twele, 2015; Townsend, 2001), although there are examples using spectral imagery (Amarnath, 2014; Kuenzer et al., 2015; Proud, Fensholt, Rasmussen, & Sandholt, 2011). Due to the scales commonly used in modelling applications and associated calibration and validation, this is likely to remain the most common technique for reach and landform scale studies.

2.3 | Real-world cross-scale applications

It is clear from the review above that remote sensing techniques are widely used across a range of domains in the river corridor but that most of the examples cited relate to research applications. However, there are numerous examples of these techniques being transferred to applied contexts. For example, many nations now routinely collect ALS data to create national datasets of topography that can be easily accessed by the public (e.g., United Kingdom [Environment Agency, 2017], Australia [Geoscience Australia, 2018], and United States [USGS, 2018]). The use of ARC-Boats, a remotely piloted unmanned surface vehicle (USV) developed by HR Wallingford and the UK Environment Agency, has enabled new practices to be developed for collecting flow, depth, and SSC data. This is designed with end users in mind and being operated in various countries around the world such as Canada and New Zealand (HR Wallingford, 2014). TLS has been employed by the National Trust on the River Ouse to produce 3D models (National Trust, 2018) used for research and science communication. Recently, there has been a demonstrable uptake in the use of UAV equipment in industry, most likely due to their versatility and relatively low cost. They have been used for monitoring programmes on the River Dee in Wales (Cranfield University, 2018) and the Forth River Trust conservation, protection, and enhancement schemes (Forth Rivers Trust, 2018). As well as monitoring, they are also used to detect leaks from water networks (Thames Water, 2018) and have the potential to be used to monitor poor farming practices (WWF, 2018), which increases run-off and sediment delivery in to the fluvial domain. Likewise, the use of Sentinel 2 satellite imagery has helped to inform Department for Environment Food and Rural Affairs about areas that may be hotspots for sediment pollution from excessive run-off (Richman & Hambidge, 2017). It is clear that remote sensing methods are primed to expand beyond research applications, with a likelihood that their use will become increasingly common practice in the future.

3 | THE STATE OF THE ART

A plethora of studies that are undertaking remote sensing of river corridors across a range of domains and scales have been highlighted. Here, we present the state of the art in river corridor remote sensing, primarily relating to the use of UAVs and multi-instrument sensing.

Despite widespread use of UAV imagery in the literature, there is an inherent reliance on ground control points for georeferencing. Eliminating this requirement reduces field time and allows surveys to take place in inaccessible locations. By recording high-accuracy positional and attitudinal information of a sensor, the need for ground control points is largely eliminated (Gabrlik, 2015), enabling greater levels of autonomy. Global navigation satellite systems (GNSS) and inertial motion unit (IMU) sensors, in conjunction with postprocessing techniques, known as postprocessing kinematic positioning, allow the user to locate a sensor and the resulting location of each pixel on the Earth's surface (Mian et al., 2015; Mostafa & Hutton, 2001). However, precise knowledge of camera parameters such as focal length and distortion are still required for accurate model location (James & Robson, 2014). This also enables the use of small-form factor laser scanners (such as the Velodyne LiDAR Puck, https://velodynelidar.com/vlp-16.html) to acquire UAV-based laser scanning (ULS). Originally, the majority of these systems relied on large UAVs (Deng, Zhu, Li, & Li, 2017; Gallay, Eck, Zgraggen, Kanuk, & Dvorny, 2016; Lin, Hyyppa, & Jaakkola, 2011; Nagai, Chen, Shibasaki, Kumagai, & Ahmed, 2009); however, lightweight systems have been developed, which can be mounted onto smaller platforms (Jaakkola et al., 2017; Mader, Blaskow, Westfeld, & Maas, 2015; Nakano, Suzuki, Omori, Hayakawa, & Kurodai, 2018; Roca, Martinez-Sanchez, Laguela, & Arias, 2016; Tommaselli & Torres, 2016). Currently, the high-accuracy GNSS and IMU systems required for ULS and direct georeferencing are expensive (upwards of £20K for ULS and ~£5K for direct georeferencing at the time of writing). A continued reduction in equipment costs will likely lead to an increased uptake in these methods, opening up avenues of research in previously inaccessible or dangerous locations or under hazardous conditions.

Combining multiple platforms and sensors is an exciting area of research that is yielding insights regarding river corridor function. The use of multiplatform configurations is not new, with multiple studies having combined ALS and satellite imagery datasets (Arroyo et al., 2010; Forzieri et al., 2010; Gilvear et al., 2004). However, there is evidence that interest in combining multiple high-resolution datasets obtained from both terrestrial, airborne, and surface systems is growing. Examples include combining aerial imagery from UAV platforms with ALS (Legleiter, 2012) and MLS (Flener et al., 2013), bathymetric ALS and ULS (Mandlburger et al., 2015), airborne imagery and ALS (Rapple et al., 2017), and multiple UAV flights with imagery and laser configurations (Mader et al., 2015). This has enabled researchers to improve their modelling of combined subaerial and subsurface morphology, better understand riparian vegetation encroachment, and enhance current data integration approaches; all of which would be more challenging through single dataset analysis.

Alongside solely airborne techniques, the combination of USVs and UAVs has become more prominent. Although there are examples of UAVs being used to “tether” USVs (Alvarez et al., 2018; Bandini et al., 2018), the majority of studies operate the platforms separately. By combining the two techniques, it is possible to collate information on either the topographic and bathymetric or the above and below canopy nature of a river corridor. Young et al. (2017) utilised a low-cost system to survey storage tanks in Bangalore with submetre accuracy. A more advanced set-up by Alvarez et al. (2018) obtained correlation results to ground truth data of $R > .98$ by combining echo sounder and SfM techniques. Alternatively, UAV and USV platforms can both collect imagery in addition to acoustics to improve estuarine mapping when compared with UAV imagery alone (Mancini, Frontoni, Zingaretti, & Longhi, 2015), although both methods are limited by vegetation shadowing. Powers, Hanlon, and Schmale (2018) performed USV tracking of a tracer dye “pollutant” from UAV imagery, demonstrating the power of real-time combined datasets, which may improve sampling and data acquisition, especially in unknown or difficult to observe environments.

Numerous vessels allow for simultaneous fluvial data collection. Both ADCP and MBES data were collected by Guerrero and Lamberti (2011), Hackney et al. (2015), and Leyland et al. (2017) for concurrent process and form measurements that are spatially and temporally homogenous, imperative for inferring flow–bed interactions. Manufacturers are increasingly providing solutions for simultaneous bathymetric and topographic data collection from small vessels for coastal research, which could easily be deployed in the fluvial domain (Kongsberg, 2013; Unique Group, 2018).

UAV surveys that utilise multiple sensor payloads have focussed on combining laser scanners and imagery for disaster recovery and river monitoring (Nagai et al., 2009); high temporal, spatial, and spectral resolution landscape dynamics research (Gallay et al., 2016); and forestry mapping (Jaakkola et al., 2010). However, most studies currently focus on the use of one sensor on UAV deployments due to weight implications relating to flight time endurance.

Currently, state of the art remote sensing tools are in their infancy. The majority of future development will revolve around two key themes: (a) producing highly accurate data in a timely and cost-effective manner and (b) processing these data to gain maximum insight. The former will rely on technological enhancement of sufficient progress to reduce the costs of high-grade IMU units that are small enough to be mounted on autonomous platforms. The latter requires advances in big data handling and point cloud/spatial data analysis techniques to handle the significant quantities of data produced and leverage the understanding from these sensors. Much like the proliferation of TLS and SfM techniques, which have progressed through proof of concept phases and are now routinely used, multisensor integration and high-accuracy attitudinal information will likely follow a similar path.

4 | FUTURE DIRECTIONS

The following section seeks to "horizon scan" for the technological advances, which may contribute to enhanced river corridor monitoring in the near future.

4.1 | UAVs

UAV swarm technology may enable fluvial research and monitoring to be performed more efficiently. Swarm technology presents an architecture that is scalable, efficient, and robust and helps to mitigate certain aspects of risk associated with UAV deployment (Howden, 2009; Zhao, Zhao, Su, Ma, & Zhang, 2017). UAV swarms can either be controlled using group decision making or individual agent response (Howden, 2009), with coverage being either "distributed" into defined zones of operation or "free" for optimum coverage through parallel decision making (San Juan, Santos, & Andujar, 2018). Applications for swarm mapping have included surveillance missions, search and rescue operations, weed mapping, and oil spill mapping (Albani, Nardi, & Trianni, 2017; Howden, 2009; Nigam, Bieniawski, Kroo, & Vian, 2012; Odonkor, Ball, & Chowdhury, 2017; Pitre, Li, & Delbalzo, 2012; San Juan et al., 2018). However, studies remain focussed on using simulations to test either algorithms (Almeida, Hildmann, & Solmaz, 2017; Chen, Ye, & Li, 2017; Yang, Ji, Yang, Li, & Li, 2017; Zhao et al., 2017) or data processing techniques (Casbeer, Kingston, Beard, & McLain, 2006; Ruiz, Caballero, & Merino, 2018). Despite the lack of real-world testing due to physical and legal constraints, swarm technology may enable rapid acquisition of data for river corridor applications on unprecedented scales.

UAV object tracking provides the opportunity for smarter surveying deployments. Current work has utilised machine learning to recognise a defined object and subsequently track it (Bian, Yang, Zhang, & Xiong, 2016; Rodriguez-Canosa, Thomas, del Cerro, Barrientos, & MacDonald, 2012; Trilaksono, Triadhitama, Adiprawita, Wibowo, & Sreenatha, 2011). There has been a recognised need for such methods to be implemented in environmental research practices (Pereira et al., 2009), with detection and tracking already being applied to features such as rivers, canals, and roads (Lee & Hsiao, 2012; Lin & Saripalli, 2012; Rathinam et al., 2007; Rathinam, Kim, & Sengupta, 2008; Zhou, Kong, Wei, Creighton, & Nahavandi, 2015). Despite the potential, there seems to be little uptake in applied river corridor research, whereby predetermined or nonautonomous flights are the norm. The heavy lift requirements, difficulty in isolating features in spectrally homogenous environments, and the potential for false feature identification currently hinder use (Lee & Hsiao, 2012; Rathinam et al., 2007). If these issues can be overcome, the potential for platforms to routinely monitor with little human input is attractive when considering highly dynamic fluvial environments.

4.2 | AUVs

Traditionally utilised in the marine environment, autonomous underwater vehicles (AUVs) use active sensing to guide them through missions such as maintaining survey depth for consistent resolution sea bed mapping (Brothers et al., 2015; Covault, Kostic, Paull, Ryan, & Fildani, 2014; Maier et al., 2013; Tubau et al., 2015), coral reef mapping (Armstrong & Singh, 2012), submarine lava identification (McClinton & White, 2015), and sea bed classification (Lucieer, Hill, Barrett, & Nichol, 2013). Terrestrial water applications are less common and require careful consideration due to the complex motion of water alongside the need for improved object detection and avoidance (Li, Xie, Luo, & Shi, 2012; Zhao, Lu, & Anvar, 2010). However, fluvial research has employed AUVs to collect variables such as temperature, salinity, conductivity, and nitrate flows in both autonomous and semiautonomous systems (Singh et al., 2007; Tester, Kibler, Hobson, & Litaker, 2006). Likewise, flow patterns and sediment loading have been studied in estuarine conditions (Kruger, Stolkin, Blum, & Briganti, 2007; Rogowski, Terrill, & Chen, 2014) as well as reservoir surveying (Socuvka & Veliskova, 2015), showing that the range of conditions AUVs can operate within. AUVs are also capable of tracking features such as pipelines and elevation contours in real world and simulated environments (Bennett & Leonard, 2000; Fallon, Folkesson, McClelland, & Leonard, 2013; Fiorelli et al., 2006; Ortiz, Simo, & Oliver, 2002; Sfahani, Vali, & Behnamgol, 2017; Xiang, Yu, Niu, & Zhang, 2016). This may allow smarter subsurface fluvial surveying techniques whereby AUVs can navigate river channels effectively, collating datasets over large areas with minimal human input or risk.

4.3 | USVs

Like UAV surveys, USVs use GNSS equipment and IMUs to provide accurate sensor locations for data collection. USV deployment in fluvial environments ranges from topographic to biophysical data collection (Casper, Steimle, Hall, & Dixon, 2009; Mancini et al., 2015; Suhari & Gunawan, 2017; Wei & Zhang, 2016; Young et al., 2017). The majority of these systems focus on bathymetric data collection from echo sounders, yet there are examples of both camera and water quality sensors being used (Casper et al., 2009; Mancini et al., 2015), as well as sensors for tracking and analysing simulated pollutants in freshwater environments (Powers et al., 2018). Not only do USVs provide the potential for collating bathymetry and water properties but also the surrounding terrestrial environment such as bank morphology and vegetation. USV surveying is likely to follow a similar pattern to UAVs in their increasing use for environmental research, whereby the technology becomes advanced enough for users to deploy a vessel with minimum human input, even in more challenging flow conditions.

4.4 | Real-time monitoring using Internet of things

The Internet of Things (IoT) in environmental monitoring is becoming increasingly prominent, with the technology available for a suite of uses. IoT is the extension of the internet in to physical devices that perform a role (Miorandi, Sicari, De Pellegrini, & Chlamtac, 2012). Sensors communicate between devices through networks, frameworks, and control centres, to share information and analyse data (Gubbi, Buyya, Marusic, & Palaniswami, 2013; Mitra et al., 2016). IoT has been used for environmental applications in remote and inaccessible locations for hazard response networks and monitoring research (Martinez et al., 2017; Miorandi et al., 2012).

IoT in the hydrological domain has focussed on engineering and infrastructure monitoring. For example, the South to North River Project in China uses over 100,000 sensors with 130 differing purposes to monitor water quality, infrastructure, and security (Staedter, 2018); all of which is fed in to a cloud infrastructure updated as frequently as every 5 min. Similar installations on smaller scales include active river and wetland management for water treatment (Wang et al., 2013), real-time sewage monitoring in the United Kingdom to mitigate flooding scenarios (Edmondson et al., 2018), as well as conceptual designs of flood embankment monitoring systems (Michta, Szulim, Sojka-Piotrowska, & Piotrowski, 2017). Uses for research include groundwater and river monitoring to better inform hydrological traits related to climatic variables, infiltration, and surface run off (Malek et al., 2017; Shi, Zhang, & Wei, 2014). Being able to effectively utilise the data captured over an IoT infrastructure may see the greatest development. Effectively using various machine learning techniques on big datasets can aid in the prediction of flood events in real time as demonstrated by Bande and Shete (2017) and Furquim et al. (2018). IoT monitoring networks not only benefit research applications but also will have a large impact on applied monitoring techniques, providing near real time information for better decision making, improving overall monitoring efficiency and performance.

4.5 | Satellite remote sensing

Given the role of satellites in revolutionising our view of fluvial systems, it would be remiss not to point out future developments in this technology, which are centred around the launch of a greater number of platforms with payloads delivering data for increasingly focused applications. The NASA-based Surface Water and Ocean Topography mission (NASA, 2019a) will be used to study the volumes of freshwater available in medium to large lakes and rivers, helping to understand water availability and any such related hazards. Similarly, the NASA-ISRO SAR mission (NASA, 2019b) will be used to not only map flood extents for hazard monitoring but also improve monitoring of groundwater, benefiting those seeking to address questions linking groundwater to surface water supply. Alongside specific sensors, the increasing availability of higher resolution imagery below 1 m such as provided by WorldView3 (Longbotham, Pacifici, Baugh, & Camps-Valls, 2014) will provide a large repository of data that may be of use to river corridor monitoring. As river corridors are affected by wider hydrological and environmental conditions, missions such as the Water Cycle Observation Mission, which is observing the water cycle under global change (Shi et al., 2016), alongside ESA Biomass and Fluorescence Explorer missions, which will help in understanding root zone soil moisture and transpiration rates respectively (McCabe et al., 2017), will all help to improve our holistic understanding of river corridors.

Alongside advances in sensors, the way in which data is processed and automated will also impact river corridor monitoring. With satellites producing such vast quantities of data, there is a need for big data infrastructure, as previously alluded to, in regard to satellite systems. These systems would likely capture, process, analyse, and create outputs to inform decision in an automated process (Raspini et al., 2018; Rathore et al., 2015). Methods that would benefit from such a structure are beginning to be employed within the river corridor, which would provide the potential for continual monitoring (Durand et al., 2016; Frasson et al., 2019; Gleason, Garambois, & Durand, 2017). Yet there will still be the need for improved algorithms to cope with the inherent environmental variability that is present across the globe.

5 | KEY CHALLENGES

The proliferation of monitoring techniques and their application to river corridors means that we are in a “golden age” of remote sensing in this domain. Research applications are broad, and proof of concept work has delivered many innovations in platforms, sensors, and data processing techniques. Nonetheless, before innovative autonomous remote sensing solutions are routinely adopted for applied river corridor management, we believe that there are five key challenges that the community, and others, must address:

1. Platform innovation: Although sensors are now well developed, platforms currently rely on human interaction for direct or assisted control in defining survey routines. Adequate object detection and avoidance alongside improved autonomy will allow for true smart systems operating beyond line of sight and in challenging conditions, performing adaptive sampling for optimal data collection over larger areas.
2. Processing innovation: Current systems have accepted methods of best practice for the production of repeatable and comparable datasets. Increasing platform autonomy needs to be accompanied by the development of computationally efficient and robust methods for data processing. Given the volumes of data being produced by mobile laser scanning and SfM techniques for example, big data and machine learning processing techniques need to be embraced and such methods should be embedded as routine tools within appropriate community repositories (see no. 5 below).
3. Efforts to improve process monitoring: Current techniques focus heavily on remotely sensing of morphology. Process data (i.e., river flow characteristics) are challenging to acquire at the desired temporal and spatial scales, and we urge the community to push the boundaries in this domain. Utilisation of multiplatform and/or multisensor integration to collect simultaneous process and form measurements may lead to the biggest gains in environmental understanding across the river corridor.
4. Legislation for autonomous systems: A significant barrier that is to be overcome before the routine use of autonomous and multiplatform systems is the legislation around operational safety, with restrictions on the operational range (e.g., within line of sight) a current limitation. Those regularly involved in river monitoring and research using these platforms need to be involved in the development of appropriate regulations by advocating safe use and practice within the domain. This should involve discussion with those implementing and developing the relevant laws and the creation of best operating practice guidelines for other researchers and practitioners to follow.
5. A river corridor data repository: The routine availability of remotely sensed river corridor data is patchy at best. Open data repositories such as the Department for Environment Food and Rural Affairs Data Services Platform (https://environment.data.gov.uk/) and the Channel Coastal Observatory (Southwest Regional Coastal Monitoring Programme, 2009) are demonstrating the benefits of well-organised, open-source data. A shift towards the community making their collected data available to a wider audience through an equivalent repository will enable others to benefit from information the original owners may have viewed as redundant, benefiting the community as a whole.

6 | CONCLUDING REMARKS

This review reveals the sheer volume of remote sensing methods that are currently used to monitor various domains of the river corridor across a range of scales. This may include finer scale studies which utilise TLS, through to larger scale studies that use ALS and satellite data to support research and applied monitoring, with UAV imagery allowing for reach-scale topographic analysis alongside subsurface data from MBES and ADCP sensors. The majority of the work in the river corridor focusses on morphological evolution, with the processes that drive such topographic change being more difficult to observe. We advocate a shift towards improved process measurement techniques to better understand the interactions between flow, morphology, and associated ecological response. This will be facilitated by improved capabilities to collect simultaneous process and form measurements on multisensor platforms, as well as by the ever-improving processing power required to deal with the resultant large datasets.

The remote sensing tools now at our disposal make it possible to obtain extensive and accurate datasets that were previously unattainable, for use in a variety of applications in river corridor research and management. Remote sensing techniques are enabling new insights into complex interacting areas, for example, riparian vegetation and flow interactions and the resultant evolution of channel morphology. The evolution of techniques and decreasing equipment costs have helped progress research, management, and industrial applications, allowing users to select the most suitable from a plethora of techniques. The monitoring needs of river corridor researchers and managers can likely be met through remote sensing techniques, meaning that careful identification of the desired spatial and temporal resolution, alongside the required outcomes are likely the most important factors in deciding which methods to use.

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DATA AVAILABILITY STATEMENT

The data used to construct Figure 4 within this study are available from the corresponding author upon reasonable request.

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