Evaluation of 'Structure-from-Motion' from a Pole-Mounted Camera for Monitoring Geomorphic Change

Rebecca K. Rossi
Utah State University

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EVALUATION OF ‘STRUCTURE-FROM-MOTION’ FROM A POLE-MOUNTED CAMER A FOR MONITORING GEOMORPHIC CHANGE

by

Rebecca K. Rossi

A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in

Watershed Sciences

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2017
ABSTRACT

Evaluation of ‘Structure-from-Motion’ from a Pole-Mounted Camera for Monitoring Geomorphic Change

by

Rebecca K. Rossi, Master of Science
Utah State University, 2017

Major Professor: Joseph M. Wheaton, Ph.D.
Department: Watershed Sciences

“Structure-from-Motion” Photogrammetry and Multi-View Stereo (hereafter referred to as SfM) is a newer technology in geomorphology for surveying topography and creating digital elevation models (DEMs). Few have used SfM to generate DEMs for repeat surveys or geomorphic change detection. All surface models have some degree of error which directly impacts the ability to accurately and precisely relate form and process through time and space. Therefore, it is important to accurately characterize error that is derived from SfM DEMs. There are many ways to characterize SfM DEM error, but other studies have shown the importance of using spatially variable error models. To answer questions about the utility of the SfM method for repeat geomorphic change detection and characterizing error I used a case study of alluvial sandbar topography along the Colorado River in Marble and Grand Canyons in Arizona. The inputs of the error model include topographic slope and roughness and interpolation error. To parameterize the output of the error model, I used 3 independent elevation uncertainty analyses and I found varying magnitudes of elevation uncertainty of SfM DEMs from each of the four analyses: 1.) bootstrapping (MAE = 0.019 m), 2.) residual (MAE = 0.135 m), and 3.) repeat (average range value of camera parameter variability repeat surveys = 0.050 m, average range value of survey method variability repeat
surveys = 0.173 m) analyses. Although investigated, I did not include the non-topographic source of elevation uncertainty, camera footprint density, in the error model, but the model could be improved with this input. The pole-mounted camera platform provided a low-angle perspective that was not ideal for image post-processing, but provided SfM DEMs that could be used for cell-by-cell geomorphic change detection. A nadir perspective would aid in more efficient generation of the sparse point cloud. However, there are many settings (including the Grand Canyon) where nadir perspectives from unmanned aerial vehicles, fixed-wing aircraft and/or tethered blimps are not legal, safe or practical. While a nadir perspective is possible from the pole, the limited field of view would make it less efficient and a slower acquisition method. Although the error model that I built in this study was based upon a large dataset acquired with the pole-mounted image platform, it is widely adaptable for other image platforms.
PUBLIC ABSTRACT

Evaluation of ‘Structure-from-Motion’ from a Pole-Mounted Camera for Monitoring Geomorphic Change
Rebecca K. Rossi

Emerging “Structure-from-Motion (SfM) photogrammetry techniques encourage faster, cheaper, and more accessible field methods for accurately reconstructing 3D topography. The SfM method consists of collecting sets of overlapping images of the ground surface with a point and shoot camera, and reconstructing surface topography from the images with developed software programs. This research develops and implements a SfM image acquisition method and post-processing workflow as a supplemental technique to the traditional total-station method to aid in monitoring sandbar change in Marble and Grand Canyons along the Colorado River in Arizona. Due to permitting in Grand Canyon National Park, a 4.9 m pole-mounted camera platform was used in this research to mimic the ground perspective of an aerial platform. This research presents an improved understanding of how the low-angle, pole-mounted camera platform affects image acquisition and ultimately 3D reconstructions of the surface topography.

Models of ground surfaces always contain some degree of elevation error, or uncertainty. As such, elevation error models are needed to distinguish whether observed changes to topographic features (in this case sandbars) are real or simply due to elevation error. There are many ways to quantify multiple sources of elevation uncertainty, but in this study the sources of elevation uncertainty were considered to vary across the surface and were characterized accordingly. Especially in river environments with complex surface topography (e.g. steep cut banks), and roughness (e.g. vegetation), quantifying the spatially variable elevation uncertainty of the surface representation is critical for interpreting actual changes in surface topography over repeat surveys. This research:

• used the sandbar images collected in Marble and Grand Canyons with the pole-mounted camera platform to generate SfM, topographic models;
• calculated spatially variable surface uncertainty derived from slope and roughness using multiple statistical analyses;

• built an error model that was calibrated based upon the statistical analyses of the spatially variable surface uncertainty;

Key findings of this research are:

• Densely vegetated topography results in high amounts of elevation uncertainty, and without additional information of the surface underlying the vegetation, the SfM tool is less operational in these areas;

• Bare, exposed topography with low to high slopes that are not covered in black shadows result in lower surface uncertainty, and are areas where SfM is an operational tool for studies of surface change.

Complementing existing topographic sampling methods with more efficient and cost-effective SfM approaches will contribute to the understanding of changing responses of the topographic features. In addition, the development and implementation of SfM and corresponding amounts of elevation uncertainty for monitoring geomorphic change will provide a methodological foundation for extending the approach to other geomorphic systems worldwide.
To my river family.
ACKNOWLEDGMENTS

The author thanks all the dedicated surveyors (especially Joe Hazel and Matt Kaplinski), river guides, and volunteers that collected data for this study. I personally thank our colleague, Ester Ramos from the University of Lleida, for enthusiastically acquiring SfM data in Grand Canyon in 2015. The funding for this project was provided by the United States Geological Survey, Grand Canyon Monitoring and Research Center. I personally thank my Utah State University cohort, namely Martha Jensen, Gracie Miller, Bruce Call, and Angus Vaughan, for helping break into graduate school and sharing research ideas. I greatly appreciate insight and support from the Ecogeomorphology and Topographic Analysis Lab and Fluvial Habitats Center, namely Dan Hamill, Konrad Hafen, Alan Kasprak, Kenny Demeurichy, Nate Hough-Snee, Pete McHugh, Wally MacFarlane, and Carl Saunders. This research builds directly off of the work of Sara Bangen and James Hensleigh, who provided excellent feedback for this project. Thank you Jack Schmidt for introducing me to large river management and water policy. I'd like to thank my busy advisors, Joe Wheaton, Dan Buscombe, and Paul Grams, who passionately shared their knowledge of geomorphic change and Grand Canyon with me. Most importantly, I thank my family, Dave, Vonda, Jessica and Sara for always supporting me.

Rebecca K. Rossi
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<td>API</td>
<td>application programming interface</td>
</tr>
<tr>
<td>ASCII</td>
<td>American standard code for information interchange</td>
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<tr>
<td>DEM</td>
<td>digital elevation model</td>
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<tr>
<td>DoD</td>
<td>digital elevation model of difference</td>
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<tr>
<td>ESPG</td>
<td>European Petroleum Survey Group</td>
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<tr>
<td>FIS</td>
<td>fuzzy inference system</td>
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<td>GPS</td>
<td>global positioning system</td>
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<td>GCMRC</td>
<td>Grand Canyon Monitoring and Research Center</td>
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<td>GCP</td>
<td>ground control point</td>
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<td>HFE</td>
<td>high flow experiment</td>
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<td>HRT</td>
<td>high resolution topography</td>
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<td>LiDAR</td>
<td>light detection and ranging</td>
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<td>LW</td>
<td>lower whisker</td>
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<td>minLoD</td>
<td>minimum level of detection</td>
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<td>NAU</td>
<td>Northern Arizona University</td>
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<tr>
<td>NAD83</td>
<td>North American datum of 1983</td>
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<tr>
<td>MAE</td>
<td>mean absolute error</td>
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<td>mean error</td>
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<td>MF</td>
<td>membership function</td>
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<td>membership function group</td>
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<td>MVS</td>
<td>multi-view stereo</td>
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<td>red-green-blue</td>
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<td>river-kilometer</td>
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<td>real-time kinematic</td>
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<td>scale invariant feature transform</td>
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<td>topographic point cloud analysis toolkit</td>
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<td>total station</td>
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<td>unmanned aerial vehicle</td>
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<td>United States Geological Survey</td>
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<tr>
<td>UW</td>
<td>upper whisker</td>
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<td>$Z_{min}$</td>
<td>minimum elevation</td>
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INTRODUCTION

1.1 Role of High Resolution Topography in Geomorphology

The introduction of high resolution topography (HRT) has not fundamentally changed the problems that geomorphologists have always sought to solve (Church, 2013; Wohl et al., 2016). However, HRT has changed the scale, frequency, and signal at which geomorphic processes can be quantified (Church, 2013; Wohl et al., 2016). This change was facilitated through technological advancements in high resolution surveying techniques such as digital photogrammetry (e.g. Chandler et al., 2002; Carbonneau et al., 2003; Lane et al., 2010), multi-beam sonar (e.g. Buscombe et al., 2014), airborne LiDAR (e.g. Cavalli et al., 2008; Passalacqua et al., 2010) and terrestrial LiDAR (e.g. Brasington et al., 2012; Smith and Vericat, 2014). HRT has allowed geomorphologists to make detailed and continuous measurements and models of the Earth’s surface (Westaway et al., 2003; Nagihara et al., 2004; Arrowsmith and Zielke, 2009; Tarolli et al., 2012; Javernick et al., 2014). In the absence of established theoretical definitions of processes that have geomorphic implications (Ashmore and Church, 1998; Lane et al., 2003; Grams et al., 2013), HRT has allowed geomorphologists to empirically quantify precise magnitudes of landform change through repeat, topographic surveys from the feature to landscape scale (Lane et al., 1994; Brasington et al., 2000; Lim et al., 2005; Vericat et al., 2014; Kasprak et al., 2017). The frequency in which most geomorphic processes occur can now be measured with HRT (Tarolli, 2014; Passalacqua et al., 2015). Lastly, geomorphic processes that contain subtle signals of topographic change compared to the noise in the topographic data can be confidently measured with HRT (Lane et al., 2003; Wheaton et al., 2010; Milan et al., 2011). Although HRT has become a popular tool for quantifying the processes that shape and change landforms, making accurate, precise and high quality repeat, HRT measurements remains a challenge (Passalacqua et al., 2015).
The challenge with HRT is even greater for monitoring applications that quantify cell-by-cell change from the digital HRT product (e.g. digital elevation model: DEM) instead of calculating summary change statistics over an entire area (Rosser et al., 2005). All DEMs predict elevations with some degree of uncertainty and error (Wechsler and Kroll, 2006; Bangen et al., 2014; Lane et al., 2003; Brasington et al., 2000; Wheaton, 2008). Uncertainty is the quantification of the doubt about the measurement result. Elevation uncertainty is introduced to the DEM throughout most stages of data acquisition and post-processing (Brasington et al., 2000; Lane et al., 2003; Wechsler and Kroll, 2006; Wheaton, 2008; Bangen et al., 2014). DEM error is the elevation difference (i.e. length) above or below (+/-) the predicted estimate of elevation. In principle errors are known and corrected. Not only does elevation error affect individual DEMs, DEM error propagates through repeat change calculations or DEMs of difference (DoD; Brasington et al., 2000; Lane et al., 2003; Wheaton et al., 2010; Milan et al., 2011).

1.2 SfM for Monitoring

Structure-from-Motion photogrammetry (SfM) and multi-view stereo (MVS), collectively referred to in this thesis as SfM, have recently become accepted, accurate HRT tools for reconstructing topography (Mancini et al., 2013; Javernick et al., 2014; Micheletti et al., 2015; Piermattei et al., 2015; Prosdocimi et al., 2015; Woodget et al., 2015; Carrivick et al., 2016; Nouwakpo et al., 2016), hydrodynamic analysis (Javernick et al., 2014; Smith et al., 2014; Westoby et al., 2014), and geomorphic change detection (James and Robson, 2012; Westoby et al., 2012; Fonstad et al., 2013; Lucieer et al., 2013; Gómez-Gutiérrez et al., 2014; Smith and Vericat, 2015; Turner et al., 2015; Clapuyt et al., 2016; Dietrich, 2016b). Despite recent advances in the use of SfM to accurately map landforms in less time and at lower costs (Carrivick et al., 2016), its utility for reliably detecting and monitoring cell-by-cell change over repeat surveys remains underexplored. The problems that already exist for HRT methods to detect and monitor geomorphic change are the same for this new SfM HRT technique. Cell-by-cell geomorphic change detection with any HRT method can be difficult, and in specific cases (e.g. fluvial environments) requires thorough accountability.
of uncertainty and error in individual DEMs (Wheaton et al., 2010). DEM error estimates are critical for the determination of propagated error magnitudes, which factor into detecting and monitoring actual geomorphic change (Brasington et al., 2000; Lane et al., 2003; Wheaton, 2008; Wheaton et al., 2010; Milan et al., 2011; Smith et al., 2014).

1.3 The SfM Method

The SfM method consists of a field survey component in which overlapping images are collected from multiple camera perspectives without exact knowledge of camera parameters, and a post-processing component in which SfM and MVS algorithms automatically resolve camera parameters and orientations from unordered image sets, producing a 3D, topographic model (James and Robson, 2012; Fonstad et al., 2013; Bartoš et al., 2014; Gomez et al., 2016; Smith et al., 2016). The field survey components of the SfM method include: image acquisition platform and design, camera type and setup, and ground control point acquisition. The post-processing components of the SfM method include: SfM and MVS algorithms/ software, the point cloud georeferencing process, DEM generation, and validation analysis of point clouds and/or DEM. In comparison to other HRT methods (e.g. aerial and terrestrial LiDAR), image collection can be easily performed in remote study areas across a variety of scales (e.g. sandbars to river corridors; Dietrich, 2016b). The image acquisition and SfM post-processing, which often requires minimal skill, time, and cost compared to other HRT methods (Figure 1.1) has led to the democratization of HRT data (Westoby et al., 2012; Fonstad et al., 2013; Smith et al., 2016).

1.3.1 SfM Field Survey

Aerial platforms (i.e. UAVs, helikites, helicopters, autogiros and traditional fixed wing aircraft) allow for an advantageous aerial perspective that maximizes image overlap and coverage (e.g. Piermattei et al., 2015). Therefore, aerial platforms are ideal for image acquisition over large features (10,000 to 1,000,000 m²; e.g. Dietrich, 2016b) that may contain diverse landcover (e.g. rills, steep headcuts, and low-lying vegetation; e.g. Smith and Vericat, 2015). Nadir aerial perspectives also increase the probability of capturing
the bare earth surface amongst densely vegetated terrain (Westoby et al., 2012; Gómez-Gutiérrez et al., 2014). The most widely used image acquisition platform is the aerial, UAV platform, which can rapidly and automatically collect near-nadir, overlapping imagery across landscape features (Harwin and Lucieer, 2012; Lucieer et al., 2013; Bemis et al., 2014; Lucieer et al., 2014; Ouédraogo et al., 2014; Tonkin et al., 2014; Vasuki et al., 2014; Puttock et al., 2015; Ryan et al., 2015; Smith and Vericat, 2015; Turner et al., 2015; Clapuyt et al., 2016). Microlight aircraft, gliders, helicopters, and autogiros provide similar image acquisition platforms to UAVs, but can be more reliable for increased camera pay loads or

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**Fig. 1.1.** Graph from (Carrivick et al., 2016) showing the lowest cost and high survey speed of the SfM method compared to other HRT Methods.
surveying during adverse weather conditions (James and Robson, 2012; James and Varley, 2012; Javernick et al., 2014; Smith and Vericat, 2015; Woodget et al., 2015; Dietrich, 2016b).

In fluvial environments, aerial platforms present challenges for image acquisition. In confined valley settings, often in narrow valleys and gorges, multi-pathing and terrain limit the safety and operability of UAVs and/or low-altitude manned aircraft (Piermattei et al., 2015). Partly confined and laterally unconfined settings often have extensive valley bottoms occupied by riparian vegetation. This riparian vegetation cover obscures the line of sight necessary for obtaining dense, ‘bare earth’ ground shots with photogrammetric methods. UAV platforms are highly functional and efficient at image capture of inaccessible terrain during normal weather conditions, but are often inoperable in heavy rain or wind conditions (e.g. Westoby et al., 2012; Tonkin et al., 2014). In the United States, UAV platforms require flying permits, and are banned or restricted from use in National Parks (Johnson et al., 2014; Whitehead and Hugenholtz, 2014). As of 2015 in the United Kingdom, small UAVs (< 7 kg) do not require a permit (Woodget et al., 2015), but require unaided visual line of sight (Tonkin et al., 2014). Thus, image acquisition requires more time to reposition the UAV unit for surveying a non-linear stream feature (Tonkin et al., 2014). Compared to helikites, helicopters, autogiros, and traditional fixed wing aircraft, the range, extent, and control of an UAV can be compromised by short battery life and limited GPS capabilities (e.g. Smith and Vericat, 2015), which could potentially result in losing the unit, especially in a narrow canyon.

Handheld and pole-mounted camera platforms are potential alternatives to aerial platforms. Handheld camera platforms that are used to acquire images of smaller features (10 to 100 m² in extent) with the sensor placed directly perpendicular to the front face of the survey feature (e.g. cliff face; James and Robson, 2012; Smith et al., 2014; Westoby et al., 2014; Micheletti et al., 2015; Prosdocimi et al., 2015) or above the feature (Gómez-Gutiérrez et al., 2014; Smith et al., 2014; Westoby et al., 2014) have resulted in complete and accurate reconstructions. Compared to handheld cameras, the underrepresented pole-mounted camera (Oldmeadow and Church, 2006; Armistead, 2013; Dietrich, 2015; Smith and Vericat,
2015) allows for a more expansive aerial perspective that can be surveyed with fewer images covering more of the study feature. For example, Dietrich (2015), maps and monitors geomorphic change for a small river restoration project using pole-mounted imagery, and highlights the benefits of the pole for multiple image acquisition scales. Additionally, the narrow ground perspective of a handheld camera can obstruct the sight of complex surface features (Smith et al., 2016). The pole-mounted camera platform is cheaper and can be easier to operate than UAVs, especially when surveying fluvial features in narrow canyons with unreliable GPS. Depending on the quality of the camera, the pole and camera setup ranges in cost from around $100 to $1000 (Dietrich, 2015). Whereas a UAV itself can cost between $400 to $600 in addition to the camera costs (Cook, 2017). The pole-mounted camera is also an alternative to UAVs in restricted flight areas (e.g. National Parks). Both the handheld and pole-mounted camera platforms present challenges for image acquisition and reconstruction, including issues of complete image coverage of large and complicated terrain, complete terrestrial access of the entire study area, jeopardized camera geometry (e.g. decreased camera footprint area and elongated camera footprint shape), and obstructions to line of sight of the bare earth surface.

Feature scale, image acquisition platform, and transect design influence survey times and the total number of images used in the reconstruction process. Large-scale features (1,000 to 1,000,000 m²) are surveyed with aerial platforms (e.g. micro-light aircraft, helicopters, autogiros, and UAVs). The high position of the aerial platform (30 to 800 m) ensures wider aerial perspectives, more image overlap and lower image counts. For example, Javernick et al. (2014) acquired 147 images of a 1 km² reach of the Ahuriri River in New Zealand with a helicopter flying 600 to 800 m above the ground surface, while Smith and Vericat (2015), flying closer to the ground surface (250 m) acquired several hundred more images (527) at the same feature scale to ensure image overlap. Small-scale features (e.g. 10 to 100 m²) are more likely to be surveyed with terrestrial platforms (e.g. handheld or pole-mounted camera) and the number of images is approximately equal to the feature scale. For example, Westoby et al. (2014) surveyed a 2,500 m long moraine, collecting 2,056
handheld images along elevated positions overlooking the moraine. Flight path designs consist of frontward and sideward overlapping (60-80%) transects parallel to the feature (e.g. Jaernick et al., 2014), multiple transects collected in semi-random directions (e.g. Fonstad et al., 2013), and multiple, circular transects around the feature (e.g. James and Robson, 2012). Terrestrial image acquisition designs consist of transects encircling the feature with convergent images (e.g. Gómez-Gutiérrez et al., 2014), transects with the sensor perpendicular to a vertical feature (e.g. James and Robson, 2012), and linear transects along an elevated and accessible part of the feature (e.g. Westoby et al., 2014).

Camera setups, including the actual camera lens/sensor, ground resolution and trigger mechanism, vary depending on the feature scale and image acquisition platform. Camera types for image acquisition include digital single lens reflex (DSLR) cameras (e.g. Gómez-Gutiérrez et al., 2014) and also lighter point and shoot (P&S) cameras (e.g. Ouédraogo et al., 2014; Smith and Vericat, 2015) with fixed focal lengths (20-55 mm). Ground resolution is determined by the focal length of the camera; smaller focal length results in a wider perspective, but coarser ground resolution (Clapuyt et al., 2016). Higher ground resolution does not necessarily equate to higher DEM quality or lower DEM error (Eltner et al., 2015). For example, Clapuyt et al. (2016) demonstrate better reproducibility with a 28 mm DSLR lens, which has lower ground resolution than the 50 mm lens alternative. Canon cameras are often used for their accessible programming capabilities to automatically trigger the camera sensor with an intervalometer script (e.g. Dietrich, 2016b). But Smith and Vericat (2015) manually triggered the camera sensor from an autogiro to avoid dome-type systematic errors caused by consistently nadir camera angles (e.g. James and Robson, 2014; Eltner et al., 2015; Gómez-Gutiérrez et al., 2015).

The collection of accurate and precise ground control points in the field is necessary for georeferencing the point clouds during post-processing (e.g. Dietrich, 2016b). The height of the camera platform relative to the ground surface influences the size of the GCP and GCP centroid; a more elevated platform (e.g. Dietrich, 2016b) will result in a larger GCP size (m) and resolvable GCP centroid in the images. Brightly colored and highly contrasted GCPs
(e.g. Lucieer et al., 2013; Smith and Vericat, 2015) allow for automatic RGB detection (e.g. Clapuyt et al., 2016) and/or facilitated, manual identification of GCPs in images. Alternatively, James and Robson (2012) use the location of hard points in the scene rather than placed GCP targets. (Dietrich, 2016b) asserts that the accuracy of the SfM DEM is dependent on the accuracy of the GCPs and recommends using a well-established control network and a TS or RTK-GPS to collect GCPs. The feature scale and platform can influence the number of GCPs, so that the larger the feature scale (e.g. 1 km² Javernick et al., 2014) and the higher the platform (e.g. 600 to 800 m; Javernick et al., 2014) the greater the GCP count (e.g. 95; Javernick et al., 2014). However, high GCP counts (e.g. 49; Westoby et al., 2014) have been used for smaller features (e.g. 2,500 m²; Westoby et al., 2014). GCPs are distributed in gridded (Clapuyt et al., 2016), random (Dietrich, 2016b) or circular (Nouwakpo et al., 2016) patterns across the surface of the feature.

1.3.2 SfM Post-Processing

The most commonly used commercial SfM software is Agisoft Photoscan Professional (Carrivick et al., 2016). Photoscan discloses less algorithmic information, making it difficult to minimize potential sources of error in 3D reconstructions and propagated error throughout topographic time-series data (Smith et al., 2016). However, it also has the easiest-to-use software and most complete workflow of any commercial or open source alternative. Bartoš et al. (2014) and Smith et al. (2016) provide detailed comparisons of SfM and MVS algorithms and software. Although SfM and MVS algorithms require large amounts of RAM and graphics cards, few studies report this information or disclose image post-processing times. All of the SfM software contain similar algorithms to create sparse and dense point cloud reconstructions. Smith et al. (2016) summarize the SfM and MVS algorithms as a 7-part process and Carrivick et al. (2016) illustrate a SfM workflow that parallels these seven steps in Figure 1.2:

1. **Feature detection**: unique key point identifiers are assigned to each image independent of perspective or scale using the Scale Invariant Feature Transform (SIFT) object recognition system.
2. **Keypoint correspondence**: identification of corresponding unique key points in multiple images.

3. **Identifying geometrically consistent matches**: removal of erroneous key point matches.

4. ‘**Structure-from-Motion**’: simultaneous estimation of 3D geometry (i.e. structure) of a scene, different camera poses (extrinsic calibration) and, camera intrinsic parameters (intrinsic calibration) using bundle adjustment algorithms.

5. **Scale and georeferencing**: seven parameter linear similarity transformation of sparse 3D point cloud includes three global translation, three rotation, and one scaling parameter.

6. **Refinement of parameter values**: known coordinates and estimated point error from the previously georeferenced point cloud provide additional correction during a second bundle adjustment step.

7. **Multi-view stereo image matching algorithms**: increases the point density of the georeferenced sparse point cloud.

The process of turning dense point clouds into DEMs remains a challenge for all HRT methods (Passalacqua et al., 2015). Many studies use direct DEM outputs from the SfM software (Lucieer et al., 2013; Mancini et al., 2013; Woodget et al., 2015; Dietrich, 2016b), but DEM errors are much less transparent. DEM errors can be better accounted for by exporting the raw dense point cloud from the SfM software. Addition questions can then be asked during the raw point cloud to DEM process: (1) how should the point cloud be cleaned (e.g. to remove vegetation/ artifacts) to produce a bare-earth subset; (2) how should the point cloud be thinned, resampled, and interpolated to allow for efficient DEM generation. Manual point cloud cleaning methods (e.g Piermattei et al., 2015) can be time-consuming and lead to accidental removal of important information (Passalacqua et al., 2015). Whereas statistical methods such as ToPCAT (e.g JaVERNICK et al., 2014; Smith et al., 2014; Westoby et al., 2014; Smith and Vericat, 2015) significantly decrease DEM
generation times, but may preserve artifacts (e.g. roughness that wasn’t eliminated from the bare earth DEM).

Fig. 1.2. General SfM post-processing workflow from Carrivick et al. (2016). Green = image matching algorithms; Blue = SfM algorithms; Red = georeferencing; Yellow = MVS algorithms used to generate sparse and dense point clouds. Dotted arrows indicate reprocessing steps that may be necessary to correct sparse point clouds.

Most SfM papers present a validation analysis of a single dataset that have been carried out by comparing a SfM point or DEM dataset with a reference dataset that is assumed to have higher accuracy. Although point clouds and DEMs derived from terrestrial and airborne LiDAR provide the most comparable data product to SfM datasets, ‘truth’ datasets with lower point densities such as GPS (Javernick et al., 2014) and total station (Harwin and Lucieer, 2012; Tonkin et al., 2014; Smith and Vericat, 2015) are used. Common validation metrics are mean error, mean absolute error, root mean square error, and standard deviate of error, which are typically reported as summary statistics for the entire point cloud or DEM (Prosdocimi et al., 2015; Smith and Vericat, 2015). Known sources of
SfM DEM error include image geometry/perspective, survey range, the number of images used in reconstructions, image overlap, post-processing and interpolation error, and camera parameter error such as lens distortion (Smith and Vericat, 2015; Smith et al., 2016). Previous studies show that accuracies for individual SfM datasets are similar in magnitude to those obtained with other HRT survey methods (Westoby et al., 2012; Fonstad et al., 2013; Clapuyt et al., 2016).

1.3.3 Repeat SfM Surveys and Propagated DEM Error

Clapuyt et al. (2016) were the first to address reproducibility of SfM surveys, and isolated internal (i.e. error associated with the SfM and MVS algorithms) and external (i.e. error associated with GCP quantity, location, and configuration) precision. Although the research resulted in high precision of the repeat surfaces, the survey was performed in a controlled environment with a uniformly flat and bare agricultural surface. Smith and Vericat (2015) used summary error statistics to propagate error through the repeat DEMs (Brasington et al., 2000). Additionally, they calculated error values for each DEM cell based upon roughness values and propagated these cell-by-cell spatially distributed error values to the DoD. Lastly, Prosdocimi et al. (2015) used several different error models and compared the outputs of the unthresholded DoDs (no uncertainty analysis), thresholded DoDs with a spatially uniform minLoD (Brasington et al., 2000), and thresholded DoDs with spatially distributed uncertainty estimates using a fuzzy inference system (Wheaton et al., 2010). The Prosdocimi et al. (2015) study tested the effects of multiple sources of SfM DEM uncertainty on DoDs, and calculated erosional and depositional change of a river bank with spatially variable topography.

1.4 Modeling DEM Error for Monitoring

HRT is of limited value without models of error that produce estimates of uncertainty (Passalacqua et al., 2015). The scale and scope of the geomorphic investigation dictates the type of error model (i.e. spatially uniform or variable) that is applied to HRT (Passalacqua et al., 2015). Spatially variable error models may be worth investing in if the error inherent
in the data approaches or exceeds the magnitude of the geomorphic signal, and if error will propagate to and between multiple datasets (Wheaton, 2008; Wheaton et al., 2010; Milan et al., 2011; Smith and Vericat, 2015). Error models require careful consideration of the factors that affect the spatial distribution of DEM uncertainty, and what techniques are appropriate to quantify the uncertainty and the practicality of those techniques. Among the factors that affect DEM error are survey point quality, survey instrument, sampling strategy, surface cover (e.g. vegetation), surface gradient, grid resolution, and interpolation method (Wise, 1998; Wechsler, 2003; Hancock, 2006; Wechsler and Kroll, 2006; Wise, 2007; Heritage et al., 2009; Schwendel et al., 2012).

There are many techniques to model error, and the fuzzy inference system (FIS) is one approach which utilizes a combination of information from the original data products and robustly characterizes extraneous data such as that contained in dense and noisy point clouds (Wheaton et al., 2010; Erwin et al., 2012; Sofia et al., 2013; Prosdocimi et al., 2015). Wheaton et al. (2010) and (Bangen et al., 2016) provide detailed FIS examples, information about the benefits of fuzzy logic and the components used to build and implement a FIS. The input variables of the inference system are selected based upon readily available data that vary in space and affect DEM error. For example, slope and roughness rasters are easily generated from the original DEM, and the minimum and maximum values of the slope and roughness rasters determine the range of values defined in each corresponding membership function with a membership of 0 to 1. The range of values assigned to the output membership function of elevation uncertainty are determined or “calibrate” from independent lines of evidence for elevation uncertainty. For example, an analysis of the spread of values from independent, repeat surveys collected and processed with the same HRT method across the same study area provides an independent line of evidence for elevation uncertainty. The most sensitive parameter in the FIS is the rule set that is defined by expert judgment, and consists of boolean statements, defining how the combination of input values affects the output elevation uncertainty. There are multiple mathematical methods to result in elevation uncertainty for each cell, and also multiple membership function shapes
1.5 Knowledge Gap and Study Area

The methodological development of SfM has not, to date, included a rigorous quantification and estimation of spatially variable uncertainty and error, respectively. Need to estimate spatially variable uncertainty of SfM can be particularly important for geomorphic change studies and monitoring applications that occur in fluvial environments, where steep and shallow topography (often in close proximity), pervasive vegetation, and shoreline areas can increase cell-by-cell error estimates. Multiple image acquisition platforms exist (e.g. unmanned aerial vehicle (UAV), autogiro, handheld) because on platform cannot be applied to all projects. For example, a UAV may provide an ideal aerial perspective, but a low-angle platform (e.g. pole-mounted camera) is a more effective platform to capture close-range imagery or specific situations such as capturing topographic features under a dense canopy. Although statistical analyses of empirical data have been used to calibration the elevation uncertainty output of the FIS for other HRT methods (Bangen et al., 2016), this calibration step has yet to be applied to SfM data.

1.5.1 Sandbar Monitoring and Research in Marble and Grand Canyons

Sandbars, located along the channel margins in Marble and Grand Canyons, are fundamental to the health of the river ecosystem, camping beaches, and protection of archaeological sites (Draut and Rubin, 2008; Wright et al., 2005; Hazel et al., 2010). Glen Canyon Dam eliminated the upstream sediment supply, negatively impacting sandbar building and dramatically altering the flow regime by increasing base flows and the range of daily fluctuations in addition to decreasing peak flows Schmidt and Graf (1990). Ten years after Glen Canyon Dam was closed in 1963, scientific efforts were made to determine any negative effects of the dam on the downstream environment and resources, namely sandbars. Laursen et al. (1976) initiated a scientific investigation of geomorphic sandbar response in Grand Canyon to dam operations. Laursen et al. (1976) determined that transport capacity exceeded the sediment supply inputs from the major tributaries (i.e. Paria and Little Col-
orado Rivers), and predicted that without pre-dam floods, the sandbars would disappear in 200 years. Howard and Dolan (1981) observed the location of sandbar formation in eddies to be mostly downstream of fixed debris fans in Grand Canyon, and unlike Laursen et al. (1976), Howard and Dolan (1981) predicted that sand deposits had reached equilibrium and were unlikely to change in the future.

Topographic sandbar measurements have aided scientific advancements in the understanding of sandbar behavior in response to normal dam operations and experimental flood releases from Glen Canyon Dam. Topographic sandbar measurements, made along cross-sections with rod and tape, at 20 sites along the Colorado River through Marble and Grand Canyons were made beginning in the early 1970s (Howard, 1975; Schmidt and Graf, 1990), and were later used in a decadal sandbar change analysis that encompassed eight years of controlled dam discharge from 1974 to 1984 and two years of flood events (Beus et al., 1985). Quantitative evaluations of sandbars directly before and after the 1983/1984 spill/flood were also made from topographic cross section data collected by (Beus et al., 1985) and Northern Arizona University. Beus et al. (1985) recognized the beach building capabilities of the 1983/1984 flood with sufficient riverbed sand, and that sandbar erosion and deposition varied across sites (Cluer, 1995). In Carpenter et al. (1995) collected data from three additional sandbar sites to Beus et al. (1985) with sensors that continually monitored stage, pore pressure, temperature, and sandbar deformation.

Schmidt (1990) defined patterns of lower velocity, recirculating flow and the effectiveness of eddies in trapping sand and mud adjacent to the main channel. Schmidt (1990) observed variation in the size and length of recirculating eddies and reattachment and separation points with changes in discharge. Schmidt and Graf (1990), used aerial imagery from before and after the 1983 flood to identify patterns in sandbar aggradation and degradation. A time-lapse camera system was installed in 1990 at representative deposit types (Schmidt and Graf, 1990, i.e. reattachment, separation, margin;) to capture rapid erosional events that were not capable of being topographically measured and to quantify rates of change in sandbar width and area. Cluer (1995) concluded that the sandbar monitoring efforts
over the previous three decades in Grand Canyon presented temporal and spatial sampling problems that lead to data biasing. Cluer (1995) asserted the sandbars are monitored less frequently than the frequency of the dominant geomorphic response, and suggested monitoring spatial and temporal changes in sediment transport.

In 1996, the first high flow experiment (HFE) was released from Glen Canyon Dam as part of a resource management strategy to rebuild sandbars, rejuvenate back water habitats, and boost native fish populations downstream of the dam (Hazel et al., 1999; Melis, 2011). The timing of the 1996 controlled flood release and the major tributary inputs from the Paria and Little Colorado Rivers were not in sync, resulting in more sandbar erosion than deposition (Melis, 2011). Similar to the sandbar response of the 1983 flood reported by Cluer (1995), the 1996 controlled flood also revealed local variation in sandbar response of erosion and deposition (Schmidt et al., 1999). After the timing of flood releases was revised to follow monsoonal sand and mud inputs from the major tributaries, two more HFEs occurred in 2004 and 2008. In 2011, a HFE protocol was established to release floods more frequently (i.e. in November or April depending on sediment inputs from the major tributaries). The HFE Protocol aimed to increase the size and abundance of the depleted sandbar resource in the sediment starved system downstream of the dam. Improved sandbar building aimed to increase backwater habitats for native fish species, potentially help preserve archaeological sites, encourage native riparian vegetation growth, provide recreational camping sites, encourage the natural flow regime, and enhance the wilderness experience (EA 2011). Due to large sediment inputs (≈ 1.2 million tons) during the monsoon seasons, HFEs occurred during November 2012, 2013, 2014, and 2016.

1.6 Thesis Aims and Objectives

This thesis aims to determine if the SfM method using pole-mounted cameras can produce sufficiently accurate and repeatable DEMs to support geomorphic change detection in a fluvial environment. Although this aim is used to highlight a specific image platform, findings are applicable across platforms. The main objectives are to quantify elevation uncertainty of the SfM DEMs and to develop a robust error models for the SfM DEMs.
Many factors contribute to elevation uncertainty of DEMs, some of which vary spatially and are accounted for in this research. The thesis seeks to answer two specific questions: 1.) How much do varying surface textures and gradients, vegetation cover, site scale, and ground control affect estimates of spatially variable uncertainty over repeat SfM surveys?, and 2.) Is a pole-based SfM method more time and cost efficient than the traditional total station survey? To the extent the answer is predicated on site conditions, under what situations might SfM be preferable to the traditional total station method?

This thesis uses a case study of thirty alluvial sandbar surveys (10 to 100 m²), located along the Colorado River through Marble and Grand Canyons, collected in fall of 2014 and 2015 with a pole-mounted camera and processed with SfM techniques. For each SfM survey, coincident total station data was collected and used to build and calibrate the spatially variable error models for the SfM DEMs. The data in this case study was collected in a fluvial environment with complex topography. The results of this research contribute to the Grand Canyon Monitoring and Research Center’s examination of geomorphic change of alluvial sandbar deposits in Marble and Grand Canyons in response to Glen Canyon Dam operations along the Colorado River in Arizona. Furthermore, this research presents an improved understanding of how the low-angle, pole-mounted camera platform affects image acquisition and ultimately SfM DEM error.

1.6.1 Management Implications of SfM in Grand Canyon

Northern Arizona University (NAU) and the Grand Canyon Monitoring and Research Center (GCMRC) have built a rich time series of annually surveyed sandbar topography and volume and area calculations at 45 sandbar sites along the Colorado River in Marble and Grand Canyons. Variation in local sandbar aggradation and erosion has persisted throughout the HFEs (Melis, 2011), and questions remain as to why some eddies fill or evacuate sediment directly after the floods (Grams et al., 2013). This unanswered question is directly connected to management concerns (i.e. the rebuilding of sandbars in Marble and Grand Canyons and prediction of how the sandbars will rebuild at specific sites). Given the SfM method’s appeal as a potentially cheap, fast and simple method to acquire
topography, GCMRC was interested in exploring its feasibility and developing standards for if it were adopted how it would be implemented. The complimentary implementation of an acquisition method that might be cheaper to survey sandbar sites and augment the traditional total station NAU surveys (especially in Eastern, Central, and Western Grand Canyons) could potentially provide a larger sandbar sample size. If this SfM method proves tractable, it is unlikely to be a replacement for traditional total station surveys, but rather an alternative candidate for extending the number of sites and/or speeding up certain sites. Even if a larger sample size is acquired, more research is required to determine what would constitute a representative sample of all the Grand Canyon sandbars to evaluate sandbar dynamics and responses to HFEs.

In addition to providing a potential means to extend the spatiotemporal sandbar data series, SfM has the potential to become an operational tool that could aid in other geomorphic investigations in Marble and Grand Canyons. If SfM proves successful and straightforward, this HRT tool could be applied to additional monitoring applications in Grand Canyon for answering potential questions related to the effects of Glen Canyon Dam operations. Traditional photogrammetric methods have previously been used in Grand Canyon to monitor daily sandbar stability (Dexter and Cluer, 1996), debris flow deposition and reworking (Yanites et al., 2006), gully and erosion control at archaeological sites (Pederson et al., 2006), and riparian resources (Davis et al., 2002). SfM has the potential to further aid in Grand Canyon research associated with campsite area monitoring (Kaplinski et al., 2014), bank erosion processes (Budhu and Gobin, 1995; Pyle et al., 1997; Alvarez and Schmeeckle, 2013), debris fan evolution (Melis et al., 1994; Melis, 1997; Griffiths et al., 2004; Hanks and Webb, 2006; Yanites et al., 2006), aeolian transport from sandbars to uplands (Draut, 2012), gully annealing and archaeological site preservation (Draut and Rubin, 2008; Sankey and Draut, 2014), backwater fish habitat (Dodrill et al., 2015), and vegetation encroachment (Turner and Karpiscak, 1980; Sankey et al., 2015). The proposed research will also investigate if it is feasible to train citizen scientists, such as recreational river runners, to acquire imagery of sufficient quality to support expanding the spatiotemporal scope of
ongoing sandbar monitoring and other research in Grand Canyon.
CHAPTER 2
TURNING ‘STRUCTURE-FROM-MOTION’ FROM A POLE-MOUNTED CAMERA INTO A VIABLE MONITORING TECHNIQUE: A CASE STUDY FROM THE GRAND CANYON

2.1 Introduction

‘Structure-from-Motion’ (SfM) with Multi-View Stereo (MVS), referred to in this thesis as SfM, has recently become a popular, high resolution topographic (HRT) tool used for accurately mapping topographic features (Javernick et al., 2014; Mancini et al., 2013; Micheletti et al., 2015; Nouwakpo et al., 2016; Piermattei et al., 2015; Prosdocimi et al., 2015; Woodget et al., 2015; Carrivick et al., 2016), hydrodynamic analysis (Javernick et al., 2014; Smith et al., 2014; Westoby et al., 2014), and morphologic monitoring/geomorphic change detection (Clapuyt et al., 2016; Dietrich, 2016b; Fonsdat et al., 2013; Gómez-Gutiérrez et al., 2014; James and Robson, 2012; Lucieer et al., 2013; Smith and Vericat, 2015; Turner et al., 2015; Westoby et al., 2012). The SfM method is based upon traditional photogrammetry and consists of a field component in which overlapping images are collected from multiple camera perspectives without exact knowledge of camera parameters. The images are then processed with robust SfM algorithms, which produce a sparse point cloud (XYZ) from the resolved camera parameters and orientations. MVS algorithms are then used to produce an even higher resolution point cloud (XYZ) (for reviews of SfM applications in geomorphology, survey techniques, algorithms, and software see section A.1 and Smith et al., 2016; Bartoš et al., 2014; Fonsdat et al., 2013; James and Robson, 2012; Gomez et al., 2016; Carrivick et al., 2016). Despite recent advances in the use of SfM to accurately map landforms in less time and at lower costs (Carrivick et al., 2016; Smith et al., 2016; Fonsdat et al., 2013; James and Varley, 2012) for one-time surveys, few studies (e.g. Clapuyt et al., 2016; Smith and Vericat, 2015; Prosdocimi et al., 2015; Cook, 2017) have demonstrated the utility of the SfM method for reliably detecting and monitoring geomorphic change from repeat surveys.

The camera platform facilitates image capture from multiple positions, angles, and
camera perspectives, which is critical for the SfM and MVS algorithms to accurately reconstruct the XYZ point cloud (Mosbrucker et al., 2017; Smith and Vericat, 2015; Smith et al., 2016; Carrivick et al., 2016). Although unmanned aerial vehicles (UAVs) are the most widely used image acquisition platform due to relatively low unit costs and ideal low-lying aerial perspectives (Bemis et al., 2014; Clapuyt et al., 2016; Harwin and Lucieer, 2012; Lucieer et al., 2013, 2014; Mancini et al., 2013; Ouédraogo et al., 2014; Puttock et al., 2015; Ryan et al., 2015; Smith and Vericat, 2015; Tonkin et al., 2014; Turner et al., 2015; Vasuki et al., 2014), UAV platforms cannot be used to collect images of the bare earth surface in all environments. In confined settings, such as narrow valleys and gorges, multi-pathing and terrain can limit the safety and operability of UAV platforms (Piermattei et al., 2015). Partially confined and laterally unconfined settings often have extensive valley bottoms occupied by riparian vegetation, which limit image acquisition of the bare earth surface. In the United States, UAV platforms are heavily regulated, and are banned or restricted from use in research areas in National Parks (Johnson et al., 2014; Whitehead and Hugenholtz, 2014). As of 2015 in the United Kingdom, small UAVs (less than 7 kg) do not require a permit (Woodget et al., 2015), but require unaided visual line of sight (Tonkin et al., 2014). The range, extent and control of an UAV can be compromised by short battery life, limited GPS capabilities (Smith et al., 2016), and adverse weather conditions (Tonkin et al., 2014; Westoby et al., 2012), which could potentially result in losing the unit.

The pole-mounted camera is a low-angle (<90 degrees), image acquisition platform that is an alternative to the UAV. Oldmeadow and Church (2006) present an early example of a pole-mounted camera to capture overlapping images of stream bed sediment structures from an elevated, aerial perspective. When surveying close-range, topographic features in narrow canyons with unreliable GPS and adverse weather conditions (e.g. high wind speeds), the pole-mounted camera may be the only practical option to capture images from an elevated, aerial perspective. The pole-mounted camera is also an alternative to UAVs in restricted flight areas (e.g. National Parks). Although the pole-mounted camera is not a practical option for surveying landforms at the landscape scale, Smith and Vericat (2015)
recommend using the pole-mounted camera to capture imagery at the small catchment scale (< 5000 m²). The authors found that the pole-mounted camera provides an ideal viewing angle for this scale, a low enough height for higher surface precision and sub-centimeter DEM error results for repeat SfM surveys. However, the pole-mounted camera platform presents additional challenges for image acquisition and the performance of the SfM and MVS algorithms to reconstruct accurate XYZ point clouds (Dietrich, 2015; Smith and Vericat, 2015; Oldmeadow and Church, 2006). Issues include incomplete image coverage of landscape scale topography, limited terrestrial access of the entire study area, jeopardized camera geometry from the low camera angle (e.g. decreased footprint area and elongated footprint shape), and incomplete reconstructions due to line-of-sight obstructions of the bare earth surface. Few studies (Smith and Vericat, 2015) have analyzed how and to what degree the pole-mounted camera platform affects the quality (i.e. accuracy, precision, and uncertainty) of SfM point clouds and DEMs, and in turn estimated the magnitude of propagated error in repeat DEMs derived from the SfM method.

All DEMs predict elevations with some degree of uncertainty and error (Wechsler and Kroll, 2006; Bangen et al., 2014; Lane et al., 2003; Brasington et al., 2000; Wheaton, 2008). Uncertainty is the quantification of the doubt about the measurement result. Elevation uncertainty is introduced to the DEM throughout most stages of data acquisition and post-processing (e.g. instrument errors (both random and systematic), sampling issues, interpolation, and processing artefacts and blunders; Bangen et al., 2014; Brasington et al., 2000; Lane et al., 2003; Wechsler and Kroll, 2006; Wheaton, 2008; Vericat et al., 2017; Heritage et al., 2009). DEM error is the elevation difference (i.e. length) above or below (+/-) the predicted estimate of elevation. In principle errors are known and corrected (James and Robson, 2014). Although error can be calculated at discrete point locations, DEMs require models to estimate error across a surface (Milan et al., 2011; Bangen et al., 2014, 2016). Not only does elevation error affect individual DEMs, DEM error propagates through repeat change calculations or DEMs of difference (DoD; Brasington et al., 2000; Wheaton et al., 2010; Lane et al., 2003; Milan et al., 2011).
The scale and scope of the geomorphic investigation should dictate the strategy for accounting for DEM uncertainty and estimating DEM error (Bangen et al., 2014; Passalacqua et al., 2015; Vericat et al., 2017). The most common strategy to estimate DEM error is approximating summary statistics of error across the entire DEM or for specific areas of a DEM (e.g. wet/dry surfaces; Brasington et al., 2000; Lane et al., 2003). One method to approximate the summary statistics of DEM error is differencing the elevations of the original DEM and the elevations of a point cloud or DEM with higher elevation accuracy. Common summary statistics of error for the DEM are mean error (ME), mean absolute error (MAE), root mean square error (RMSE), and standard deviation of error (SD), which are error values reported for the entire DEM (e.g. Prosdocimi et al., 2015; Smith and Vericat, 2015). If the DEM error does not exceed the geomorphic change signal in question, the spatially uniform error strategy is a viable option (Passalacqua et al., 2015). Also, the data (e.g. original point cloud) required for more complex error assessments may not be available (e.g. Bossi et al., 2015). In specific cases where complex topography (e.g. steep and shallow slopes in close proximity; variable surface roughness) can cause over- or underestimation of volume change, many geomorphologists (Cavalli et al., 2017; Erwin et al., 2012; Kuo et al., 2015; Milan et al., 2011; Norman et al., 2017; Rengers et al., 2016) have adopted the alternative DEM error strategy of approximating error on a cell-by-cell basis. For example, Smith and Vericat (2015) use a spatially variable error model based upon topographic roughness because the erosional processes were spatially variable and elevation changes were relatively small compared to the error in the DEMs.

The primary purpose of this paper is to determine whether the SfM method, utilizing the pole-mounted camera platform, is an accurate, precise (i.e. repeatable), and tractable method for monitoring/geomorphic change detection analyses. To fulfill this purpose, a case study was performed to collect imagery of alluvial sandbars with complex slope and roughness and to generate SfM point clouds and DEMs. Given the importance of adopting a spatially variable DEM error strategy, especially in environments with complex topography, a spatially variable error model using the data acquired with the pole-mounted camera
platform was produced to support future GCD analyses/monitoring. The implications for use of repeat SfM DEMs for studies of geomorphic change and monitoring are discussed with a GCD demonstration of the alluvial sandbars from 2014 to 2015. Insights for how the pole-mounted camera platform and data acquisition techniques affect the quality (i.e. accuracy, precision, and uncertainty) of SfM datasets generated from an environment with complex topography are also discussed. Although this work highlights an error model developed for a pole-mounted camera platform, the methodological findings are applicable across all image platforms used for the SfM method.

2.2 Methods

2.2.1 Study Sites

The closure of Glen Canyon Dam in 1963 fundamentally altered the downstream, fluvial environment along the Colorado River in Glen, Marble, and Grand Canyons by heavily regulating the flow and sediment regime (Wright et al., 2005; Howard and Dolan, 1981; Hazel et al., 2010, 2006). The maximization of efficient hydropower resulted in decreased flood magnitudes and increased base flow magnitudes, and daily/seasonal flow fluctuations (Topping et al., 2003). The dam reduced the delivery of upstream sediment by 95% (Hazel et al., 2006), and shifted the fine sediment source to relatively low inputs from the Paria and Little Colorado River tributaries. The combination of post-dam flow and sediment shifts led to the degradation of an environmental and recreational resource in Marble and Grand Canyons (i.e. alluvial sandbars; Figure C.5) that formed after flood recession during the pre-dam period. Efforts to mitigate the effects of Glen Canyon Dam on sandbars include the release of high flow experiments, which mobilize fine sediment from the channel bed downstream to increase the size and abundance of sandbar deposits (Melis, 2011). The sand and flow used to build and maintain sandbars downstream of the dam are important to the health of the river ecosystem, camping beaches, and protection of archaeological sites (Draut and Rubin, 2008; Hazel et al., 2010; Wright et al., 2005).

Sandbar type (i.e. recirculation, separation, or undifferentiated) in Marble and Grand
Fig. 2.1. Examples of typical sandbar site conditions from a variety of perspectives in this case study. Sites are named by river kilometer, and the site location on the left (L) or right (R) side of the river (oriented in the direction of channel flow). A, C, E, and G: Site view of sandbar sites 48R, 113R, 146R, and 343L. B, D, F, and H: view from the 4.9 m tall, pole-mounted camera platform used in this study of the same sites.
Canyons is dictated by the geomorphic framework of the river system, comprising of rigid channel geometries caused by immobile debris fans protruding into the channel, and lower velocity, recirculating flows in eddies directly downstream of the debris fans and rapids (Schmidt and Graf, 1990). Reattachment sandbars form at the downstream ends of eddies where higher velocity flow from the upstream rapid recirculates into the eddy, and fine sediment deposits (Schmidt and Graf, 1990). Separation sandbars form at the upstream end of eddies and the downstream end of debris fans, where recirculating flow is returning to the channel and fine sediment has a low velocity location to aggrade (Schmidt and Graf, 1990). Undifferentiated sandbars lack the distinctive morphology of separation and reattachments bars, but are prevalent along the channel margins in Marble and Grand Canyons (Hazel et al., 2010). Post-dam vegetation encroachment has led to segregation of sandbar sites into actively changing deposits of unvegetated sand, silt and clay and inactive, higher elevation, densely vegetated deposits of coarser sand (Melis, 2011). Changes in sand area and volume of alluvial sandbars (10 to 100 m²) are monitored annually by the United States Geological Survey, Grand Canyon Monitoring and Research Center (GCMRC) and Northern Arizona University (NAU) with a feature-based Total Station (TS) survey (Hazel et al., 2010; Hazel Jr. et al., 2008). Forty-five sandbar monitoring sites (Figure C.2) are distributed along 362 river kilometers (RKM), from Lees Ferry (0 RKM) to Diamond Creek (RKM 362), and vary in size, shape, gradient, and surface roughness (i.e. vegetation and grain size; Hazel et al., 2010). The GCMRC uses a site naming convention of number representing river kilometer downstream from Glen Canyon Dam and ”R” is river Right and ”L” is river left (e.g. Site 48R is on river right at river mile 48). Out of the 45 sandbar monitoring sites in Marble and Grand Canyons, I used 30 image surveys that I collected across 13 sandbar sites during the 2014 and 2015 sandbar monitoring trips because the 13 sites are spatially representative of the sandbar monitoring network, represent the three sandbar site types (i.e. recirculation, separation, and undifferentiated) in Marble and Grand Canyons, and contain variable size, gradient, and surface roughness (i.e. vegetation and grain size; Figure C.2).
2.2.2 Field Methods

Image Acquisition

The pole-mounted camera platform (Figure C.1) was one of the few, permissible camera platforms for collecting images of sandbar topography from a close-range, aerial perspective in Grand Canyon National Park (see section A.5). The pole and adjustable camera mount that worked best for collecting images across the sandbar sites for this project can be purchased online (http://youngbloodphotographic.com/the-elevator/) for $250 (3.7 m pole height) to $275 (4.9 m pole height). The 3.7 m tall pole is adjustable from between 1.8 m and 3.7 m and the 4.9 m tall pole is adjustable from 2.4 m to 4.9 m. I chose a 4.9 m pole height and a low camera angle (<90 degrees; Figure C.1) to maximize the ground footprint.

Fig. 2.2. Map of the sandbar monitoring sites that I used in this case study (RKM are approximate locations). Figure contains a 10 m DEM basemap from GCMRC and is modified from (Hazel et al., 2010).
of the camera, while ensuring vertical stability of the pole and image capture of surfaces with low-lying and intermediate vegetation (see section A.2). Compared to a nadir camera orientation, the low camera angle (Figure C.1) caused narrower ground footprint size, but captured more sandbar area with less images. Also, the low camera angle (Figure C.1) minimized the capture of background features, which add noise to the SfM point clouds. In 2014, I collected images with a Canon T4i digital single lens reflex camera (8 MP, fixed focal length = 18 mm) mounted on a 4.9 m tall pole. Considering the accuracies of SfM DEMs from former studies (Micheletti et al., 2015) and the portability/durability of consumer grade cameras, during the 2015 trip, I also used the Canon D30 point and shoot camera (12 MP, fixed focal length = 38 mm) in addition to the Canon T4i camera.

As the sandbar monitoring trip occurs once a year in a remote location, I acquired more than enough images (60-80% overlap) to ensure high image coverage of the surface, and to ensure that images were taken from enough camera perspectives (Fonstad et al., 2013; Westoby et al., 2014; Javernick et al., 2014). I used two trigger mechanisms to test the trade-offs between image clarity, and the speed and ease of image capture. I acquired convergent images at 3 to 5 second intervals or approximately every 3 m with a manual trigger along linear transects (Figures 2.4 and 2.5). I lifted the pole slightly off the ground and slowly carried the pole along the image transects to ensure the near-vertical position of the pole and capture of clear imagery in drastically variable lighting conditions. The transects consisted of paired image sets with the camera sensor oriented in the upstream and downstream or upslope and downslope directions, resulting in a grid-like pattern of image coverage (Figures 2.4 and 2.5). Based on the size and shape of the sandbar, I continuously walked transects either in the upstream, downstream, upslope, or downslope direction to ensure overlapping strips of convergent imagery that were more likely to reconstruct with the SfM and MVS algorithms (Figures 2.4 and 2.5; Dietrich, 2015). I collected additional divergent images at points along the transect by capturing an image every 90 degrees in a circular rotation. In 2015, I acquired fewer images with the circular rotation technique because the SfM algorithms failed to reconstruct point clouds due to the minimal image
Fig. 2.3. The pole-mounted camera platform setup that I used in this study. A. The 4.9 m tall, pole platform with camera mount that I used to acquire the majority of sandbar images. B. Surveyor collecting images of a sandbar with the pole-mounted camera platform setup in Marble Canyon (site 90R). C. Comparison of camera angle perspectives from the 4.9 m tall pole (site 48R). I captured most of the images with a low-angle perspective from the pole. The square targets are 0.3 x 0.3 m for scale.
overlap. If I did use the circular rotation technique, to increase image overlap, I acquired images with lower rotation angles (i.e. more images captured around the pole rotation). In 2015, I added convergent perimeter transects, with the camera oriented in towards the center of the sandbar (Figures 2.4 and 2.5) to aid in reconstruction along the edges of the survey (see section A.3). I used a handheld camera less frequently, oriented normal to near-vertical slopes, to aid in connecting the top and bottom of steep cutbank features. I also used a handheld camera to capture convergent images through open tunnels in vegetated corridors to connect topography from the actively reworked part of the sandbar to the higher elevation sandbar deposit (Figure 2.5).

**Ground Control Acquisition**

Although the SfM method can generate millions of XYZ points, the SfM points were indirectly measured (i.e. estimates) and are assumed to be less accurate compared to the less dense XYZ points measured directly with the TS instrument within a primary control network (minimum horizontal and vertical accuracy of ±0.05 m Hazel et al., 2006). Therefore, to validate the SfM data against a dataset with higher point measurement precision and accuracy, myself and other surveyors collected coincident image and TS surveys during the fall 2014 and 2015 sandbar monitoring trips. Although image surveys aimed to cover the same extents as coincident TS surveys, I was limited to acquire images in areas where vegetation heights were lower than the height of the pole platform (<4.9 m). In addition to the coincident feature-based TS point surveys, to scale and georeference the SfM point clouds, I surveyed ground control points (GCPs; numbered, 0.3 x 0.3 m vinyl checkerboards) with the TS for each image survey (Figures 2.4 and 2.5). The number of GCPs varied based upon the size and topography of each sandbar, and I placed each GCP ≈ 10 m apart to evenly cover (offset grid pattern) the sandbar surface and survey boundary. To aid in quantifying SfM DEM uncertainty of DEMs generated with different camera survey parameters, in 2015, I collected repeat image surveys with varying camera types, image counts and trigger mechanisms at four sandbar sites (48R: n = 3, 80R: n = 2, 192R: n = 2, 198L: n = 2) without changing the GCP locations at each site. I also performed nine repeat image
Fig. 2.4. Typical image acquisition workflow shown at a site (48R) with minimal vegetation. A. I acquired images along transects with upstream/downstream (blue/red line), upslope/downslope, and inward orientations (green line). I used few handheld transects (white line) to connect the top and bottom of steep cut banks. B. Camera pitch angle and orientation along survey transects (each camera angle is represented with a blue rectangle) within the Photoscan graphical user interface. In 2015, I acquired fewer images with the fan orientation (i.e. images taken 365 degrees around the same point) due to failed reconstructions in Photoscan. Background orthomosaic generated from images in Photoscan.
Fig. 2.5. Typical image acquisition workflow shown at a site (146R) with dense vegetation. A. I acquired images along transects with upstream/downstream (light blue/red line), upslope/downslope (dark blue/red line), and inward orientations (green line). I used handheld transects (yellow line) to link topography through tunnels in vegetated corridors. B. Camera pitch angle and orientation along tunnel transects (each camera angle is represented with a blue rectangle) within the Photoscan graphical user interface. Background orthomosaic generated from images in Photoscan.
surveys at an additional site (i.e. 343L) to capture imagery of a subarea with spatially variable slope and roughness. For the nine repeat image surveys, three different surveyors acquired images with the point and shoot camera, and each surveyor had 10 minutes per survey to collect images along the repeat transects. I kept a constant camera type and survey time and area to test SfM DEM uncertainty caused by the acquisition of variable camera positions and angles (i.e. the surveying method).

2.2.3 SfM Data Processing

Although SfM is recognized as a low-cost and time efficient method for field acquisition of images (Fonstad et al., 2013; James and Robson, 2012), the post-processing workflows are time-consuming and may offset the time 'savings' from field acquisition. Some degree of manual image sorting is required for all image sets to remove blurry, non-feature, and closely captured images. The most widely used SfM software is Agisoft Photoscan Professional (Smith et al., 2016), which provides a comprehensive package of SfM and MVS algorithms that generate exportable products including XYZRGB dense point clouds and bare earth DEMs. Depending on the computing power of the machine and number of images, stages within Photoscan can take hours to months to complete and require manual (e.g. georeferencing) and supervised post-processing (e.g. realignment of sparse point cloud). 

External software (e.g. CloudCompare, ToPCAT) are alternatively used to manually clean, filter and generate SfM DEMs. Filtering out noise in HRT point clouds, particularly in point clouds generated from fluvial environments, remains a challenge. Surface roughness, namely vegetation, remains a known limitation of the SfM method, and is a source of DEM uncertainty for bare earth surface generation in the point cleaning and point cloud to DEM interpolation phases (e.g. Javernick et al., 2014).

SfM Data Processing Workflow

The SfM data post-processing workflow (Figure 2.6) that I used in this study transforms image sets into DEMs and consists of five steps, which are also used in the methods of Javernick et al. (2014) and Smith and Vericat (2015), including 1.) image sorting, 2.) point cloud building, 3.) point cloud filtering/cleaning, 4.) point cloud decimation, and 5.) DEM
Fig. 2.6. The post-processing workflow that I used to generate SfM point clouds in Photoscan Professional and batch generate SfM DEMs using python scripts. SfM point cloud and DEM from site 48R.

Due to the lighting changes in the canyon, and the camera movement throughout image capture, I manually removed blurry, non-feature and closely captured images that generated noise in the point clouds. The "Estimate Image Quality..." setting in Photoscan, proved unreliable and I visually sorted all images (n = 21,084). I generated sparse and dense point clouds and orthomosaics with separate projects for each survey in Agisoft Photoscan Professional (Version 1.2.4 64-bit). After performing sensitivity tests within Photoscan (Javernick et al., 2014) to obtain the most complete and seemingly correct alignments, I selected a “Key point limit” = 10,000 points, a “Tie point limit” = 0 points, “Pair preselection” = Disabled, and “Accuracy” = Low to High (depending on image count) to generate the sparse point clouds. For multiple surveys, I corrected and aided the initial image alignment through manually resetting and realigning images to correct artifacts in the sparse point cloud (Figure 2.7A-B). After correctly aligning the sparse point cloud, I performed a
series of additional steps, summarized in Figure 2.7C-E to decimate and clean the sparse point cloud, which eliminated redundant points/point layers in the sparse point cloud prior to dense point cloud generation. For example, I used the “Reprojection uncertainty” setting (“Level=20”) within the “Gradual Selection...” tool to decimate the sparse points by no more than 50% (Figure 2.7D). I adopted the default distortion coefficients in Photoscan (i.e. Fit f, cx, cy, k1, k2, k3, b1, b2, p1 and p2) to perform an initial bundle adjustment (i.e. optimization) for each sparse point cloud. The k4, p3, and p4 distortion coefficients can cause the overall camera model to be unstable (personal correspondence with Tommy Noble, TN Photogrammetry LLC) if there are inaccurate/noisy points within the sparse point cloud. Therefore, I used the k4, p3 and p4 distortion coefficients in addition to the default distortion coefficients to optimize the cleaned (gradual selection tool) and georeferenced sparse point clouds. The camera optimization parameters are critical for minimizing lens distortion, especially without field camera calibration for the point and shoot, Canon D30, camera lens.

Continuing point cloud building in Photoscan, I scaled and georeferenced the sparse point clouds utilizing the projected (NAD83 Arizona Central ESPG: 26949) XYZ coordinates of the GCPs surveyed with the TS. The GPS in the canyon is unreliable, so I did not use image geotagging, which has been shown to considerably speed up post-processing in other study locations. I only used GCPs with a clearly visible number marked on each panel to scale and georeference the sparse point clouds. Although Photoscan coarsely estimates the center of the GCP panel, I adjusted the centroid placement of each GCP manually. I used all surveyed GCPs unless GCPs shifted during the image/TS survey and/or returned a high GCP, root mean square error (RMSE) value (i.e. >0.10 m) in Photoscan. After updating the scaling and georeferencing, I optimized the sparse point cloud a final time using all of the camera parameters. After performing sensitivity tests, I automatically generated dense point clouds with the settings of “Quality” = Low to Medium (depending on sparse point count) and “Depth filtering” = Aggressive. Although I reduced the “Quality” setting for some surveys to significantly reduce post-processing time, all dense point clouds
Fig. 2.7. Example of correcting, realigning, thinning, and optimizing the SfM sparse point cloud in Photoscan prior to georeferencing the sparse point cloud and generating the dense point cloud. A. After the first alignment of all images, some cameras are incorrectly aligned. B. I reset cameras in Photoscan by highlighting the incorrectly aligned cameras and resetting the cameras. C. I realigned the reset cameras, and more sparse points were added to the sparse point cloud. D. I used the gradual selection tool to thin the sparse point cloud. E. I optimized the thinned sparse point cloud. SfM point clouds are from site 198L.
contained at least one million points. I exported the projected coordinates (XYZ) and color values (RGB) of each dense point as an ASCII file from Photoscan to use in the filtering of SfM point clouds and generation of SfM DEMs.

**SfM Point Cloud and DEM Generation**

Due to the time it would take to initially mask out the surface roughness and background features in individual images, I opted to manually filter and clean the dense point clouds to save time. Given the size of my sites, this was deemed to be a time savings, but manual processing of larger sites might warrant using a roughness based masking technique (e.g. Jaervinck et al., 2014). Although I saved time by not masking individual images, I spent additional time filtering the noise from the exported dense point clouds. I was unable to completely filter out surface roughness with the filter settings in CloudCompare, including the CANUPO plugin (Brodu and Lague, 2012). Instead, I filtered the dense point clouds first by color with a python script that filters points based upon ranges of RGB values. For example, green colors in the dense point clouds correspond to vegetation and I filtered out dense point clouds with a “green” RGB range (Figure 2.8). Then, I carefully cleaned the dense point clouds by manually removing points in CloudCompare (Figure 2.8). I removed noisy edges of the surveys (e.g. deep, turbid water), and I only included points along the edges in shallowly inundated areas with clear water. Although I was unable to visually remove all surface roughness, the persistent surface roughness in the dense point clouds (e.g. low-lying vegetation on steep bank; Figure 2.8) served as a useful input for later elevation error modeling.

As I needed to quickly generate multiple SfM DEMs and DEM products (e.g. slope and roughness rasters) from dense SfM point clouds to quantify DEM uncertainty, I used ToPCAT (Brasington et al., 2012; Jaervinck et al., 2014; Smith and Vericat, 2015) and a custom python script to batch decimate the SfM point clouds and generate SfM DEMs, respectively. I decimated each cleaned, dense point cloud with ToPCAT using a 10 cm moving window with a minimum of four points per window (Passalacqua et al., 2015) to calculate the minimum elevation (i.e. \( Z_{\text{min}} \); Brasington et al., 2012; Jaervinck et al., 2014)).
Fig. 2.8. Example of RGB filter, and SfM dense point cloud cleaning. A. XYZRGB dense point cloud exported from Photoscan before filtering/cleaning; B. Points filtered with the “green” RGB filter python script; C. Dense point cloud after RGB filter and manual cleaning. Even after manually cleaning the dense point cloud, surface roughness persists. The boat in panel A is approximately 4.9 km in length, and the SfM point clouds are from site 192R.

After examining the results of a 10 cm, 50 cm, and 1 m ToPCAT window size, I determined that the 10 cm moving window size was best for preserving the variability in topography, while maintaining reasonable post-processing times. I then used the $Z_{min}$ SfM point cloud from ToPCAT as an input into the python script that batch generates SfM DEMs with any specified grid resolution and extent. I used a 10 cm resolution for the SfM DEMs because the high $Z_{min}$ SfM point cloud density supported this resolution (Passalacqua et al., 2015). I also chose the 10 cm DEM as a representative resolution to use in my DEM error model for monitoring geomorphic processes with repeat surveys (Passalacqua et al., 2015). Although other interpolation techniques (e.g. triangular irregular network: TIN) have been used to generate SfM DEMs (e.g. Javernick et al., 2014), I used a nearest neighbor method because a.) I could not implement a batch TIN script and b.) the point density is high enough in the $Z_{min}$ SfM point clouds to directly convert from $Z_{min}$ point cloud elevations to grid
node elevations in the DEM. To average/smooth out the SfM DEM elevation estimates to provide a more representative DEM, I also used inverse distance weighting, where the weight = 1.0/ distance$^2$, to average up to 100 $Z_{\text{min}}$ SfM point cloud estimates per grid node. The nearest neighbor, inverse distance weighting method alone did not introduce high interpolation error going directly from the $Z_{\text{min}}$ SfM point cloud to the SfM DEM. However, I did interpolate up to 2 m across the holes in each SfM DEM that were caused from cleaning the cloud. For example, in areas (<2 m wide) where I manually removed equipment that protruded from the ground in the SfM point cloud, I interpolated over the hole up to 2 m with the elevation value of the nearest neighbor because I was confident the elevation remained constant across the hole. I did not consider the SfM DEM uncertainty of areas greater than the 2 m interpolation distance for this analysis because I was not confident that the elevation remained constant over that area. Thus, I assigned nodata values to areas with large holes (e.g. areas of dense vegetation) in the SfM DEMs.

2.2.4 Analytical methods

Three analytical methods were performed to determine the quality (i.e. accuracy, precision, and uncertainty) of the SfM datasets for each sandbar survey performed with the pole-mounted camera platform: 1.) accuracy and precision assessment of individual SfM point and DEM elevation values; 2.) quantification of lines of evidence for spatially variable uncertainty of SfM DEMs; 3.) building an error model. I used method 1 to determine the quality (i.e. accuracy and precision) of the SfM point clouds and DEMs that were generated from the pole SfM method. Although the quality of the SfM point clouds and DEMs are likely to be similar due to the density of the original point clouds, I used both the point-to-point and the DEM-to-point analyses because the former gives an estimate of the SfM point accuracy/precision, while the latter gives an estimate of surface accuracy/precision. Also, I used method 1 to determine how much the quality (i.e. accuracy and precision) of individual SfM point cloud and DEM elevation estimates varied spatially with changes in slope and roughness across the sandbar surface. For method 1, I was restricted to quantifying accuracy and precision of the SfM point and DEM estimates where I had TS point measurements. I
used methods 2 and 3 to estimate DEM error across the entire DEM surface on a cell-by-cell basis. I used method 2 to quantify spatially variable SfM DEM uncertainty with multiple, independent lines of evidence to calibrate the error model. I used method 3 to build an error model for the entire SfM DEM, including interpolated areas, and calibrate the model with the multiple, independent lines of evidence for the spatially variable SfM DEM uncertainty.

Analytical Method 1: Accuracy and Precision Assessment of Individual SfM Point and DEM Elevation Values

Error, the difference between an estimated or measured value, is commonly described with accuracy (e.g. ME and MAE) and precision metrics (e.g. RMSE and SD; Bangen et al., 2014). Elevation error of individual points in a point cloud and individual cell values in a DEM can be calculated by differencing the individual elevation estimates of the point cloud and/or DEM with the point elevations of a topographic surveying method with higher point measurement precision and accuracy (e.g. TS; Bangen et al., 2014; Smith and Vericat, 2015). For my first analysis, to calculate accuracy and precision for individual SfM point and DEM estimates, I differenced the coincident TS point elevation measurements with the SfM point \( Z_{SfMP} - Z_{TSPT} \) and DEM elevation estimates \( Z_{SfMDEM} - Z_{TSPT} \) for each survey (Figure 2.9). For the \( Z_{SfMP} - Z_{TSPT} \) analysis, I used the difference of each SfM point elevation estimate within a 0.05 m radius of each TS point elevation measurement to calculate accuracy and precision metrics (Figure 2.9). I determined that the 0.05 m radius was representative of the horizontal distance of the footprint of the TS survey rod from Hazel et al. (2006). I considered all of the point elevation differences within the 0.05 m radius so I would not smooth out the resulting accuracy and precision metrics. For the \( Z_{SfMDEM} - Z_{TSPT} \) analysis, I extracted each SfM DEM elevation estimate for each overlying TS point elevation measurement and differenced the two values. I used ME as an accuracy metric for each SfM point cloud and DEM because it shows whether or not systematic bias exists in the data. An appreciable systematic bias can directly affect the over- or understimation of point/DEM cell elevation (Bangen et al., 2014). RMSE, which is a combination of random (i.e. variance) and systematic error (i.e. bias) is a robust metric
of precision for a normally distributed dataset with the mean centered at zero (Bangen et al., 2014). I did not use the RMSE as a metric of precision for the SfM point clouds and DEMs because the ME showed a positive systematic bias in my data (Bangen et al., 2014). Therefore, I used the standard deviation of error (SD) as a metric of precision for the SfM point clouds and DEMs.

Spatially explicit accuracy and precision metrics are also useful for determining which surface cover types lead to higher or lower amounts of error for the SfM method. For example, do areas of a DEM that are covered in black shadow lead to higher amounts of DEM error? To calculate spatially explicit accuracy and precision for the \( (Z_{\text{SfM}_{PT}} - Z_{\text{TS}_{PT}}) \) and \( (Z_{\text{SfM}_{DEM}} - Z_{\text{TS}_{PT}}) \) analyses for each SfM point cloud and DEM, I overlaid the TS points on top of the orthomosaics generated from the survey images, and I visually attributed each TS point elevation measurement with one of nineteen surface cover categories (Table 2.1). I then calculated the same accuracy and precision metrics (ME and SD) for the SfM point clouds and DEMs by surface cover type.

**Analytical Method 2: Quantification of Lines of Evidence for Spatially Variable Uncertainty of SfM Derived DEMs**

In the second analytical method, I used three independent analyses (illustrated in Figure 2.10) to quantify spatially variable uncertainty of each SfM DEM. I then used the results of the three independent, spatially variable DEM uncertainty analyses to calibrate an error model. I used multiple lines of evidence to quantify DEM uncertainty and a large number of replicate surveys across a range of sandbar types using different camera types/ settings to increase the confidence of the SfM DEM uncertainty magnitudes. I also used this approach of quantifying spatially variable DEM uncertainty because Bangen et al. (2016) showed that multiple lines of evidence lead to a more representative DEM error model calibration (Bangen et al., 2016).

With point densities higher than necessary to capture topography from the SfM point clouds, I first performed a bootstrapping analysis to gauge DEM uncertainty. (Figure 2.10A; Wheaton, 2008). I randomly selected 90% of the \( Z_{\text{min}} \) SfM points from ToPCAT (Bras-
Fig. 2.9. Graphical representation of the methods used to calculate accuracy and precision of individual SfM PT/DEM elevation values. A. Each TS point elevation (gray circle) was subtracted from every SfM point elevation (red circle) within a 0.05 m TS point uncertainty radius (yellow buffer). B. Each TS point elevation (white circle) was subtracted from the extracted, underlying SfM DEM cell (0.10 m cell resolution) elevation value. The TS point cloud and SfM DEM are from site 113R. C. Example of the surface cover attributes assigned to each TS points for the spatially explicit accuracy/precision SfM point/DEM analysis (see Table 2.1 for detailed surface cover descriptions). Numbered, white circles represent TS points. The SfM orthophoto is from site 267L.
<table>
<thead>
<tr>
<th>Number</th>
<th>Name</th>
<th>Description</th>
<th>Surface Texture</th>
<th>Sample (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ground Control Point</td>
<td>surface of control target</td>
<td>low</td>
<td>24,287 501</td>
</tr>
<tr>
<td>2</td>
<td>Saturated Clay/Silt</td>
<td>adjacent to edge of water</td>
<td>low (reflective)</td>
<td>21,752 495</td>
</tr>
<tr>
<td>3</td>
<td>Slightly Saturated, Exposed Sand</td>
<td>between saturated clay/silt and dry/exposed sand</td>
<td>low</td>
<td>25,954 621</td>
</tr>
<tr>
<td>4</td>
<td>Gravel</td>
<td>adjacent to debris fan/wash</td>
<td>moderate</td>
<td>25,005 393</td>
</tr>
<tr>
<td>5</td>
<td>Dry, Exposed Sand</td>
<td>between slightly saturated/exposed sand and upland</td>
<td>low</td>
<td>82,405 2,050</td>
</tr>
<tr>
<td>6</td>
<td>Breakline</td>
<td>visible break in slope (e.g. cut bank)</td>
<td>low</td>
<td>10,926 178</td>
</tr>
<tr>
<td>7</td>
<td>Top of Bank Edge</td>
<td>top edge of the break in slope</td>
<td>low</td>
<td>8,898 175</td>
</tr>
<tr>
<td>8</td>
<td>Gear</td>
<td>surface of gear (survey equipment, boats, clothing, etc.)</td>
<td>moderate to high</td>
<td>1,868 74</td>
</tr>
<tr>
<td>9</td>
<td>Breakline in Shadow</td>
<td>shadowed break in slope (e.g. cut bank)</td>
<td>low</td>
<td>8,626 142</td>
</tr>
<tr>
<td>10</td>
<td>Shadow</td>
<td>sporadically found throughout surface (in addition to #12)</td>
<td>low to extreme</td>
<td>3,014 58</td>
</tr>
<tr>
<td>11</td>
<td>Edge of Water</td>
<td>adjacent to saturated clay/silt</td>
<td>low (reflective)</td>
<td>17,440 496</td>
</tr>
<tr>
<td>12</td>
<td>Rock</td>
<td>cobble, talus, boulder usually at the upland edge of survey</td>
<td>moderate to extreme</td>
<td>4,628 186</td>
</tr>
<tr>
<td>13</td>
<td>Canopy Vegetation</td>
<td>sporadically found on dry/saturated sand</td>
<td>moderate to extreme</td>
<td>11,572 664</td>
</tr>
<tr>
<td>14</td>
<td>Edge of Survey</td>
<td>upland edge of survey</td>
<td>low to extreme</td>
<td>8,354 257</td>
</tr>
<tr>
<td>15</td>
<td>Low-lying Vegetation</td>
<td>sporadically found on dry/saturated sand</td>
<td>moderate to high</td>
<td>23,003 606</td>
</tr>
<tr>
<td>16</td>
<td>Edge Vegetation</td>
<td>vegetation at the upland edge of the survey</td>
<td>moderate to extreme</td>
<td>5,586 134</td>
</tr>
<tr>
<td>17</td>
<td>Submerged, Turbid Water</td>
<td>between edge of water and river channel (further into channel)</td>
<td>low (reflective)</td>
<td>669 50</td>
</tr>
<tr>
<td>18</td>
<td>Submerged, Shallow, Clear Water</td>
<td>between edge of water and river channel</td>
<td>low (reflective)</td>
<td>970 51</td>
</tr>
<tr>
<td>19</td>
<td>Submerged, Deep, Clear Water</td>
<td>between edge of water and river channel (further into channel)</td>
<td>low (reflective)</td>
<td>438 25</td>
</tr>
</tbody>
</table>

Table 2.1 Surface Cover Descriptions for Spatially Explicit Accuracy and Precision Analyses
ington et al., 2012) to generate a new SfM DEM. Again, I used a 10 cm resolution for this bootstrapping analysis because the high $Z_{min}$ SfM point cloud density supported this resolution (Passalacqua et al., 2015). I used the elevation values of the remaining 10% of the randomly sampled $Z_{min}$ points to compare to the corresponding elevation cell values of the newly generated SfM DEM. Even though I carefully cleaned the point clouds before ToPCAT post-processing, artifacts and extraneous point elevations remained in the point clouds. I found that five iterations with five different subsamples for each iteration was enough to guarantee there were no extraneous point elevations that were biasing the results. If I had found the outliers affected the consistency of the results between the five iterations, I would have opted to use a more sophisticated Monte Carlo analysis. I then used the mean absolute difference ($|Z_{SFM} - Z_{SFMDEM}|$) and the median of the absolute difference distribution to calibrate uncertainty magnitudes in the error model.

In the second DEM uncertainty analysis, I compared TS DEM values with SfM DEM values for all surveys (Figure 2.10B). The DEM resolution of this analysis was limited to 1 m due to the density of the TS points. Although I performed this analysis at a coarser resolution (1 m), the comparison between the SfM and TS DEMs provided an additional, independent line of evidence for SfM DEM uncertainty. I used the mean absolute difference ($|Z_{SFMDEM} - Z_{TSDEM}|$) and the median of the absolute difference distribution to calibrate uncertainty magnitudes in the error model.

Lastly, I compared two groups of repeat surveys (Figure 2.10C) to quantify the effects of 1.) camera parameter and 2.) survey method variability on SfM DEM uncertainty. The first group consisted of repeat surveys of unchanging surfaces from four sites with varying degrees of surface slope and roughness, and images for these surveys were collected with two different camera types. The second group compared elevation values between 9 repeat SfM DEMs generated from a subarea of an additional site. I used the mean range of values ($|Z_{SFMDEM_{max}} - Z_{SFMDEM_{min}}|$) between all SfM DEM cells within the two groups of repeat surveys to calibrate the error model.

### Analytical Method 3: Building the Error Model
Fig. 2.10. Diagram illustrating the three analyses that I used in this study to build uncertainty distributions of SfM DEMs that I then used to calibrate an error model. A. Bootstrapping analysis that I used to calculate the mean absolute elevation uncertainty (m) by differencing a removed sample of 10% $Z_{\text{min}}$ points and the corresponding $Z_{\text{min}}$, SfM DEM (generated with the remaining 90% $Z_{\text{min}}$ points) elevations (10 cm DEM resolution). B. SfM and TS DEM residual analysis that I used to calculate the mean absolute elevation uncertainty by differencing the cell values of the orthogonal/concurrent SfM and TS DEMs (1 m resolution); C. Repeat analysis that I used to calculate the mean range (i.e. maximum - minimum) between the SfM DEM cells of each group of repeat surveys (10 cm resolution). This diagram is based upon point clouds and DEMs are from site 48L.
The factors contributing to the elevation uncertainty/error across a DEM will vary depending on the type of environment being surveyed (e.g. instream bar feature vs. vegetated floodplain) and survey method (e.g. terrestrial LiDAR). In the specific case of the pole SfM method, the main sources of DEM uncertainty are arguably topographic slope and roughness, camera geometry, and interpolation error. Error models are used to account for and quantify sources of elevation uncertainty, and ensure better estimates of elevation error of DEMs and propagated DEM error through time. Although spatially implicit error metrics of individual SfM points/DEMs are commonly generated by comparison with higher accuracy, topographic surveying methods, these are less representative of DEM uncertainty (Bangen et al., 2014). Geomorphologists commonly use these single metrics to model DEM error and often uniformly apply these single metrics to the entire surface to acquire estimates of elevation error of SfM DEMs. Geomorphologists have adopted spatially variable error models for studies of geomorphic change where the magnitude of the topographic change signal is lower or nearing the magnitude of the noise in the topographic data (e.g. fluvial environment). In these particular cases of low signal to high noise, spatially variable error models have proven to more reliably estimate DEM elevation change (Wheaton et al., 2010, 2013; Bangen et al., 2016, 2014; Erwin et al., 2012). Given the importance of adopting a spatially variable DEM error strategy, a spatially variable error model using all of the data acquired with the pole-mounted camera platform was produced to support future GCD analyses/monitoring.

Unlike other error modeling techniques that either uniformly quantify DEM uncertainty with residual statistics or consider singular variables that affect surface uncertainty (i.e. roughness), fuzzy inference systems are used to combine types of information from the original data to characterize extraneous information (such as non-topographic) contained in dense and noisy point clouds (Erwin et al., 2012; Prosdocimi et al., 2015; Sofia et al., 2013; Wheaton et al., 2010; Bangen et al., 2016). As additional noise was introduced into the SfM data from the fluvial environment in this study (e.g. vegetation), and from the low-angle pole platform (e.g. limited perspective and narrow ground footprint) an FIS approach
was justified. Also, this study aimed to model multiple sources of spatially variable SfM DEM uncertainty, and a FIS provided a pragmatic way to build multiple sources into an error model. The intended contributions of the error model in this study were 1.) the FIS error model calibration for the pole SfM DEMs and 2.) general guidelines and SfM DEM uncertainty analyses that can be used to recalibrate the FIS for other datasets that were generated in areas with different topographic morphologies (e.g. eroding cliff faces) or that were generated with different SfM platforms (e.g. UAVs). For the error model in this study (Figure 2.12), I used the four FIS steps described by Bangen et al. (2016), and I implemented an additional step outside of the FIS.

**FIS Inputs: DEM Slope and Roughness**

First, I defined the input categories of the FIS. I initially considered using FIS inputs (slope, roughness, interpolation error, point density) that have been previously used to model error with a FIS (Heritage et al., 2009; Bangen et al., 2016, 2014; Wheaton et al., 2010). I used DEM slope because it can easily be derived from the SfM DEM. DEM slope is also a proxy for topographic complexity for the SfM DEMs (e.g. large increases in slope can lead to large vertical errors; Wheaton et al., 2010; Bangen et al., 2016; Hensleigh, 2013). For the FIS, I generated slope (degrees) rasters from the $Z_{\text{min}}$ SfM DEMs as the maximum rate of change in a 3 x 3 cell window (Bangen et al., 2016).

Surface roughness affects the ability to reconstruct the SfM point cloud and becomes a source of DEM uncertainty. For the SfM method to work, you need some roughness to generate the textures that are needed for the point matching. But if the surface is too rough, occlusions occur and the estimated DEM elevation is ambiguous. Multiple types of roughness exist in the SfM DEMs, and each of these types are manifested differently at the multiple vertical scales of DEM roughness. The bare earth surface contains DEM roughness from the undulating sand surface. Although I manually cleaned the SfM point clouds for vegetation and artifacts, DEM roughness was introduced by vegetation that I could not physically remove (especially low-lying vegetation). Lastly, there is DEM roughness caused by noise in the SfM point cloud (fliers and outliers). I generated roughness rasters for the
FIS by gridding the standard detrended deviation values obtained from ToPCAT (Brasington et al., 2012) and using these values as a proxy for roughness. This is one approach to quantifying DEM roughness, and this approach does not consider how the different types of DEM roughness at multiple scales may have different effects on DEM uncertainty. I took this approach to quantifying roughness at one scale (10 cm) because I could easily produce roughness rasters and I was interested in how DEM roughness generally affects DEM uncertainty. Recent efforts by Buscombe (2016) have developed a more robust approach (PySESA) for being able to quantify the multiple vertical scales of surface roughness, over varying horizontal scales.

I also considered using point density, distance to GCP, and camera footprint density as additional FIS inputs. With such dense point clouds (e.g. 100 pts/m²), I opted not to use point density. Although there were decreases in point density around the edges of the point clouds, these areas also contained higher surface roughness. Therefore, the DEM uncertainty was already accounted for with the DEM roughness FIS input. I also did not use a distance to GCP input after finding that the GCP networks I used did not lead to increased DEM uncertainty with greater distances from each GCP. Although less is known about how much non-topographic parameters (e.g. camera footprint density) affect spatially variable uncertainty in SfM DEMs, these parameters greatly affect the success of SfM reconstructions and are potentially internal contributors to elevation uncertainty (Clapuyt et al., 2016). In other words, 60-80% image overlap (e.g. Ouédraogo et al., 2014; Javernick et al., 2014; Dietrich, 2016b; Clapuyt et al., 2016) is widely known to result in correct and accurate point clouds from SfM algorithms (e.g. SIFT and MVS), but how much camera footprint overlap spatially affects elevation uncertainty has not, to date, been quantified. The complexity of the SfM algorithms and the amount of images and camera angles used in the reconstruction limits the isolation of non-topographic sources of uncertainty. Therefore implementing additional, non-topographic sources of surface uncertainty into an error model is difficult. I investigated if a relationship exists between camera overlap and elevation uncertainty. I used camera footprint density to approximate camera overlap. Camera footprint vertices
for each image were calculated through the Photoscan, python API as the intersection of the mesh with each central camera axis. I then generated camera footprint polygons by connecting the XY vertices of each camera (Figure 2.11A). I calculated camera footprint density by counting the number of times each camera footprint overlapped in each DEM cell and creating a camera footprint density raster (1 m resolution; Figure 2.11B). I compared the camera footprint density raster values and corresponding elevation uncertainty DEM values (derived from the bootstrapping and residual analyses from section 2.2.4). I ended up not using camera footprint density as an FIS input because the camera footprint data were cumbersome to extract from Photoscan, and the relationship between DEM uncertainty and the number of overlapping cameras was unclear across the SfM surveys.

The slope and roughness input FIS variables I chose were represented in the FIS model as continuous, fuzzy membership functions (MFs: Figure 2.12). MFs contain partially overlapping membership function groups (MFGs), which are a distinctive attribute of the FIS. Fuzzy MFGs differ from discrete, crisp membership classes, and are advantageous in quantifying uncertainty of noisy data acquired in environments with complex topography (Bangen et al., 2016). Similar to Bangen et al. (2016), I determined the number of MFGs for each input variable, and used the summary cell statistics from the input rasters of slope and roughness to compute bounds for each MFG. I defined four MFGs (“low”, “moderate”, “high”, and “extreme”) as 1.) zero to the first quartile ($Q_{25}$), 2.) $Q_{25}$ to the third quartile ($Q_{75}$), 3.) $Q_{75}$ to the upper whisker (UW = $Q_{75} + 1.5*(Q_{75} - Q_{25})$), and 4.) UW to the maximum value (Max) of the dataset. I then computed summary statistics a second time for each of the four MFGs, and I used the second set of statistics to define the partial overlap between each MFG (Bangen et al., 2016). For example, I computed the mean ($\mu$), standard deviation ($\sigma$), first quartile ($Q_{25}$), median ($Q_{50}$), third quartile ($Q_{75}$), UW, and maximum (Plausible Max.) separately for each of the four MFGs, and I used these statistics to define the MFG node values (Table 2.2). The four node values for each of the four MFGs resulted in a trapezoidal shape representation of each MFG (Figure 2.12).

**FIS Output: Elevation Uncertainty**
Fig. 2.11. Camera overlap represented with camera footprint density that I considered as a source of DEM uncertainty and a FIS input. A. Subset (n = 6 camera footprints) of the 320 camera locations and point/polygon vertices/footprints for a SfM survey that I performed at the 48R sandbar site. B. Camera density raster that I generated for the same survey (n = 320 camera footprints) by counting how many camera footprints overlap in a 1 x 1 m cell.
Fig. 2.12. I used a 2-input FIS (Bangen et al., 2016) to take the input rasters of slope and roughness, and generate spatially variable elevation uncertainty output values for each SfM DEM, using the defined membership functions. I then updated the elevation uncertainty with another input raster (interpolation error) outside of the FIS, by taking the maximum uncertainty value between the FIS output elevation uncertainty and the corresponding interpolation error value. Although I used 10 cm resolution FIS inputs/output, the FIS input MFGs can be easily calibrated with different input raster resolutions. This diagram is based upon rasters from site 198L.
Table 2.2 Statistical Breaks in the Input Data Used to Define the Input MFG Node Values and Overlap Between Input MFGs in the FIS

<table>
<thead>
<tr>
<th>MFG1</th>
<th>2nd Node</th>
<th>3rd Node</th>
<th>4th Node</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Node</td>
<td>0</td>
<td>0</td>
<td>$2\sigma_{MFG1}$</td>
</tr>
<tr>
<td>MFG2</td>
<td>$2\sigma_{MFG1}$</td>
<td>$Q_{25} + \sigma_{MFG}$</td>
<td>$Q_{25} + 2\sigma_{MFG2}$</td>
</tr>
<tr>
<td>MFG3</td>
<td>$Q_{25} + 2\sigma_{MFG2}$</td>
<td>$Q_{75} + \sigma_{MFG3}$</td>
<td>$Q_{75} + 2\sigma_{MFG3}$</td>
</tr>
<tr>
<td>MFG4</td>
<td>$Q_{75} + 2\sigma_{MFG3}$</td>
<td>$Q_{UW} + 2\sigma_{MFG3}$</td>
<td>Plausible Max.</td>
</tr>
</tbody>
</table>

Based upon the resulting summary statistics of the elevation uncertainty analyses performed in section 2.2.4, I calibrated (Bangen et al., 2016) the output MFGs of elevation uncertainty (defined as “low”, “moderate”, “high”, and “extreme”). The FIS model is particularly sensitive to the output MFGs, and the upper limit of the fourth, output MFG (i.e. “extreme” MFG; Bangen et al., 2016). I defined the upper limit of the fourth (i.e. “extreme”), output MFG by taking the average cut bank height difference between the top and bottom of the bank (Bangen et al., 2016). At representative, cutbank locations I calculated the average cut bank height by averaging the difference in elevations of the bank top and bottom (identified from the SfM orthomosaics).

**FIS Ruleset**

To meaningfully relate each input variable to the output variable of elevation uncertainty, I defined a ruleset (Table 2.3). I determined each rule with expert judgement and known relationships between each input variable and elevation uncertainty (Wheaton et al., 2010; Bangen et al., 2016). For example, for other HRT methods, DEM elevation uncertainty increases as DEM slope increases (Bangen et al., 2016). Both high and minimal roughness result in an increase in elevation uncertainty for the SfM method. For example, minimal surface texture/homogeneous texture causes the pixel matching algorithms to fail (e.g. Rule 1: Table 2.3). Too much surface texture can lead to occlusions that result in
losses of information and failure of the pixel matching algorithms (e.g. Rule 8: Table 2.3). All but one rule uses conditional “AND” statements. For instance, if DEM slope is “Low” “AND” DEM roughness is “Moderate”, THEN elevation uncertainty is “Low”. The one “OR” statement was used to assign “High” elevation uncertainty if either slope or roughness was in the input “Extreme” MFG.

Table 2.3 Ruleset for the 2-input FIS Component of the Error Model

<table>
<thead>
<tr>
<th>Rule</th>
<th>Slope (degrees)</th>
<th>Roughness (m)</th>
<th>Elevation Uncertainty (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Low</td>
<td>Bare Smooth Sand</td>
<td>Moderate</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>Gravel</td>
<td>Low</td>
</tr>
<tr>
<td>3</td>
<td>Low</td>
<td>Talus/Boulder</td>
<td>Moderate</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>Vegetation</td>
<td>High</td>
</tr>
<tr>
<td>5</td>
<td>Moderate</td>
<td>Bare Smooth Sand</td>
<td>Moderate</td>
</tr>
<tr>
<td>6</td>
<td>Moderate</td>
<td>Gravel</td>
<td>Moderate</td>
</tr>
<tr>
<td>7</td>
<td>Moderate</td>
<td>Talus/Boulder</td>
<td>Moderate</td>
</tr>
<tr>
<td>8</td>
<td>Moderate</td>
<td>Vegetation</td>
<td>High</td>
</tr>
<tr>
<td>9</td>
<td>High</td>
<td>Bare Smooth Sand</td>
<td>Moderate</td>
</tr>
<tr>
<td>10</td>
<td>High</td>
<td>Gravel</td>
<td>Moderate</td>
</tr>
<tr>
<td>11</td>
<td>High</td>
<td>Talus/Boulder</td>
<td>High</td>
</tr>
<tr>
<td>12</td>
<td>High</td>
<td>Vegetation</td>
<td>High</td>
</tr>
<tr>
<td>13</td>
<td>Extreme</td>
<td>Vegetation</td>
<td>Extreme</td>
</tr>
<tr>
<td>14</td>
<td>Extreme</td>
<td>Vegetation</td>
<td>High</td>
</tr>
</tbody>
</table>

**FIS Methods**

I implemented the FIS with the Scikit Fuzzy python package (https://github.com/scikit-fuzzy/scikit-fuzzy). I defined the overall range of values that define each MFG input and output. Although there are other MFG shapes that control the amount of membership for each input and output MFG, I used the trapezoidal shape for each MFG (Table 2.2) based upon the previous work of Bangen et al. (2016). To obtain an elevation uncertainty value for each DEM cell, I applied the combination of the corresponding slope and roughness
raster values to the ruleset. To calculate the elevation uncertainty for each SfM DEM cell, I used a centroid defuzzification method, which returns the center of mass under the output MFG curve. The 30 uncertainty rasters (10 cm resolution) took an average of 10 minutes per SfM DEM to batch generate in python.

Lastly, I incorporated interpolation error as an additional source of DEM uncertainty. I did not build interpolation error into the FIS as a third input raster because I think interpolation error is more efficiently incorporated outside the FIS. Interpolation error is intended to represent isolated incidents of high to extreme DEM uncertainty. Interpolation error occurs during the DEM generation phase when a raw point elevation is manifested into a DEM cell elevation (Bangen et al., 2016). As interpolation was introduced through the SfM DEM generation methods used in this study (from a.) interpolation over 2 m holes in the SfM point clouds and b.) inverse distance weighting), interpolation error was included in the error model to flag extraneous areas of inaccurate elevation caused by interpolation (Bangen et al., 2016). Interpolation error rasters were generated by calculating the absolute difference of each SfM elevation ($Z_{\text{min}}$) point value and corresponding $Z_{\text{min}}$ SfM DEM cell value. The interpolation error rasters were the same size and resolution as the FIS input rasters. Therefore, the output elevation uncertainty rasters were easily updated with the interpolation error rasters, and the higher value between the two rasters was used as the final elevation uncertainty raster (Figure 2.12).

2.3 Results

2.3.1 Image Acquisition and SfM Point Clouds

Image, GCP, and SfM point cloud statistics are summarized for all surveys in Table 2.4. As I mostly collected convergent images along transects oriented in opposite directions, the first image alignment contained sparse points from only one direction of transects. For complete image alignment, I had to realign images that I collected along the same transect in the opposite direction to allow the bundle adjustment to include those images in the sparse point cloud. Although handheld images were useful in connecting the tops and bottoms
of steep cut banks (>1.5 m), and filling in densely vegetated corridors through sandbars, they resulted in fewer sparse points. The contrast in angle and perspective between the handheld and pole mounted camera caused failed image alignments. To achieve correct sparse point cloud alignments in Photoscan, I spent additional time (between 30 minutes and 2 hours/survey depending on the size of the sandbar site and the quality of the images) to correct and realign multiple sparse point clouds. The average, XYZ RMSE values for all of the SfM, sparse point clouds were 0.028 m (X), 0.034 cm (Y), and 0.007 m (Z). The high vertical and horizontal accuracy (0.04 m) of the TS instrument and the primary control network resulted in low GCP RMSE values for the SfM point clouds (Dietrich, 2016b).

For each survey, I acquired image sets in minutes to hours in the field, but image sorting, georeferencing, and sparse/dense point cloud generation took over a month to complete for all surveys, with an individual SfM DEM requiring 1 to 5 days to generate. The post-processing times include: automatic sparse and dense point cloud post-processing (50%), manual image sorting and georeferencing (30%); dense point cloud cleaning/filtering (15%), and SfM DEM generation (<5%).

2.3.2 Accuracy and Precision Assessment of Individual SfM Point and DEM Elevation Values

Spatially implicit results for the residuals between the TS point measurements and the SfM point/DEM cell estimates are shown for each survey in Figure 2.13 and Table 2.5. For individual SfM point and DEM elevation models, there was a range (point analysis: 0.014 m to 0.099 m; DEM analysis: 0.002 m to 0.097 m) in mostly (point analysis: n = 29+/1- surveys; DEM analysis: n =24+/6- surveys) positive elevation bias in both the distribution of residuals and ME estimates for both analyses (Figure 2.13). As this positive bias was appreciable (i.e. ME >0.005 m) for most surveys, I used ME and SD (instead of RMSE) to calculate bias and precision of the SfM point and DEM elevation models. Due to the appreciable bias, I also used MAE over ME for quantifying DEM uncertainty and calibrating the elevation uncertainty output in the FIS. The MAE values for the point-to-point and point-to-DEM analyses varied across the SfM surveys with differences ranging from 0.001
Table 2.4 Data Acquisition Summary Statistics Across All SfM Surveys (N = 30)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Std.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Images (count)</td>
<td>703</td>
<td>147</td>
<td>1372</td>
<td>295</td>
</tr>
<tr>
<td>Pitch Angle* (degrees)</td>
<td>61</td>
<td>34</td>
<td>74</td>
<td>7</td>
</tr>
<tr>
<td>GCPs (count)</td>
<td>17</td>
<td>7</td>
<td>43</td>
<td>8</td>
</tr>
<tr>
<td>X RMSE (m)</td>
<td>0.028</td>
<td>0.006</td>
<td>0.073</td>
<td>0.018</td>
</tr>
<tr>
<td>Y RMSE (m)</td>
<td>0.034</td>
<td>0.004</td>
<td>0.224</td>
<td>0.039</td>
</tr>
<tr>
<td>Z RMSE (m)</td>
<td>0.007</td>
<td>0.0017</td>
<td>0.021</td>
<td>0.005</td>
</tr>
<tr>
<td>XYZ RMSE (m)</td>
<td>0.041</td>
<td>0.011</td>
<td>0.104</td>
<td>0.024</td>
</tr>
<tr>
<td>SfM DEM Area (m²)</td>
<td>2,612</td>
<td>497</td>
<td>8,458</td>
<td>1,876</td>
</tr>
<tr>
<td>SfM Sparse Points (count)</td>
<td>164,761</td>
<td>27,447</td>
<td>586,993</td>
<td>119,678</td>
</tr>
<tr>
<td>SfM Dense Points (count)</td>
<td>19,235,538</td>
<td>1,707,900</td>
<td>115,495,947</td>
<td>21,574,713</td>
</tr>
<tr>
<td>SfM Cleaned Points (count)</td>
<td>15,845,751</td>
<td>1,422,290</td>
<td>114,590,800</td>
<td>20,795,166</td>
</tr>
<tr>
<td>SfM Zmin Points (count)</td>
<td>244,677</td>
<td>47,078</td>
<td>841,306</td>
<td>173,107</td>
</tr>
<tr>
<td>SfM Zmin Point Density (pts/m²)</td>
<td>296</td>
<td>264</td>
<td>308</td>
<td>8</td>
</tr>
<tr>
<td>TS Points (count)</td>
<td>222</td>
<td>87</td>
<td>448</td>
<td>83</td>
</tr>
</tbody>
</table>

*Pitch angle is the angle of the camera lens relative to horizontal.

m to 0.060 m. Across all surveys (n = 30), the SfM point precision estimated relative to TS point measurement ranged from 0.026 m to 0.187 m (Table 2.5). Across all surveys (n = 30), the SfM DEM precision estimated relative to TS point measurement ranged from 0.046 m to 0.279 m (Table 2.5).

Spatially explicit results for the residuals between the TS point measurements and the SfM point/DEM cell estimates are shown for each survey in Figure 2.14 and Table 2.6. For each of the 19 spatially explicit surface cover categories, the positive elevation bias remains with ME values ranging from -0.001 m (ground control points) to 0.341 m (submerged, deep, clear water) for the point-to-point residual and from -0.031 m (canopy vegetation) to 0.328 (submerged, deep, clear water) for the DEM-to-point residual. Across all surface cover categories, the SfM point precision estimated relative to TS point measurement range from 0.001 m (ground control point) to 0.341 m (submerged, deep, clear water; Table 2.6). Across all surface cover categories, the SfM DEM precision estimated relative to TS point
measurement range from -0.031 m (canopy vegetation) to 0.328 m (submerged, deep, clear water; Table 2.6). In alignment with the limitations of the SfM method that have been previously investigated (Smith et al., 2016), elevation error was largest in submerged and vegetated areas. The removal of isolated clumps of dense vegetation or survey equipment were more easily removed than low-lying ground vegetation. Therefore, areas with canopy vegetation yielded lower elevation error compared to areas of low-lying ground vegetation. The edge of the survey also contained higher elevation error due both to dense vegetation and artifacts that were protruding from the edge of the water. There were less artifacts at the edge of clear, shallow water than turbid, deep water, resulting in less elevation error at the edge of clear, shallow water. The MAE of dry, exposed sand (0.034 m to 0.035 m) is an order of magnitude lower than the MAE of the edge of the survey (0.107 m to 0.120 m) where vegetation is taller than the camera pole height and elevation uncertainty is high. A breakline not in shadow (SD = 0.021 m to 0.024 m) has twice the precision as a breakline in shadow (SD = 0.069 m to 0.047 m).
Fig. 2.13. Spatially implicit summary boxplots for each SfM survey. White boxplots show the summary statistics for the difference between the SfM point estimates and the TS point measurements. Blue boxplots show the summary statistics for the difference between the SfM DEM estimates and the TS point measurements. Sites are named by river kilometer, and the site location on the left (L) or right (R) side of the river (oriented in the direction of channel flow). The repeat surveys are from the same time, not different years.
Table 2.5 Summary Statistics for SfM Estimates Compared to TS Measurements

<table>
<thead>
<tr>
<th>Survey Name</th>
<th>$Z_{SfM_{PT}} - Z_{TS_{PT}}$</th>
<th>$Z_{SfM_{DEM}} - Z_{TS_{PT}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ME</td>
<td>MAE</td>
</tr>
<tr>
<td>48R: 150925 (DSLRT18)*</td>
<td>0.030</td>
<td>0.034</td>
</tr>
<tr>
<td>48R: 150925 (DSLRT)*</td>
<td>0.017</td>
<td>0.022</td>
</tr>
<tr>
<td>48R: 150925 (PST)*</td>
<td>0.015</td>
<td>0.026</td>
</tr>
<tr>
<td>80R: 140927 (DSLRIR)</td>
<td>0.032</td>
<td>0.060</td>
</tr>
<tr>
<td>80R: 140927 (DSLRIS)</td>
<td>0.032</td>
<td>0.046</td>
</tr>
<tr>
<td>80R: 150927 (PSIS1)*</td>
<td>0.044</td>
<td>0.053</td>
</tr>
<tr>
<td>80R: 150927 (PSIS2)*</td>
<td>0.057</td>
<td>0.066</td>
</tr>
<tr>
<td>105R: 140929 (DSLRI)</td>
<td>0.014</td>
<td>0.035</td>
</tr>
<tr>
<td>105R: 150929 (PSI)</td>
<td>0.030</td>
<td>0.056</td>
</tr>
<tr>
<td>113R: 140930 (DSLRI)</td>
<td>0.021</td>
<td>0.026</td>
</tr>
<tr>
<td>113R: 150930 (DSLRI)</td>
<td>0.060</td>
<td>0.061</td>
</tr>
<tr>
<td>146R: 141002 (DSLRI)</td>
<td>0.043</td>
<td>0.078</td>
</tr>
<tr>
<td>146R: 151002 (PSI)</td>
<td>0.028</td>
<td>0.069</td>
</tr>
<tr>
<td>192R: 141003 (DSLRI)</td>
<td>0.053</td>
<td>0.061</td>
</tr>
<tr>
<td>192R: 151003 (DSLRI)*</td>
<td>0.014</td>
<td>0.038</td>
</tr>
<tr>
<td>192R: 151003 (PSI)*</td>
<td>0.034</td>
<td>0.053</td>
</tr>
<tr>
<td>198L: 141004 (DSLRI)</td>
<td>0.091</td>
<td>0.095</td>
</tr>
<tr>
<td>198L: 151004 (DSLRI)*</td>
<td>0.023</td>
<td>0.047</td>
</tr>
<tr>
<td>198L: 151004 (PSI)*</td>
<td>0.037</td>
<td>0.049</td>
</tr>
<tr>
<td>220L: 151004 (PSI)</td>
<td>0.041</td>
<td>0.048</td>
</tr>
<tr>
<td>233L: 151005 (DSLRI)</td>
<td>0.026</td>
<td>0.049</td>
</tr>
<tr>
<td>267L: 141006 (DSLRI)</td>
<td>0.016</td>
<td>0.027</td>
</tr>
<tr>
<td>267L: 151006 (DSLRI)</td>
<td>0.026</td>
<td>0.037</td>
</tr>
<tr>
<td>267L: 151006 (PSI)</td>
<td>0.011</td>
<td>0.025</td>
</tr>
<tr>
<td>312L: 141007 (DSLRI)</td>
<td>-0.007</td>
<td>0.069</td>
</tr>
<tr>
<td>312L: 151007 (PSI)</td>
<td>0.015</td>
<td>0.025</td>
</tr>
<tr>
<td>325R: 141008 (DSLRI)</td>
<td>0.008</td>
<td>0.020</td>
</tr>
<tr>
<td>325R: 151007 (PSI)</td>
<td>0.084</td>
<td>0.091</td>
</tr>
<tr>
<td>343L: 141008 (DSLRI)</td>
<td>0.141</td>
<td>0.149</td>
</tr>
<tr>
<td>343L: 151008 (PSI)</td>
<td>0.099</td>
<td>0.137</td>
</tr>
</tbody>
</table>

Error metrics reported in m; *repeat survey; "48R" = sandbar site river kilometer and river right (R) or river left (L); "150925" = survey date: 09/25/2015; DSLR = Canon T4i digital single lens reflex camera (8 megapixels otherwise denoted); PSI = Canon D30 point and shoot camera (12 megapixels); T = trigger camera mechanism; I = intervalometer trigger camera mechanism
Fig. 2.14. Spatially explicit summary boxplots for each surface cover type. White boxplots show the summary statistics for the difference between the SfM point estimates and the TS point measurements by surface cover type. Green boxplots show the summary statistics for the difference between the SfM DEM estimates and the TS point measurements by surface cover type. Sites are named by river kilometer, and the site location on the left (L) or right (R) side of the river (oriented in the direction of channel flow).
Table 2.6 Summary Statistics for the SfM and TS Point Elevation Residual and the SfM DEM and TS Point Elevation Residual

<table>
<thead>
<tr>
<th>Number</th>
<th>Name</th>
<th>( Z_{SfM_{PT}} - Z_{TS_{PT}} )</th>
<th>ME</th>
<th>MAE</th>
<th>SD</th>
<th>ME</th>
<th>MAE</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ground Control Point</td>
<td>-0.001</td>
<td>0.013</td>
<td>0.001</td>
<td>-0.006</td>
<td>0.020</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Saturated Clay/Silt</td>
<td>0.009</td>
<td>0.020</td>
<td>0.009</td>
<td>0.000</td>
<td>0.023</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Slightly Saturated, Exposed Sand</td>
<td>0.009</td>
<td>0.025</td>
<td>0.009</td>
<td>-0.001</td>
<td>0.022</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Gravel/Cobble</td>
<td>0.019</td>
<td>0.026</td>
<td>0.019</td>
<td>0.005</td>
<td>0.023</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Dry, Exposed Sand</td>
<td>0.021</td>
<td>0.035</td>
<td>0.021</td>
<td>0.019</td>
<td>0.034</td>
<td>0.019</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Breakline</td>
<td>0.024</td>
<td>0.043</td>
<td>0.024</td>
<td>0.021</td>
<td>0.055</td>
<td>0.021</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Top of Bank Edge</td>
<td>0.034</td>
<td>0.060</td>
<td>0.034</td>
<td>0.030</td>
<td>0.093</td>
<td>0.030</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Survey Equipment</td>
<td>0.045</td>
<td>0.055</td>
<td>0.045</td>
<td>0.052</td>
<td>0.066</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Breakline in Shadow</td>
<td>0.047</td>
<td>0.085</td>
<td>0.047</td>
<td>0.069</td>
<td>0.097</td>
<td>0.069</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Shadow</td>
<td>0.050</td>
<td>0.072</td>
<td>0.050</td>
<td>0.097</td>
<td>0.138</td>
<td>0.097</td>
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<tr>
<td>11</td>
<td>Edge of Water</td>
<td>0.052</td>
<td>0.060</td>
<td>0.052</td>
<td>0.041</td>
<td>0.053</td>
<td>0.041</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Boulder/Bedrock</td>
<td>0.066</td>
<td>0.075</td>
<td>0.066</td>
<td>0.135</td>
<td>0.158</td>
<td>0.135</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Canopy Vegetation</td>
<td>0.069</td>
<td>0.089</td>
<td>0.069</td>
<td>-0.031</td>
<td>0.194</td>
<td>0.031</td>
<td></td>
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<tr>
<td>14</td>
<td>Edge of Survey</td>
<td>0.070</td>
<td>0.088</td>
<td>0.070</td>
<td>0.075</td>
<td>0.104</td>
<td>0.075</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Low-lying Vegetation</td>
<td>0.073</td>
<td>0.082</td>
<td>0.073</td>
<td>0.049</td>
<td>0.077</td>
<td>0.049</td>
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<tr>
<td>16</td>
<td>Edge Vegetation*</td>
<td>0.096</td>
<td>0.120</td>
<td>0.096</td>
<td>0.043</td>
<td>0.107</td>
<td>0.043</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>Submerged, Turbid Water</td>
<td>0.191</td>
<td>0.192</td>
<td>0.191</td>
<td>0.239</td>
<td>0.242</td>
<td>0.239</td>
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</tr>
<tr>
<td>18</td>
<td>Submerged, Shallow, Clear Water</td>
<td>0.200</td>
<td>0.201</td>
<td>0.200</td>
<td>0.147</td>
<td>0.150</td>
<td>0.147</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>Submerged, Deep, Clear Water</td>
<td>0.341</td>
<td>0.341</td>
<td>0.341</td>
<td>0.328</td>
<td>0.328</td>
<td>0.328</td>
<td></td>
</tr>
</tbody>
</table>

*Edge Vegetation = densely vegetated areas at the edge of a survey; contain lower point density.

2.3.3 Variability in Lines of Evidence for Elevation Uncertainty

Out of the three SfM DEM uncertainty analyses, the bootstrapping analysis resulted in the smallest estimates of elevation uncertainty with a mean absolute difference of 0.019 m, and standard deviation of 0.036 m averaged across all surveys and bootstrapping samples (Table 2.7; Figure 2.15). The survey method variability distribution between all 9 repeat surveys at site 343L resulted in the highest elevation uncertainty with a mean range of 0.173 m (Table 2.7; Figure 2.15). The point to point, bootstrapping (absolute difference),
residual and repeat analyses contain right-skewed distributions with a mean value of 0.010 m to 0.107 greater than the median value. Due to the positive bias in the elevation difference distributions for the bootstrapping and residual analyses (Figure 2.16), I calibrated the error model with the absolute difference and range distributions. The range distribution of the camera parameter variability group (9 surveys from 4 different sites), exhibits a significantly lower average elevation uncertainty (0.050 m) compared to the range distribution (mean = 0.173) of the survey method variability group (9 repeat surveys at the additional 343L site). The higher precision of the camera parameter variability group is likely due to the number of repeat surveys acquired (i.e. sample size of 2 to 3 surveys compared to 9 surveys) and compared in the repeat range distributions.

Table 2.7 Summary Statistics for the Four Elevation Uncertainty Analyses

<table>
<thead>
<tr>
<th></th>
<th>Bootstrap</th>
<th>Group1*</th>
<th>Residual</th>
<th>Group2**</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\delta_Z$ (m)</td>
<td>$</td>
<td>\delta_Z</td>
<td>$ (m)</td>
</tr>
<tr>
<td>Sample</td>
<td>3,670,077</td>
<td>3,670,077</td>
<td>930,525</td>
<td>73,115</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.001</td>
<td>0.019</td>
<td>0.050</td>
<td>0.038</td>
</tr>
<tr>
<td>Std.</td>
<td>0.041</td>
<td>0.036</td>
<td>0.088</td>
<td>0.216</td>
</tr>
<tr>
<td>LW</td>
<td>-0.023</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.198</td>
</tr>
<tr>
<td>Min.</td>
<td>-3.415</td>
<td>0.000</td>
<td>0.000</td>
<td>-2.085</td>
</tr>
<tr>
<td>$Q_{25}$</td>
<td>-0.009</td>
<td>0.004</td>
<td>0.010</td>
<td>-0.048</td>
</tr>
<tr>
<td>$Q_{50}$</td>
<td>0.000</td>
<td>0.009</td>
<td>0.023</td>
<td>0.021</td>
</tr>
<tr>
<td>$Q_{75}$</td>
<td>0.009</td>
<td>0.021</td>
<td>0.055</td>
<td>0.115</td>
</tr>
<tr>
<td>UW</td>
<td>0.038</td>
<td>0.038</td>
<td>0.124</td>
<td>0.349</td>
</tr>
<tr>
<td>Max.</td>
<td>2.466</td>
<td>3.415</td>
<td>1.896</td>
<td>2.488</td>
</tr>
</tbody>
</table>

*Group1 = Camera parameter variability, repeat surveys
*Group2 = Survey method variability, 9 repeat surveys.

The appreciable variability in average elevation uncertainty for the three independent analyses for all surveys led to the different calibration of the elevation uncertainty output MFGs in the FIS component of the error model (Table 2.8). For the low elevation uncertainty MFG node values, I used the bootstrapping analysis with the lowest median and mean absolute difference values of 0.009 m and 0.019 m. For the moderate elevation un-
Fig. 2.15. Boxplots summarizing the varying distributions for all three elevation uncertainty analyses. The center black line is the median of the distribution, and the red circle is the mean of the distribution. Box colors correspond to histograms in Figure 2.16.
Fig. 2.16. Histograms for complimentary elevation uncertainty analyses. A. Bootstrapping analysis (SfM point elevation (m) - SfM DEM elevation (m)). B. Bootstrapping analysis (|SfM point elevation (m) - SfM DEM (m)|). C. Camera parameter variability analysis (range DEM (m) = maximum DEM (m) - minimum DEM (m)). D. Survey method variability analysis (range DEM (m) = maximum DEM (m) - minimum DEM (m)). E. Residual analysis (SfM DEM (m) - TS DEM (m)). F. (|SfM DEM (m) - TS DEM (m)|).
certainty MFG node values, I used the median and mean values of the camera parameter variability analysis (0.023 m to 0.046 m). To determine the high elevation uncertainty MFG node values, I used the average of the residual analysis and the survey method variability analysis. Lastly, for the upper node value of the extreme MFG, I used an average cut bank height of 2 m.

Table 2.8 Elevation Uncertainty Output MFG Calibration for FIS Component of Spatially Variable Error Model

<table>
<thead>
<tr>
<th></th>
<th>1st Node</th>
<th>2nd Node</th>
<th>3rd Node</th>
<th>4th Node</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low $\delta Z$</td>
<td>0</td>
<td>0</td>
<td>$Q_{50_{bootstrap}}$</td>
<td>$\mu_{bootstrap}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.009)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Moderate $\delta Z$</td>
<td>$Q_{50_{bootstrap}}$</td>
<td>$\mu_{bootstrap}$</td>
<td>$Q_{50_{group1}}$</td>
<td>$\mu_{group1}$</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.019)</td>
<td>(0.023)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>High $\delta Z$</td>
<td>$Q_{50_{group1}}$</td>
<td>$\mu_{group1}$</td>
<td>$Q_{50_{group2}}$</td>
<td>$\mu_{group2}$</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.046)</td>
<td>(0.072)</td>
<td>(0.154)</td>
</tr>
<tr>
<td>Extreme $\delta Z$</td>
<td>$Q_{50_{group2}}$</td>
<td>$\mu_{group2}$</td>
<td>$CutBankHeight$</td>
<td>$CutBankHeight$</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.154)</td>
<td>(2.000)</td>
<td>(2.000)</td>
</tr>
</tbody>
</table>

*Group1 = Camera parameter variability, repeat surveys
*Group2 = Survey method variability, 9 repeat surveys.

2.3.4 Spatially Variable Elevation Uncertainty of SfM DEMs

Slope and Roughness

Although the error model was built upon average DEM uncertainty values that represent a wide range of surface roughness and slope in the fluvial environment, the spatial structure of the DEM uncertainty is revealed through the DEM uncertainty distributions at each site (e.g. Figure 2.17A). For example, for the bootstrapping analysis, individual surveys show increased variability in DEM uncertainty (i.e. mean absolute differences rang-
Fig. 2.17. A. Elevation difference (absolute value) between modeled SfM DEM and points held back by site shown for the bootstrapping analysis. All 30 surveys are shown, but sites alternate between the white and gray boxplots. Repeat surveys are also shown. B. Plot showing the relationship between slope (degrees) and elevation difference (m) for the bootstrapping analysis. Data are averaged over 100 bins to clarify trends in data (black points). C. Plot showing the relationship between roughness (m) and elevation difference (m) for the bootstrapping analysis. Data are averaged over 100 bins to clarify trends in data (black points).
ing from 0.009 m to 0.037 m, and the standard deviation ranging from 0.016 m to 0.070 m) compared to the total DEM uncertainty for all surveys. The variability in DEM uncertainty at individual sites is caused by the spatial relationships between slope/roughness and DEM uncertainty, and are illustrated with the bootstrapping analysis in Figure 2.17B and Figure 2.17C. But these spatial relationships between DEM uncertainty and either slope or roughness are not clearly defined. This ambiguity is one justification for my use of the FIS to resolve real world ambiguity. Generally, higher DEM uncertainty values (e.g. MAE) calculated from the bootstrapping analysis (e.g. 0.034 m, 0.030 m, 0.032 m, 0.037 m) are represented at sites with higher slope and roughness (e.g. 105R, 192L, 233L and 343L), whereas lower DEM uncertainty values (e.g. 0.009 m, 0.009 m, 0.013 m, and 0.011 m) are represented at sites with lower slope and roughness (e.g. 198L, 220L, 113R, and 267L).

The survey method variability analysis also resulted in spatial patterns of DEM uncertainty that correlate to patterns of slope and roughness (Figure 2.18). After categorizing surface cover of the survey area (Figure 2.18), and calculating the weighted average of DEM uncertainty for each cover type, differences in DEM uncertainty emerge for the surface cover types (Table 2.9). The weighted averages show that slope has less effect on DEM uncertainty (e.g. weighted average = 0.006 m) than surface roughness (e.g. varying surface textures in the bedrock surface category result in a weighted average of DEM uncertainty = 0.039 m). Lastly, similar spatial patterns of DEM uncertainty are seen through the residual analyses. For example, at the exposed 48R site, the three, residual, repeat surveys show similar spatial patterns of higher uncertainty along the cut bank (Figure 2.19). At the 192R site, two residual, repeat surveys show greater amounts of uncertainty on a steep, vegetated bank compared to an exposed bank (Figure 2.20). The resulting spatial structure of DEM uncertainty determined that variables of slope and roughness were viable inputs for the error model.
Fig. 2.18. Survey method variability DEM uncertainty analysis with 9 repeat SfM surveys at site 343L. A. Surface cover types overlaid on top of orthomosaic. B. Elevation uncertainty raster that shows the range (m) (maximum (m) - minimum (m)) elevation values between 9 repeat DEMs. White arrow indicates flow direction. Note that the talus surface cover type is comprised of boulders/bedrock on a steeper slope.
Table 2.9 DEM Uncertainty (m) by Surface Cover Type for the Survey Method Variability Analysis

<table>
<thead>
<tr>
<th>Area</th>
<th>Bare Flat</th>
<th>Canopy Vegetation</th>
<th>Low-lying Vegetation</th>
<th>Cut Bank</th>
<th>Base of Cut Bank</th>
<th>Bedrock</th>
<th>Talus Edge of Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.063</td>
<td>0.195</td>
<td>0.368</td>
<td>0.374</td>
<td>0.210</td>
<td>0.119</td>
<td>0.408</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.022</td>
<td>0.017</td>
<td>0.030</td>
<td>0.006</td>
<td>0.011</td>
<td>0.039</td>
<td>0.021</td>
</tr>
<tr>
<td>Std.</td>
<td>0.007</td>
<td>0.172</td>
<td>0.273</td>
<td>0.288</td>
<td>0.218</td>
<td>0.212</td>
<td>0.291</td>
</tr>
<tr>
<td>Min.</td>
<td>0.004</td>
<td>0.011</td>
<td>0.010</td>
<td>0.021</td>
<td>0.016</td>
<td>0.006</td>
<td>0.032</td>
</tr>
<tr>
<td>$Q_{25}$</td>
<td>0.022</td>
<td>0.072</td>
<td>0.172</td>
<td>0.173</td>
<td>0.089</td>
<td>0.036</td>
<td>0.192</td>
</tr>
<tr>
<td>$Q_{50}$</td>
<td>0.030</td>
<td>0.132</td>
<td>0.323</td>
<td>0.280</td>
<td>0.138</td>
<td>0.054</td>
<td>0.344</td>
</tr>
<tr>
<td>$Q_{75}$</td>
<td>0.057</td>
<td>0.276</td>
<td>0.495</td>
<td>0.480</td>
<td>0.246</td>
<td>0.110</td>
<td>0.532</td>
</tr>
<tr>
<td>Max.</td>
<td>2.350</td>
<td>2.319</td>
<td>3.881</td>
<td>1.928</td>
<td>2.332</td>
<td>3.323</td>
<td>2.657</td>
</tr>
</tbody>
</table>
Fig. 2.19. Residual (SfM - TS DEM) surfaces for the exposed, 48R sandbar site. A-C. Show orthomosaics, and inset maps from three consecutive surveys performed at this site. A. and B. used a DSLRI camera, and C. used a point and shoot camera. D-F. Corresponding elevation uncertainty maps, showing spatially variable elevation uncertainty around the cut bank. G-I. Histograms for the elevation uncertainty distribution. Blue bars represents areas where the SfM surface is higher than the TS surface, and red bars represent areas where the TS is higher than the SfM surface. J-L. Scatter plots showing how closely SfM and TS elevations compare. The red line represents a 1:1 line through the data.
Fig. 2.20. Residual (SfM - TS DEM) surfaces for the exposed/vegetated, 119R sandbar site. A-B. Show orthomosaics, and inset maps from two consecutive surveys performed at this site. A. used a DSLRI camera, and B. used a point and shoot camera. C-D. Corresponding elevation uncertainty maps, showing spatially variable elevation uncertainty around the exposed cut bank, and even higher elevation uncertainty on the vegetated cut bank. E-F. Histograms for the elevation uncertainty distribution. Blue bars represents areas where the SfM surface is higher than the TS surface, and red bars represent areas where the TS is higher than the SfM surface. G-H. Scatter plots showing how closely SfM and TS elevations compare. The red line represents a 1:1 line through the data.
2.3.5 Modeled SfM DEM Uncertainty Results

The error model resulted in conservative estimates of cell-by-cell, SfM DEM uncertainty (Figure 2.21). The mean SfM DEM uncertainty at exposed sites resulted in 0.038 m, whereas highly vegetated sites with steep slopes resulted in a mean SfM DEM uncertainty of 0.300 m (Table 2.10). The modeled mean values of SfM DEM uncertainty are higher than the median values.

Fig. 2.21. Distributions of modeled, SfM DEM uncertainty, sorted by mean SfM DEM uncertainty value and grouped by site. Medians are represented by red horizontal lines, whereas means are represented by red circles. The maximum elevation uncertainty value (displayed outside of the plot) for site 343L is 2.808 m. The boxplots are colored by general roughness and gradient categories.
Table 2.10 Modeled, SfM DEM Uncertainty Values (Grouped By Site and Sorted by Mean Elevation Value)

<table>
<thead>
<tr>
<th>Sample</th>
<th>Mean</th>
<th>Std.</th>
<th>Min.</th>
<th>Q_{25}</th>
<th>Q_{50}</th>
<th>Q_{75}</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>220L</td>
<td>0.038</td>
<td>0.065</td>
<td>0.012</td>
<td>0.024</td>
<td>0.024</td>
<td>0.039</td>
<td>1.029</td>
</tr>
<tr>
<td>198L</td>
<td>0.055</td>
<td>0.108</td>
<td>0.012</td>
<td>0.024</td>
<td>0.025</td>
<td>0.058</td>
<td>1.614</td>
</tr>
<tr>
<td>267L</td>
<td>0.056</td>
<td>0.125</td>
<td>0.012</td>
<td>0.023</td>
<td>0.024</td>
<td>0.056</td>
<td>1.029</td>
</tr>
<tr>
<td>48R</td>
<td>0.063</td>
<td>0.139</td>
<td>0.012</td>
<td>0.024</td>
<td>0.038</td>
<td>0.049</td>
<td>1.569</td>
</tr>
<tr>
<td>325R</td>
<td>0.086</td>
<td>0.170</td>
<td>0.012</td>
<td>0.033</td>
<td>0.044</td>
<td>0.063</td>
<td>1.029</td>
</tr>
<tr>
<td>146R</td>
<td>0.088</td>
<td>0.182</td>
<td>0.012</td>
<td>0.024</td>
<td>0.043</td>
<td>0.067</td>
<td>1.029</td>
</tr>
<tr>
<td>113R</td>
<td>0.089</td>
<td>0.151</td>
<td>0.012</td>
<td>0.041</td>
<td>0.057</td>
<td>0.083</td>
<td>1.029</td>
</tr>
<tr>
<td>312L</td>
<td>0.092</td>
<td>0.193</td>
<td>0.012</td>
<td>0.025</td>
<td>0.039</td>
<td>0.073</td>
<td>1.365</td>
</tr>
<tr>
<td>192R</td>
<td>0.102</td>
<td>0.215</td>
<td>0.012</td>
<td>0.024</td>
<td>0.039</td>
<td>0.079</td>
<td>1.118</td>
</tr>
<tr>
<td>233L</td>
<td>0.110</td>
<td>0.212</td>
<td>0.013</td>
<td>0.025</td>
<td>0.049</td>
<td>0.086</td>
<td>1.029</td>
</tr>
<tr>
<td>80R</td>
<td>0.125</td>
<td>0.227</td>
<td>0.012</td>
<td>0.031</td>
<td>0.056</td>
<td>0.087</td>
<td>1.029</td>
</tr>
<tr>
<td>105R</td>
<td>0.131</td>
<td>0.240</td>
<td>0.012</td>
<td>0.026</td>
<td>0.059</td>
<td>0.087</td>
<td>1.029</td>
</tr>
<tr>
<td>343L</td>
<td>0.300</td>
<td>0.359</td>
<td>0.012</td>
<td>0.066</td>
<td>0.088</td>
<td>0.565</td>
<td>2.808</td>
</tr>
</tbody>
</table>

Slope and roughness were the primary, topographic factors that I used to model spatially variable SfM DEM uncertainty. Flat to steep slopes that are bare/sparsely vegetated contained lower amounts of modeled SfM DEM uncertainty (Figure 2.21). Whereas, steep slopes and high surface roughness contained higher amounts of modeled SfM DEM uncertainty (Figure 2.23). Bimodal distributions are seen in the histograms with areas of higher gradient (Figure 2.21F) and dense vegetation (Figure 2.23F).
Fig. 2.22. Examples of bare and flat SfM DEMs that contain low DEM uncertainty. Site 48R contains a bare surface and low gradient, resulting in lower, modeled DEM uncertainty compared to site 233L, which has a bare surface but areas with steep gradient. A-B. Orthomosaics of sites 48R and 233L. Transparent arrows indicate direction of flow. C-D. Modeled SfM DEM uncertainty raster. E-F. Corresponding histograms, showing the frequency of the SfM DEM uncertainty.
Fig. 2.23. Examples of SfM DEMs at sandbar sites with greater amounts of vegetation. Site 113R contains patchy vegetation, but also contained lower gradient, resulting in lower DEM uncertainty compared to site 343L, which has high vegetation and high gradient. A-B. Orthomosaics of sites 233L and 343L. Transparent arrows indicate direction of flow. C-D. Modeled SfM DEM uncertainty raster. E-F. Corresponding histograms, showing the frequency of the SfM DEM uncertainty.
2.4 Discussion

The primary purpose of this thesis was to determine whether the SfM method, utilizing the low-angle, pole-mounted camera platform, is an accurate, precise (i.e. repeatable), and tractable method for monitoring/geomorphic change detection (see section A.8). In short, I not only demonstrated that the pole-based SfM method is accurate, precise and repeatable, but I also documented how this can be done, and provided a means for spatially variable error modeling to be performed to support change detection. I used a case study of 30 SfM surveys (including a large number of replicate surveys across a range of sandbar types using different camera types/settings and coincident TS surveys) to quantify multiple, independent lines of evidence for elevation uncertainty of the SfM DEMs. I then demonstrated how different magnitudes of SfM elevation uncertainty can be used to calibrate an error model. Unlike previous SfM studies in the geomorphology literature, I found contrasting magnitudes of elevation uncertainty, and I adjusted the error model accordingly. A conservative error model is a cautious approach for estimating error and volume change from repeat DEMs, but is warranted for early uses of the SfM method for cell-by-cell geomorphic change detection/monitoring. A conservative error model is also justified for detecting small-scale geomorphic change amongst a noisy dataset. Change detection workflows should account for multiple sources of elevation uncertainty utilizing pragmatic methods (e.g. FIS). SfM datasets acquired in fluvial environments are especially prone to increased amounts of elevation uncertainty, and are prime candidates for the characterization of elevation uncertainty.

2.4.1 SfM Error Model Calibration

The error model calibration that was used in this study required consideration of multiple sources of elevation uncertainty that were calculated with both raw point and SfM DEM data from a sample of sites that best represented 1.) the SfM survey method in use (i.e. pole-based method) and 2.) the varying topographic slope and roughness in the particular surveying environment (i.e. sandbars deposited along the Colorado River in Marble and Grand Canyon). Therefore, this research provides a tangible contribution (i.e. pole-based
SfM error model) to geomorphologists using repeat, SfM DEMs that are collected with the pole-based method and that are generated from a similar environment by providing an error model that can be directly adopted and applied to future GCD analyses.

When using repeat, SfM DEMs from different environments, the same error modeling approach that was used in this study can be adopted, but the statistics for the error model calibration (Table 2.8) must be recalculated to best represent 1.) the SfM survey method/image platform in use and 2.) the varying topographic slope and roughness and environmental factors. Ideally, to recalibrate the error model for a different environment, the raw SfM point data and validation point/DEM data are available to perform the statistical calibration in Table 2.8. As seen in this study, analyses involving raw points (point residuals and bootstrapping) provided too liberal of elevation uncertainty magnitudes alone, which will result in estimates of elevation error that are too low and that are misrepresentative of actual volume changes over time. Therefore, additional SfM DEM analyses (e.g. I used repeat DEM analyses) are needed to obtain more realistic elevation uncertainty values. In the case of limited data, performing at least two independent elevation uncertainty analyses could provide estimates of different magnitudes of elevation uncertainty, which could be used to inform the error model. The error model in this study was based upon a 2-input approach to the FIS (and the consideration of interpolation error outside the FIS to flag extraneous elevation values located at the edge of the survey boundary), but other FIS inputs can be added with additional and accessible raw data.

2.4.2 Elevation Uncertainty of SfM DEMs

Generally, I found a consistent positive elevation bias throughout the independent analyses performed to characterize elevation uncertainty of SfM DEMs, and calibrate the FIS component of the error model. This positive elevation bias is significant to cell-by-cell change detection (Bangen et al., 2014). Similar positive bias has also been reported by previous studies with a SfM - TLS DEM comparison of a mostly bare surface, badland environment (Smith and Vericat, 2015). The positive bias found in this study is likely caused by vegetation, but more importantly the way the camera surveys the topography compared
to the TS method. For example, the survey rod sinks into the sand at least a few centimeters while it is being surveyed by the TS instrument, while the camera directly surveys the top of the surface for the SfM method. The positive bias could lead to the overestimation of volume change of repeat surveys, and is likely to result in misinterpretation of geomorphic change, especially in systems with a low geomorphic change to high data noise ratio.

The SfM DEMs of steep slopes and high surface roughness contain amounts of spatially variable elevation uncertainty that are, without other additional HRT methods to account for this elevation uncertainty, less operational for studies of geomorphic change in systems with low change signals to high noise in the data. Previous studies of geomorphic change using the SfM method, to date, are performed in environments with areas of low surface slope and roughness (Clapuyt et al., 2016). Or steep slopes (Smith and Vericat, 2015) and dense, riparian vegetation (Prosdocimi et al., 2015) are discounted for the change detection. This study contributes to the magnitude of spatially variable elevation uncertainty for various surface cover types. For example, areas of a SfM DEM, with bare, steep, shadowed slopes contains less elevation uncertainty than densely vegetated, steep slopes.

In addition, higher, modeled SfM DEM uncertainty was connected to steep, vertical cut banks that are poorly defined due to complete shadowing (i.e. solid black) in the original imagery, whereas cut banks defined in areas of soft shadowing contained lower DEM uncertainty. The lack of accurate characterization of steep banks in fluvial environments is common for all topographic surveying techniques (Bangen et al., 2014), but for the SfM method is mostly likely due to the inability of SfM algorithms to accurately and precisely reconstruct a steep feature in completely black shadow. Lastly, the elevation uncertainty of survey edges should be carefully considered for repeat topographic studies. Reflective, wet and fine clay/sand areas near the survey boundary yielded low amounts of elevation uncertainty, but repeat surveys show lower precision along the edge of water, and along the vegetated survey boundary located at the backside of the sandbars. Interpolation error was used to flag extraneous elevation uncertainty values often located at the edges of the survey where point density decreases and point noise increases.
2.4.3 Utility of Error Model for Geomorphic Change Detection

For cell-by-cell monitoring and geomorphic change detection, the type of DEM elevation uncertainty and error (i.e. spatially variable or uniform) will affect the amount and distribution of propagated elevation error of multi-temporal DEMs. To demonstrate 1.) how the error model that I built in this study can be used/modified for geomorphic change detection with SfM DEMs and 2.) how propagated SfM DEM error differs with the application of a spatially variable and spatially uniform error model, I performed geomorphic change detection at 3 representative (i.e. variable slope and roughness) sandbar sites (80R, 113R, and 343L). I generated pairwise SfM and TS DEMs of Difference (DoDs) while applying the spatially variable FIS error model and a spatially uniform error model, respectively. For the spatially uniform error model, I simply applied a uniform elevation error of 0.04 m (Hazel Jr. et al., 2008) to all of the DEM cells in the GCD software (Wheaton et al., 2010). To make a comparison between the geomorphic change/propagated error of the spatially variable SfM method and the spatially uniform TS method I had to generate all DEMs at the resolution of the TS DEMs, which in this case was 1 m. To use the FIS error model that I built in this study for this demonstration, I had to generate 1 m slope, roughness, and interpolation rasters and recalibrate the FIS input membership functions of slope and roughness. For the recalibration, I calculated summary statistics of the newly generated, 1 m slope and roughness rasters (n = 30) and redefined the MFG node values based upon the statistical breaks that I originally established (Table 2.2). I did not recalibrate the output DEM elevation uncertainty MFGs for the 1 m resolution. For an entirely different topographic dataset (e.g. cliff faces), I recommend recalibrating both the input and output MFGs of the FIS.

From the geomorphic change detection table Table 2.11, the straight/unthresholded DoDs show the same signals of thickness change for both the spatially uniform TS method and spatially variable SfM method. The unthresholded DoD maps (Figure 2.24) also show the same elevation changes taking place in particular locations for both methods. The spatially variable SfM method appears to be a tractable method for geomorphic change
detection compared to the spatially uniform TS method. But the DoDs thresholded at the 85% confidence interval show different magnitudes of thickness change across the three sites for the spatially uniform TS method and spatially variable SfM method (Table 2.11). Also, the location in which the thickness change is occurring at the 85% CI differs between the spatially uniform TS method and the spatially variable SfM method (Figure 2.25). The SfM method with the spatially variable error model shows less change is actually occurring or is detectable compared to the spatially uniform TS error model.

Table 2.11 SfM/ TS Pairwise DoD Comparisons for Three Sandbar Sites in Grand Canyon

<table>
<thead>
<tr>
<th>Site</th>
<th>SfM Z Greater</th>
<th>TS Z Greater</th>
<th>Net</th>
<th>Propagated Error - 85% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>SfM Z Greater</td>
</tr>
<tr>
<td>50R</td>
<td>0.10</td>
<td>0.10</td>
<td>0.00</td>
<td>0.03 ± 0.01</td>
</tr>
<tr>
<td>70R</td>
<td>0.17</td>
<td>0.17</td>
<td>0.00</td>
<td>0.08 ± 0.03</td>
</tr>
<tr>
<td>213L</td>
<td>0.39</td>
<td>0.38</td>
<td>0.01</td>
<td>0.27 ± 0.08</td>
</tr>
</tbody>
</table>

The type of elevation error that should be used for DoDs is dependent on the magnitude of the geomorphic change compared to the noise in the topographic data (Passalacqua et al., 2015). For example, if geomorphic change detection is performed when a large geomorphic change signal outweighs the noise in the topographic data, spatially uniform error may be sufficient. If the geomorphic change signal is subtle in comparison to the noise present in the topographic data, then spatially variable error can be used to detect how much of the small changes are detectable or real. With better quantification of geomorphic change, more meaningful interpretations can be made about the change. Ultimately for monitoring and geomorphic change detection, spatially variable DEM uncertainty affects the amount of elevation error that is propagated through DEMs and can lead to the over or underestimation of volume change (Passalacqua et al., 2015). The coarser resolution,
Fig. 2.24. Example results of unthresholded (i.e., straight) DEMs of Difference (DoDs; fall 2015 - fall 2014) on the left for the SfM spatially variable method and the DoDs calculated using the spatially uniform TS method on the right. Unlabeled black arrows signify flow direction.
Fig. 2.25. Pairwise comparisons of the thresholded SfM DEMs on the left for the SfM spatially variable method using propagated FIS SfM elevation uncertainty estimates thresholded at a 85% CI and the DoDs (fall 2015 - fall 2014) calculated using the spatially uniform TS method using propagated spatially uniform elevation uncertainty estimates thresholded at a 85% CI on the right. Areas colored in dark gray represent areas where observed discrepancies were not significant at the 85% CI. Unlabeled black arrows signify flow direction.
sand thickness comparison is useful in environments where large changes in volume can be detected even through noisy signals in the data (e.g., sandbar change in Marble and Grand Canyons), but is less useful for conducting geomorphic change detection where small geomorphic changes are more difficult to detect amongst noisy data signals. The resolution of the SfM DEMs could, in fact, affect interpretations of geomorphic change and links between form and process, and thus the original error model in this study is designed to generate finer resolution elevation uncertainty surfaces. For example, the sediment transport through time associated with the hillslope process of creep may warrant finer resolution SfM DEMs and models of spatially variable elevation uncertainty than the larger, more distinct topographic signal of landslides.

2.4.4 Pole-based SfM Data Acquisition Strategies

A secondary component of this work is to provide suggestions for data acquisition techniques that minimize elevation uncertainty of SfM DEMs generated with the low-angle pole platform, and maximize survey efficiency. All three analytical steps in this study show that SfM DEM uncertainty varies depending on the location of elevation, and thus the SfM method is an accurate, precise, and tractable method for monitoring/geomorphic change in particular areas and in particular image acquisition conditions. Armistead (2013), Dietrich (2015), and Smith and Vericat (2015) advocate for use of the pole-mounted camera platform to generate SfM products at the small catchment scale (< 5000 m²), but this study further quantifies the amount of elevation error associated with the pole-mounted camera platform under certain survey conditions and in specific survey areas. Dark shadows were inevitably captured in many of the image sets, and were magnified on specific areas of sandbars in Grand Canyon (e.g., clumps of vegetation and cut banks). I draw attention specifically to the elevation uncertainty of a breakline in shadow having twice the elevation uncertainty as a breakline not in shadow. Not only do the location of breaklines severely affect volume calculations, an operational conundrum is now posed (do you wait until the light changes to collect images, or do you continue with the survey and move downstream)? The cleaning phase of the SfM workflow contributes greatly to the magnitude of elevation uncertainty for
surface roughness. Isolated clumps of dense vegetation are more easily removed than low-lying ground vegetation. Tools to completely filter and clean the dense point clouds remain limited and lead to higher elevation uncertainty. Even with improved tools to clean dense point clouds, supplemental information from additional topographic surveying methods is needed to fill in gaps amongst densely vegetated areas.

The low-angle camera, elevated to 4.9 m is an operational platform for acquiring convergent imagery, but is not ideal for image acquisition of flat surfaces due to the shallow perspective and narrow image footprints. Although a near-nadir camera orientation results in decreased ground coverage, and requires more images to obtain adequate image overlap, the perpendicular orientation to the surface results in a wider/fuller image footprint, is more conducive to SfM reconstruction in the SIFT/bundle adjustment phases, and eliminates background objects (e.g., water, sky) in the image (see section A.4). A nadir orientation would require positioning the camera away from the pole to avoid inclusion of the pole in the images. Images collected along a grid with a near-nadir, camera orientation on flat surfaces may allow for a shorter pole height, and increased maneuverability of the pole. Whereas the image acquisition transects used in this study acquired imagery in the upstream and downstream orientation along each transect, a near-nadir orientation would eliminate the need to repeat each transect (see section A.9). Future work is needed to compare spatially variable elevation uncertainty of SfM DEMs from different image platforms, to determine ideal height and resolution conditions. This work recommends a nadir perspective pole-platform, but more work is needed to determine if the nadir perspective is better (i.e. survey time and elevation uncertainty) than the low-angle pole perspective.

Both SfM DEMs generated from images collected with the Canon T4i DSLRI or D30 point and shoot camera resulted in similar estimates of elevation uncertainty, and are suitable for acquiring SfM imagery of repeat surveys. Albeit the smaller camera footprint, the shockproof/waterproof point and shoot camera is easier to maneuver on the pole and is more practical for fieldwork in fluvial environments. Both trigger mechanisms worked to acquire imagery, but without easily hearing the shutter click for the point and shoot cam-
era, gridded imagery is hard to acquire. With less control over when an image is taken, the intervalometer trigger mechanisms results in exorbitant amounts of blurry imagery that must be manually sorted before image post-processing. The manual trigger mechanism minimizes blurry images, but requires a physical chord from the camera to the on-off switch that is cumbersome to setup for each survey. The physical trigger also results in greater opportunity for gaps in surface coverage. To avoid gaps in coverage and blurry images, but minimize setup and survey times, this study recommends more carefully acquiring imagery using the point and shoot camera with the intervalometer trigger mechanism set at longer time intervals.

Even though the non-topographic variable of camera footprint density was not used in the error model due to an inconclusive relationship between elevation uncertainty and camera footprint density within each survey, this variable provides further insight into more efficient image post-processing. Across all surveys, the relationship between elevation uncertainty and camera density shows that elevation uncertainty does not significantly decrease with an increased amount of overlapping images. In fact, the data point to the contrary (i.e. excessive image overlap results in increased elevation uncertainty). A closer examination at one of the flat, bare sandbar sites in this study (198L), shows that decreasing the amount of images by half and creating reconstructions from the two image sets, and then again dividing the original image set into thirds, does not significantly increase or decrease elevation uncertainty of the SfM DEM (Table 2.12). This is similar to terrestrial laser scanning, in that multiple LiDAR returns of an area only increase the accuracy of the point cloud to a certain threshold. Therefore, acquiring abundant imagery from the remote location is suggested, but thinning image sets prior to sparse point cloud generation is highly recommended to aid in noise reduction of the sparse point clouds (e.g. duplicate surfaces from images collected in close proximity). The decimation of image sets also ensures a significant reduction in post-processing time of repeat image surveys over large or multiple study sites.

Lastly, emphasis must be placed on the accuracy of the primary control network and
### Table 2.12 Summary Statistics for Image Bootstrapping Test

<table>
<thead>
<tr>
<th>Survey Name</th>
<th>Original</th>
<th>Half 1</th>
<th>Half 2</th>
<th>Third 1</th>
<th>Third 2</th>
<th>Third 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image Count</td>
<td>803</td>
<td>396</td>
<td>391</td>
<td>249</td>
<td>254</td>
<td>256</td>
</tr>
<tr>
<td>GCP Count</td>
<td>15</td>
<td>15</td>
<td>14</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>GCP RMSE (Photoscan)</td>
<td>0.046</td>
<td>0.039</td>
<td>0.033</td>
<td>0.032</td>
<td>0.032</td>
<td>0.035</td>
</tr>
<tr>
<td>TS/SfM DEM Cell Count</td>
<td>1725</td>
<td>1727</td>
<td>1713</td>
<td>1675</td>
<td>1690</td>
<td>1677</td>
</tr>
<tr>
<td>MAE</td>
<td>0.124</td>
<td>0.124</td>
<td>0.127</td>
<td>0.118</td>
<td>0.121</td>
<td>0.129</td>
</tr>
<tr>
<td>ME</td>
<td>0.080</td>
<td>0.077</td>
<td>0.081</td>
<td>0.074</td>
<td>0.079</td>
<td>0.084</td>
</tr>
<tr>
<td>SD</td>
<td>0.158</td>
<td>0.161</td>
<td>0.163</td>
<td>0.156</td>
<td>0.156</td>
<td>0.166</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.177</td>
<td>0.178</td>
<td>0.183</td>
<td>0.172</td>
<td>0.175</td>
<td>0.186</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.965</td>
<td>0.964</td>
<td>0.963</td>
<td>0.966</td>
<td>0.965</td>
<td>0.961</td>
</tr>
<tr>
<td>Min.</td>
<td>-0.940</td>
<td>-0.714</td>
<td>-0.576</td>
<td>-0.920</td>
<td>-0.730</td>
<td>-0.736</td>
</tr>
<tr>
<td>$Q_{25}$</td>
<td>0.004</td>
<td>0.002</td>
<td>0.001</td>
<td>0.002</td>
<td>0.000</td>
<td>0.001</td>
</tr>
<tr>
<td>$Q_{50}$</td>
<td>0.046</td>
<td>0.045</td>
<td>0.045</td>
<td>0.039</td>
<td>0.040</td>
<td>0.045</td>
</tr>
<tr>
<td>$Q_{75}$</td>
<td>0.162</td>
<td>0.159</td>
<td>0.164</td>
<td>0.156</td>
<td>0.160</td>
<td>0.171</td>
</tr>
<tr>
<td>Max.</td>
<td>0.761</td>
<td>0.853</td>
<td>0.927</td>
<td>0.784</td>
<td>0.759</td>
<td>0.784</td>
</tr>
</tbody>
</table>
Fig. 2.26. Example of how GCP accuracy affects elevation uncertainty. A. Orthomosaic of site 198L with inset map. B. Elevation uncertainty derived from residual analysis with incorrectly positioned GCP. C. Elevation uncertainty derived from residual analysis with correctly positioned GCP. Incorrect GCP located in black circle in panes B. and C.
TS instrument that were used in Marble and Grand Canyons to acquire GCPs, and its effect on elevation uncertainty of repeat SfM DEMs. Simply including a GCP that was misplaced, resulted in a significant, localized increase in elevation uncertainty (e.g. Figure B.2). The configuration of GCPs did not result in spatially variable elevation uncertainty, and the number and configuration used in this study are recommended. The primary control network in this study is well-established throughout Marble and Grand Canyons, and is not typical of all control networks used by geomorphologists acquiring SfM data. Unlike this study, the accuracy of the GCPs could be a larger source of elevation uncertainty compared to either slope or roughness.

The low uncertainty estimates found at sites with exposed surfaces and low to high gradients have great potential for studies of grain size distributions. The close proximity and high resolution of the pole platform is suitable to use the SfM method for this purpose. For example, at the 267L site, SfM could be used to understand the reworkings of various grain sizes of an active debris fan. Also, this study uses the standard detrended deviation statistic derived from ToPCAT as a proxy for roughness, but other methods such as PySESA (Buscombe, 2016) could be used to more robustly quantify roughness from different resolutions from the raw point clouds.

2.5 Conclusion

Without quantification of uncertainty of SfM DEMs, the SfM method cannot be used as an operational tool for studies of cell-by-cell geomorphic change and monitoring. The type of elevation uncertainty (i.e. spatially variable or uniform) used to estimate elevation error significantly affects estimates of total elevation error of SfM DEMs, which would further contribute to how and where error propagates through multi-temporal SfM DEMs. In this study, I used conservative amounts of elevation uncertainty of SfM DEMs for changes over repeat surveys. The type of geomorphic change in question should always determine the type of error used in a cell-by-cell change detection analysis. For example, the error model that I built in this study may not be necessary if a high change signal to low noise ratio exists. Each HRT method struggles to fit all methodological roles, and a combination of
HRT methods is the current solution in many fluvial environments with dense vegetation. Again, robust error models may be needed to quantify spatially variable error of combining other HRT techniques with the SfM method. This study shows that the low-angle pole-mounted camera is a viable image platform option for surveying smaller-scale (10 to 1000 m$^2$), close-range topography and using the SfM data for studies of geomorphic change detection and monitoring. The pole platform has limited coverage of tall vegetation and on edges of features, but is a low-cost, suitable alternative to restricted aerial platforms. Not only has the SfM method democratized the acquisition of high resolution data, this method is providing more rapidly accessible data that can be used to monitor changing landforms through repeat surveys.
CHAPTER 3

IMPLICATIONS AND CONCLUSIONS

In Chapter 1, the role of HRT for geomorphology is explained, how the SfM method fits into studies of geomorphic change is described, and the purpose and objectives of this thesis are outlined. Chapter 2 presents four, independent analyses to quantify spatially variable uncertainty that are then used in the error model that is used to estimate elevation error. Chapter 3 places the findings of Chapter 2 into the context of large river management in Marble and Grand Canyons, and provides suggestions for future use of the SfM method for GCDAMP, GCMRC and other studies of geomorphic change through three Appendices. Appendix A is an accumulation of short pieces of writing that describe certain parts of my research in greater detail. Appendix B contains a protocol for surveying sandbars and post-processing sandbar imagery. A memorandum in Appendix C addressed to GCDAMP provides the conclusive results of this study and the implications of the SfM method for monitoring cell by cell change in Marble and Grand Canyons.

In addition to providing a potential means to extend the spatiotemporal sandbar data series, the SfM method is currently being used as an operational tool to aid in other geomorphic investigations in Marble and Grand Canyons. Traditional photogrammetric methods have previously been used in Grand Canyon to monitor daily sandbar stability (Dexter et al., 1996), debris flow deposition and reworking (Yanites et al., 2006), gully and erosion control at archaeological sites (Pederson et al., 2006), and riparian resources (Davis et al., 2002). The SfM method has the potential to further aid in Grand Canyon research associated with campsite area monitoring (Kaplinski et al., 2014), bank erosion processes (Budhu and Gobin, 1995; Alvarez and Schmeeckle, 2013; Pyle et al., 1997), debris fan evolution (Griffiths et al., 2004; Hanks and Webb, 2006, Melis et al., 1994; Melis, 1997; Yanites et al., 2006), aeolian transport from sandbars to uplands (Draut, 2012), gully annealing and archaeological site preservation (Draut and Rubin, 2008; Sankey and Draut, 2014), backwater fish habitat (Dodrill et al., 2015), and vegetation encroachment (Sankey et al., 2015; Turner and Karpiscak, 1980). Several of the geomorphic questions tied to the research in Marble
and Grand Canyons require finer resolution HRT for discriminating signals of geomorphic change from noise in the data. Unlike the large signals of topographic change investigated in this study, research surrounding aeolian transport processes is likely to require SfM DEM resolutions finer than 1 m. These more subtle investigations of geomorphic change also require robust uncertainty models that are already built from this study.

The SfM method has major limitations for generating repeatable SfM DEMs for studies of geomorphic change in areas with dense vegetation. This also is significant for image survey design in Marble and Grand Canyons. As sandbars are increasingly becoming detached from the floodplain, densely vegetated, higher elevation deposits are not operational to survey with the SfM method. But if the sandbar monitoring campaign retires the higher elevation deposits that do not contain significant changes in sand volume, the actively changing areas of the bars with vegetation lower than 4.9 m are prime candidates for the SfM method. Even in actively changing areas with tall vegetation, a sparse amount of TS points have the potential to fill in the gaps of the SfM survey. Moving forward, if hard points (i.e. fixed markers that are identifiable in aerial imagery such as immobile boulders) are used in place of GCPs to georeference the SfM surveys, citizen scientists (see section A.7 and section A.6) and recreational river runners could easily collect the imagery without a surveyor during additional points in time. Hard point usage for georeferencing sandbars with the SfM method needs additional testing, but has potential at sites with large boulders located around the perimeter of the site.

The contribution in this work bridges the gap between using the SfM method for mapping applications and confidently using the SfM method for repeat SfM DEM applications such as monitoring geomorphic change. Unlike previous research, this work recommends practicing more caution when making estimates of topographic change through time using the SfM method. This caution translates to the identification of multiple sources of elevation uncertainty, the characterization of spatially variable elevation uncertainty, and modeling of spatially variable error. The varying surface textures, gradients, vegetation cover, lighting conditions, and site scale addressed in this study are present in other complex environments.
These conditions affect spatially variable elevation uncertainty and must be quantified to result in accurate topographic changes and interpretations of actual geomorphic change. Although this research presents results of spatially variably elevation uncertainty of SfM DEMs acquired with the pole-mounted camera platform, the calibration methods are widely applicable to any image platform. In fact, this study encourages the future quantification of spatially variable elevation uncertainty for SfM DEMs acquired from other image platforms. For example, the near-nadir perspective of a low-flying UAV may result in even lower estimates of elevation uncertainty than the pole platform, and interpolation across vegetation may be more feasible with the near-nadir perspective. Additional sources of elevation uncertainty can be easily added to the error model built in this study. For example, a study of geomorphic change detection in a small, shallow wadeable stream, could account for elevation uncertainty caused by light refraction through the shallow water column (Dietrich, 2016a).

With the results of this study, the low-angle, pole-mounted platform is a feasible image platform for monitoring geomorphic change with the SfM method in environments with exposed substrate that is sparsely vegetated. The low-angle, pole platform has applicability for use in small, shallow wadeable streams with clearly defined corridors through vegetation. The pole-mounted camera is a feasible image platform for surveying exposed, topographic features that are 10 to 1000 m$^2$ in area. Although additional sources of elevation uncertainty from interpolation would be introduced, the pole-platform paired with the acquisition of additional feature based points allows for obtaining the ground elevation through dense patches of vegetation. The near-nadir image acquisition suggestions provided in this study will cut down on post-processing times, including the realignment of incorrect sparse point cloud generation. This research contributes to the understanding of the use of the SfM method for quantifying actual geomorphic change.
REFERENCES


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Hensleigh, J., 2013. Geomorphic change detection using multi-beam SONAR.


Howard, A.D., 1975. Establishment of Benchmark Study Sites along the Colorado River in Grand Canyon National Park for Monitoring of Beach Erosion Caused by Natural Forces and Human Impact.


APPENDICES
APPENDIX A

SFM RESEARCH VIGNETTES

The following 9 research vignettes provide more documentation for some of the methods, ideas, and analyses I explored throughout this thesis. I think the additional information is useful for scientists who are using or plan to use the SfM method and especially if the pole-mounted camera platform is used. I found the SfM literature lacked details about image acquisition for non-aerial platforms (e.g. handheld, pole). However, the image acquisition design and camera geometry are critical for the SfM and MVS algorithms to produce successful reconstructions. Thus, these vignettes include more information about how to collect images with the pole-mounted camera to ensure successful reconstructions. These vignettes are ordered by the completion date and build on the previous vignettes. The vignettes are also referenced throughout the SfM protocol in section A.8.
A.1 Review of ‘Structure-from-Motion’ as an Emerging Photogrammetry Technique for Geomorphological Applications

**QUESTION / PROBLEM**  09/07/2014

Within the past five years, ‘Structure-from-Motion’ (‘SfM’) has emerged as a photogrammetry tool for applications in geomorphology due to lower costs and portability in remote study areas. Across a variety of scales (e.g., hand-sample lava bombs to coastal cliff outcrops), geomorphologists are using ‘SfM’ techniques for various research analyses, including gully morphology and erosion rates (Kaiser et al., 2014), and volcanic landscape evolution associated with geologic hazards (James and Robson, 2012). ‘SfM’ is rooted in photogrammetric algorithms that build 3-D structure (i.e., digital elevation models) from overlapping, offset 2-D images acquired from a camera. Unlike conventional photogrammetry, the ‘SfM’ algorithms automatically recreate scene geometry, camera position, and camera orientation without former establishment of a target network with known 3-D locations (Westoby et al., 2012). Before the ‘SfM’ technique is exclusively implemented, more robust techniques (i.e., terrestrial LiDAR) are necessary to quantify known error within the new methodology.

The question then arises if the ‘SfM’ technique will be successful for geomorphological applications (e.g., quantifying sandbar change) in Grand Canyon. To investigate the idiosyncrasies and strength of the method, a brief literature review is presented, highlighting three ‘SfM’ themes: (1) application and scale, (2) methods (e.g., image acquisition, ground control network, and software/algorithms options), and (3) accuracy and limitations (e.g., non-linear deformation and textural/coverage requirements).

**IDEA / HYPOTHESIS**

Due to repeated successes of the ‘SfM’ technique in recent, geomorphology literature, the technique will provide a new, potentially robust method for extending the sandbar surveying network in Grand Canyon as well as studying sandbar dynamics in the future. Albeit success, thorough measures are needed to quantify non-linear deformation and error throughout the ‘SfM’ process.

**‘SfM’ THEMES**

1 Application and Scale

The novel nature of the ‘SfM’ technique results in proof of concept publications with associated geomorphological, ecological (Dandois and Ellis, 2010; Bryson et al., 2012), paleontological (Falkingham, 2012), and archaeological (Verhoeven, 2011) applications. The ‘SfM’ technique is tested using various features/study areas across varying spatial scales. Table 1 reviews the different features, applications, and scales associated with the geomorphological, ‘SfM’ literature. Similar to most topographical, data acquisition techniques, the scale of the 3-D reconstructed feature and/or study area is pertinent to photo acquisition design for the ‘SfM’ technique.
Table 1. Recent (within the past three years), geomorphological literature, which uses the emerging ‘SfM’ technique for various applications at varying scales.

<table>
<thead>
<tr>
<th>Source</th>
<th>Feature/Study Area</th>
<th>Feature/Study Area Scale</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niethammer et al., 2012</td>
<td>Super-Sauze Landslide, Southern French Alps</td>
<td>Extends 850 m with average slope of 25°</td>
<td>Landslide fissure imaging, surface displacement measurements</td>
</tr>
<tr>
<td>Castillo et al., 2012</td>
<td>A gully reach, 10 km west of Cordoba Spain</td>
<td>7.1 m long</td>
<td>Gully erosion in an agricultural catchment (soil loss/sediment yield)</td>
</tr>
<tr>
<td>James and Robson, 2012</td>
<td>a.) Volcanic bomb hand-sample</td>
<td></td>
<td>a.) Proof of Concept</td>
</tr>
<tr>
<td></td>
<td>b.) Summit craters of Piton de la Fournaise volcano</td>
<td></td>
<td>b.) Geo-hazard Assessment/Proof of Concept</td>
</tr>
<tr>
<td></td>
<td>c.) Coastal cliff at Sunderland Point, U.K.</td>
<td></td>
<td>c.) Coastal cliff temporal erosion sequences</td>
</tr>
<tr>
<td>Westoby et al., 2012</td>
<td>a.) Exposed rocky coastal cliff</td>
<td>a.) ~ 80 m high</td>
<td>Proof of concept; high-resolution topographic data acquisition</td>
</tr>
<tr>
<td></td>
<td>b.) Breached moraine-dam complex</td>
<td>b.) ~ 650 m wide and 80 m high terminal moraine</td>
<td></td>
</tr>
<tr>
<td></td>
<td>c.) Glacially-sculpted bedrock ridge</td>
<td>c.) 80 x 19 x 8 m</td>
<td></td>
</tr>
<tr>
<td>James and Varley, 2012</td>
<td>Active lava dome at Volcan de Colima, Mexico</td>
<td>2.14 x 10⁶ m³</td>
<td>Change detection for prediction of dome collapse or explosive activity</td>
</tr>
<tr>
<td>Fonstad et al., 2013</td>
<td>Pedernales River, TX (highly diverse limestone, bedrock topography)</td>
<td>36,000 m² area</td>
<td>Remotely sensed topographic data (proof of concept)</td>
</tr>
<tr>
<td>Armistead, 2013</td>
<td>2 River channel cross-sections in Souhegan River, NH</td>
<td>110 and 90 m long</td>
<td>Extracting cross-sectional elevation data to study channel change rates</td>
</tr>
<tr>
<td>Mancini et al., 2013</td>
<td>Beach dune system in Marina di Ravenna, Italy</td>
<td>200 m wide</td>
<td>Proof of concept; Coastal system processes</td>
</tr>
<tr>
<td>Gomez, 2014</td>
<td>Sakurajima volcano, Japan</td>
<td>Kilometer Scale</td>
<td>Diachronic reconstruction of geomorphological landscape evolution</td>
</tr>
<tr>
<td>Dewez, 2014</td>
<td>Coastal cliffs</td>
<td>7 km long coast</td>
<td>Coastal cliff collapse hazard assessment</td>
</tr>
<tr>
<td>Kaiser et al., 2014</td>
<td>Complex gully morphology, southern Morocco</td>
<td>Meter Scale</td>
<td>Analyzing and monitoring soil loss, gully head retreat and plunge pool development from heavy rain events</td>
</tr>
<tr>
<td>Gienko and Terry, 2014</td>
<td>Several coastal boulders with varying lithologies in two locations</td>
<td>Average volume of a boulder (~ 4 m³)</td>
<td>3-D Boulder surface reconstruction and volume calculations for interpreting characteristics of high-energy wave processes</td>
</tr>
<tr>
<td>Lucieer et al., 2014</td>
<td>Home Hill landslide, southeast Tasmania</td>
<td>125 x 60 m</td>
<td>Proof of concept; Quantify, map, and monitor terrain displacement</td>
</tr>
</tbody>
</table>
Methods

2.1 Image Acquisition

The number of images acquired varies throughout geomorphic scales, and is primarily based upon the desired model resolution, terrain complexity and accessibility, available ‘SfM’ software, and former knowledge/perspective of the area (Kaiser et al., 2014). The majority of ‘SfM’ methodologies use a digital, single-lens reflex camera, although lower resolution, point and shoot cameras return lower point cloud densities (Niethammer et al., 2012; Castillo et al., 2012, Fonstad et al., 2013; Table 2). Workarounds exist for lower resolution point and shoot cameras via increasing point cloud density (i.e., 10-20 times) using software such as PMVS2 (Fonstad et al., 2012). Denser ‘SfM’ point clouds are necessary to compare error to more robust methods with denser point cloud data (i.e., terrestrial LiDAR).

Unlike conventional photogrammetry, ground control points are not required to reconstruct 3-D topographical models with a relative coordinate system using ‘SfM’ software (Westoby et al., 2012). Most geomorphological studies tie the modeled surface into an absolute coordinate system using ‘SfM’ software (Westoby et al., 2012). Distinct features in the landscape can also act as ground control points, which can then be used in the ‘SfM’ software to transform the relative coordinate system to an absolute coordinate system (Gomez, 2014). Placement and quantity of ground control targets depends on the scale of the study area, desired resolution outcomes, and surface cover/gradient.

Table 2. Summary statistics for ‘SfM’ literature.

<table>
<thead>
<tr>
<th>Source</th>
<th>Image Acquisition Type</th>
<th>Camera Info.</th>
<th># of GCPs</th>
<th># of Photos Taken</th>
<th>‘SfM’ Software</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niethammer et al., 2012</td>
<td>Unmanned Aerial Vehicle (UAV)</td>
<td>Praktica Luxmedia 8213: Point and Shoot (P&amp;S)</td>
<td>199</td>
<td>1486</td>
<td>Videometric and Survey Network Solutions (VMS); GOTCHA (image matching algorithm)</td>
</tr>
<tr>
<td>Castillo et al., 2012</td>
<td>Terrestrial</td>
<td>Canon EOS 450D (SLR)</td>
<td>6</td>
<td>191</td>
<td>James et al., 2012 sfm_georef Surfer</td>
</tr>
<tr>
<td>James and Robson, 2012</td>
<td>a.&amp; c.) Terrestrial, b.) micro-light aircraft</td>
<td>a.) Canon EOS 450D, b.) Canon EOS D60, c.) Canon EOS 450D</td>
<td>a.) N/A, b.) 45, c.) N/A</td>
<td>a.) 210, b.) 133, c.) 133</td>
<td>“SfM-MVS”: Scale Invariant Feature Transform (SIFT) PMVS2 &amp; Clustering views for MultiView Stereo (CMVS) sfm_georef (Matlab)</td>
</tr>
<tr>
<td>Westoby et al., 2012</td>
<td>a-c.) Terrestrial</td>
<td>a-c.) Panasonic DMC-G10 (SLR)</td>
<td>a.) 35</td>
<td>a.) 889</td>
<td>SiftGPU Bundler CMVS PMVS2 Horn’s absolute orientation algorithm</td>
</tr>
<tr>
<td>James and Varley, 2012</td>
<td>Light aircraft (four flights)</td>
<td>a.) Konica Minolta Dimage Z5 (SLR) b-d.) Nikon D90</td>
<td>N/A</td>
<td>a.) 58, b.) 28, c.) 114, d.) 192</td>
<td>Bundler Photogrammetry Package “SfM-MVS”</td>
</tr>
<tr>
<td>Fonstad et al., 2013</td>
<td>Helikite</td>
<td>Canon A480 (P&amp;S)</td>
<td>10</td>
<td>304</td>
<td>Photosynth SynthExport MeshLab JAG3D</td>
</tr>
<tr>
<td>Armistead, 2013</td>
<td>Pole (4.8 m) mounted camera</td>
<td>Nikon D90 (SLR)</td>
<td>8 (4-10 m spacing)</td>
<td>650</td>
<td>Agisoft Photoscan</td>
</tr>
<tr>
<td>Mancini et al., 2013</td>
<td>UAV</td>
<td>Canon EOS 550D (SLR)</td>
<td>10</td>
<td>&gt;800</td>
<td>Agisoft Photoscan</td>
</tr>
<tr>
<td>Gomez, 2014</td>
<td>GSI, historical aerial imagery</td>
<td>N/A</td>
<td>Established landmarks</td>
<td>140</td>
<td>Agisoft Photoscanpro</td>
</tr>
</tbody>
</table>
2.2 ‘SfM’ Software

This section is intended to list ‘SfM’ software package options and component algorithms. James and Robson (2012), Westoby et al. (2012), and Fonstad et al. (2013) provide helpful step-by-step workflows for open-source ‘SfM’ algorithms (Figure 1). Mancini et al. (2013) steps through the automated algorithms of the low-cost ($179) Agisoft PhotoScan package. The Agisoft PhotoScan Professional version (educational license: $549) outputs more developed products in the workflow (e.g., GCP-georeferenced, digital elevation models (DEMs)).

**Open-source Packages** (contain combinations of the below component algorithms):

1.) SFMToolkit3 (URL: http://www.visual-experiments.com/demos/sfmtoolkit/)
2.) VisualSFM (URL: http://ccwu.me/vsfm/)
3.) AUTODESK 123D (URL: http://www.123dapp.com/)

**Low-Cost Commercial Packages** (provide more straightforward interfaces, Fonstad et al., 2013)

1.) Agisoft PhotoScan: Standard Edition (URL: http://www.agisoft.ru/products/photoscan/standard/)
2.) Agisoft PhotoScan: Professional Edition (URL: http://www.agisoft.ru/products/photoscan/professional/)

**Component Algorithms** (open-source; Fonstad et al., 2012):

1.) Microsoft Photosynth (URL: https://photosynth.net/): Outputs a low 3D point density using ‘sparse bundle adjustment’.
2.) SiftGPU (URL: http://cs.unc.edu/~ccwu/siftgpu/): Scale Invariant Feature Transform object recognition system. Image matching algorithm, which relies on multiscale image brightness and color gradients to identify conjugate features.
3.) Bundler (URL: http://www.cs.cornell.edu/~snavely/bundler/): Alternative for Microsoft Photosynth; uses ‘sparse bundle adjustment to output a 3D point cloud.
4.) CMVS (URL: http://www.di.ens.fr/cmvs/): Clustering Views for Multi-view Stereo. Requires output from Bundler and splits point clouds into chunks.
5.) PMVS2 (URL: http://www.di.ens.fr/pmvs/): Inputs Photosynth data to create a more dense point cloud (increase of points by ten or twenty times).
6.) Sfm_georef (URL: http://www.lancaster.ac.uk/staff/jamesm/software/sfm_georef.htm; James and Robson, 2012): Scales and geo-references ‘SfM’ point clouds to a real-world coordinate system using GCPs.

<table>
<thead>
<tr>
<th>Dewez, 2014</th>
<th>Parachuting plane</th>
<th>Nikon D7000 (SLR)</th>
<th>Geotagged Photos</th>
<th>568</th>
<th>VisualSFM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kaiser et al., 2014</td>
<td>Terrestrial</td>
<td>Canon EOS 350D (SLR)</td>
<td>Objects w/ known dimensions</td>
<td>40-600</td>
<td>Agisoft Photoscan</td>
</tr>
<tr>
<td>Gienko and Terry, 2014</td>
<td>Terrestrial</td>
<td>Nikon Coolpix L110 (SLR)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Lucieer et al., 2014</td>
<td>UAV</td>
<td>Canon EOS 550D (SLR)</td>
<td>24</td>
<td>224</td>
<td>Agisoft Photoscan</td>
</tr>
</tbody>
</table>

Figure 1. ‘SfM’ workflow from Westoby et al. 2012
3 Accuracy and Limitations

Westoby et al. (2012) and Fonstad et al. (2012) emphasize the potential introduction of non-linear deformation into the 3-D model. If introduced, the distortion persists through the map coordinate registration and jeopardizes the accuracy of the technique. Quantification of non-linear distortion remains in question (Westoby et al. 2012). Difference DEMs of ‘SfM’ datasets and robust, terrestrial LiDAR datasets reveal the potential of the ‘SfM’ technique (Figure 2).

Figure 2. Both images display DEM difference maps of TLS and ‘SfM’ datasets. The landslide difference map on the left, modified from Niethammer et al. (2012), shows outlier (-2 m and >3.0 m) areas of difference in vegetated and near vertical areas. Outlier (<2 m and >2 m) difference values in the figure to the right (modified from Westoby et al., 2012) were also correlated to areas of dense shrub and bush cover.

The above examples and other TLS-‘SfM’ data comparisons reveal ground cover limitations in the ‘SfM’ algorithms. In Table III, Gienko and Terry (2014) provide a detailed list of surface texture and camera lighting problems (e.g., glare from wet surfaces) and solutions. Pertinent to ‘SfM’ data collection of sandbars in Grand Canyon is the low-texture surface of bare sandbars. Additional ground control targets will assist the algorithm in sound image matching.

FUTURE WORK

Further investigation of ‘SfM’ software is needed to determine the most suitable workflow for 3-D reconstruction of sandbars in Grand Canyon. Preliminary workflows in Agisoft Photoscanpro shed promising results, but an entirely open-source workflow needs refinement for use in surveying GC sandbars through the citizen science program. Further TLS and ‘SfM’ DEM comparisons may shed light on the accuracy of the ‘SfM’ technique.
REFERENCES

Armistead, C., 2013. Applications of 'structure from motion' photogrammetry to river channel change studies, unpublished B.S. thesis, Boston College, USA.


A.2 Summary of Sandbar Image Acquisition in Marble and Grand Canyons

On September 23, 2014 to October 9, 2014, overlapping images of sandbars in Grand Canyon were collected to provide proof of concept for the emerging ‘Structure-from-Motion’ (‘SfM’) photogrammetry technique. Several questions persisted throughout the fieldwork:

1.) What is the most efficient way to capture overlapping images from multiple viewpoints on sandbars with varying size, topography, sand texture, vegetation cover, and environmental/light conditions?
2.) How many image sites are necessary at each sandbar and how many images per site are necessary?
3.) What are the limitations of image acquisition of sandbars in Grand Canyon for the ‘SfM’ technique?

This vignette addresses the above questions through survey design explanation/reasoning, presentation of future image acquisition improvements, and predictions of future ‘SfM’ reconstruction outcomes.

IDEA / HYPOTHESIS

The textural and topographic diversity of sandbars in Grand Canyon encouraged a non-universal, sandbar survey approach. Image surveys were tailored to specific sandbar features (e.g., steep cut bank), which were thought to provide robust images for the ‘SfM’ reconstructions.

Additional insight from on-site ‘SfM’ reconstructions suggested that the number of images needed increases as the area of the bar and complexity of sandbar topography increases.

METHODS

A total of 36 sandbars were surveyed between Lees Ferry (RM 0) and Diamond Creek (RM 225) on the Colorado River in Marble and Grand Canyon.

This vignette focuses on the survey methods used to collect images from 19 sandbars upstream of Phantom Ranch (~RM 87.5). Approximately 10,000 sandbar images were taken. More images were collected downstream due to the increasing complexity in sandbar topography, surface cover (i.e., texture and vegetation), and area. Most images (~90%) were taken with an EOS Rebel T4i SLR camera set on autofocus and mounted on a 16 ft high pole. To capture the widest field of view (FOV), the SLR lens was fixed at 18 mm, and the camera mount angle was fixed at an oblique angle. To maximize the FOV throughout an archaeological site survey, a 22 ft pole was used instead of the 16 ft pole (Figure 1).
The remaining images were taken from ground level with an EOS Rebel T4i SLR and various point and shoot (P&S) cameras (Sony, Panasonic, Canon). Five different survey types (A-E; Table 1) allowed for a diverse collection of sandbar imagery from varying angles, heights, and viewpoints. Several survey types were used in combination at multiple sandbars to maximize the image diversity. Due to the camera visibility and pole stability, image collection was limited to dry weather and low winds.

Figure 1. SLR camera mounted with an oblique angle to a 22 ft pole. Ground control target behind pole.

<table>
<thead>
<tr>
<th>Survey Type</th>
<th>Camera Position</th>
<th>Collection Method</th>
<th>Camera Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>16ft pole (other: 8/12ft)</td>
<td>remote shutter/intervalometer</td>
<td>SLR</td>
</tr>
<tr>
<td>B</td>
<td>higher elevation above bar</td>
<td>Handheld</td>
<td>SLR (other: P&amp;S)</td>
</tr>
<tr>
<td>C</td>
<td>higher elevation on opposite bank</td>
<td>Handheld</td>
<td>P&amp;S</td>
</tr>
<tr>
<td>D</td>
<td>rafting alongside sandbar</td>
<td>Handheld</td>
<td>P&amp;S</td>
</tr>
<tr>
<td>E</td>
<td>directly in front of cut bank</td>
<td>Handheld</td>
<td>SLR</td>
</tr>
</tbody>
</table>

Images collected with survey type A were systematically captured along transects. The strategy for maximizing image overlap was capturing images along transects that covered the bank, middle, and back of the bar from upstream to downstream. At each image site along the transect, the camera was rotated clockwise four times at 90 degrees, capturing four images. Few site surveys captured more than four images at each site, rotating the camera at smaller increments. The image collector, moving the pole between image sites, remained the same throughout the surveys, maintaining consistent pacing between each image site. The camera pole mount angle was adjusted to a more acute angle to image steep, topographic slopes, and paces were shortened between image sites.

The first fifteen sandbars were surveyed with a remote controlled shutter that required a second person to trigger the camera. The remote shutter image acquisition method averaged 1 hour. The survey strategy was modified downstream for more complex and larger sandbars with the use of an intervalometer instead of remote shutter. The free firmware, Magic Lantern, allowed for image collection at two second intervals, eliminating the need for a second person and allowing faster image collection (at least half the time of the remote shutter method).

Images from higher elevations (i.e., survey types B and C) were used to capture varying viewpoints from distant locations above the sandbars. Surveys (i.e., type E) were intended to capture the steep, cut-bank face that may otherwise be missed by the oblique angle of the pole mounted camera. Both survey types B&E were completed in ~30 min, but required climbing above the sandbar and walking waste deep in the river. Lastly, “drive by” images (i.e., type D) were taken in rafts with P&S cameras. This survey method did not require physical access to the sandbar, and was used to test the resolution of the P&S camera in collecting data remotely.
The setup of ground control points (GCPs) remained similar throughout sandbar surveys. Checker board targets were systematically placed from the upstream to downstream ends of the sandbars. Ten to twenty GCPs covered the bars, and were surveyed using a total station. The homogeneous surface texture and steep sand pile slope of 30-Mile sandbar led to a 50 GCP setup to test the ‘SfM’ algorithm.

The most crucial aspect to collecting the data was taking detailed notes on environmental conditions that could affect the outcome of the reconstruction (e.g. moving vegetation) and survey adjustments. Field notes were collected using the following format:

Sandbar Name – River Mile – Date
Environmental Conditions (E.C.)
   Changing Environmental Conditions (C.E.C.)
Bar vegetation (B.V.)
Other surface characteristics (O.S.C.)
   Texture:
   Gradient:

<table>
<thead>
<tr>
<th>Survey #</th>
<th>start time:</th>
<th>end time:</th>
<th>duration:</th>
</tr>
</thead>
</table>

Survey description
   Camera settings: camera type, focal length, camera mount angle
   Pole settings: name of pole, height
GCP setup: # of GCPs; GCP arrangement on bar surface
Image acquisition (always started image collection at upstream end of bar): who acquired images; image acquisition type; # of image photo locations; # of images collected at each image location; # of paces in between image sites/explanation
Other notes:

PRELIMINARY RESULTS

Although point cloud creation of sandbars in the Photoscan Professional (Agisoft) software was limited, initial runs provided insight for survey design downstream. In the first point cloud reconstruction of Cathedral Wash (Figure 1), only 5 out of 151 images were used in the image alignment.

Figure 1. First point cloud reconstruction of Cathedral Wash (RM 2.5L) sandbar using 151 images.
More experimentation in the Photoscan Professional software onsite would have allowed for refinement of image acquisition. The first point cloud observations resulted in the mentality that collecting more images provided more overlap and viewpoints, especially on larger, more complex sandbars.

PRELIMINARY INTERPRETATIONS

Unfortunately, time restrictions with the Photoscan Professional software onsite prohibited additional insights needed to refine image acquisition strategies. The overabundant images provided ample viewpoints and overlap, but will require more sorting time in the lab. The ‘SfM’ reconstructions are predicted to vary with different survey types, environmental conditions, and surface texture. For example, images taken directly facing and along the cut bank (type E) are expected to produce robust reconstructions, whereas the drive by images (type D) will result in lower resolution reconstructions due to the lower camera resolution and limited sandbar view. Vegetation often moves throughout image collection, and was absent in the Cathedral Wash reconstruction. Dense vegetation collected in low wind conditions is predicted to reconstruct with the ‘SfM’ technique, whereas younger, moving, less dense vegetation will cause holes in the point cloud reconstruction. Lastly, homogeneous surface textures (e.g., footprint texture on Redwall Cavern sandbar) and steep slopes (30-Mile sandbar) will challenge the ‘SfM’ algorithm.

FUTURE WORK & QUESTIONS

This fieldwork is the beginning of an image collection protocol that will continue to be refined based upon new insights from the ‘SfM’ software. A series of future vignettes will document how the ‘SfM’ software responds to the five survey types as well as varying environmental conditions, gradient, vegetation, and surface texture. These reconstructions will help refine how sandbar images are collected in the future. The reconstruction results will also help guide in house experimentation to find the ideal pole height and mount angle, resolve steep gradients and homogeneous surface textures, and understand the reconstructions of varying vegetation densities. The future vignettes will also resolve how many images are needed and the necessary image coverage to reconstruct sandbars in Grand Canyon.

The field data and preliminary results strongly suggests future success for the proof of concept phase for the ‘SfM’ technique. Initial improvements for future fieldwork include consistent use of numbered GCPs that are visible in the images, ample battery life and field laptops with the Photoscan Professional software, stitching software to preview image overlap, and multiple SLR cameras with intervalometer settings. Survey efficiency will improve with detailed survey maps and image transects/GCP designs prior to data collection.

In conclusion, a series of questions are posed from this data acquisition:

1.) How effective is changing camera mount angle upslope and downslope?
2.) Is there an ideal GCP configuration?
3.) Can the ‘SfM’ software consistently distinguish between vegetation densities; can vegetation be stripped from the bare sand surface?
4.) What are the protocols needed for a citizen science to collect the necessary amount and type of images?
A.3 SfM Image Alignment and Point Cloud Generation for Cathedral (RM 2.5L) Sandbar

Proof of concept for the ‘SfM’ methodology results in a two-part investigation. The first part explores the image alignment and point cloud generation capabilities of the ‘SfM’ software, Photoscan Professional (Agisoft), for constructing 3D, sandbar models from 2D image sets collected in Grand Canyon. The second part will provide proof of concept for georeferencing the 3D reconstructions to a real world coordinate system within the ‘SfM’ software. The following research vignette addresses the image alignment and point cloud generation capabilities of the ‘SfM’ software for Cathedral sandbar, located at river mile 2.5.

The strategy used for reconstructing the first sandbar (Cathedral) will be implemented to each bar downstream, resulting in initial sandbar reconstruction vignettes. A summary vignette will follow, adding any new strategies and presenting reconstruction results.

**IDEA**

In the field, the idea that collecting more images would increase sandbar representation and overlap led to an increase of image collection at downstream sandbars. Although hundreds of images are more representative, the efficiency (i.e., time and reconstruction) of ‘SfM’ software will be compromised by using all images. To reduce processing time, images will require sorting before entry. Removal of background objects (e.g., canyon walls) will aid in exclusively reconstructing areas of interest. The ‘SfM’ software will better recognize image groups by survey type due to the similar focal lengths and camera elevation. Finally, the image quality outweighs the image quantity.

**METHODS**

After importing images into Photoscan, the workflow produces an image alignment and dense point cloud. The image alignment searches for common points amongst the images and outputs a set of camera positions. The dense point cloud is built from the estimated camera positions and images. At Cathedral, images were collected using two different survey types (i.e., pole mounted and handheld camera). Models were run separately for individual survey types and combined survey types. After selecting the images grouped by survey type with the most representative reconstruction, these image sets were further refined by eliminating blurry and unaligned images. Photoscan also scores the image quality of each image. All images with an estimated image score lower than 0.5 were removed from the image set. Lastly, image masks and boundary readjustments were applied to test background feature (e.g., canyon walls) elimination.
RESULTS

Image sets including all images across multiple survey types returned reconstructions with duplicate features and abstract artifacts (Figure 1). The estimated camera positions were also incorrect. Image sets grouped by survey type returned clearer reconstructions (Figure 1).

Figure 1. Cathedral reconstruction comparison of image set containing all survey types (A: 267 images) and survey collected with a handheld camera from adjacent, higher talus slope (B: 10 images). Blue rectangles are estimated camera positions.
The Photoscan manual discourages image alteration (e.g., cropping) prior to reconstruction. The masking feature (Figure 2) and boundary redefining tool provide alternatives that eliminate background interference (Figure 3). The masking process is applied to each image and is a time consuming process.

Figure 2. Individual photos can be masked in Photoscan to remove unwanted background features. The river and two image shadows (Dan and Joe) are masked from the reconstruction.

Figure 3. A - Reconstruction of Cathedral sandbar using the mask feature. Both (A & B) reconstructions used the same six images.
Although the first sandbar is less complex topographically, several components of the reconstruction will translate into downstream reconstructions. Processing times for both the image alignment and dense point cloud reconstructions with highest accuracy settings were twice as long when image sets contained over 100 images. Refined image sets are needed to produce more accurate and faster reconstructions. Less time is spent sorting images before importing them than waiting for processing times. The results clearly indicate that images should be sorted by image type. As with traditional photogrammetric image sets, the same focal distance aids in reconstructions. Low accuracy alignments also provide a quick assessment of photo matching capabilities. Images along the bank often capture large areas of the river and canyon walls. Image masking and redefining the working boundary are ways to address these persistent, background objects. Manually isolating areas in each image with the mask tool takes a significant amount of time. More investigation into masks may speed up this process.

The edges of Cathedral sandbar were best reconstructed along the water compared to the vegetation lining the back and downstream end of the bar. Both survey types provided robust reconstructions of the upstream portion of the sandbar. The downstream end of the bar was less represented due to images with poor alignment in that area. Only six images aligned from the pole survey, suggesting improper overlap or light variation. The lighting conditions did change throughout the survey and can be seen in the varying color and intensities in the images. This also suggests that fewer images can result in reconstructions, but only with the right images. Collecting overabundant images in the field takes more time, but ensures the right images were collected and can be sorted and used in the reconstruction. In addition, sorting thousands of photos also takes time.

This preliminary set of tests on the first sandbar has helped develop a strategy for processing the remaining 35 sandbars downstream in Grand Canyon. Additional model reconstruction questions include:

- Will the mask tool help to eliminate shadow effects as seen at Cathedral?
- Will vegetation continue to blur the edges of the sandbar and/or create holes in the reconstruction?
- What camera configurations provide the best reconstructions?
- Which survey type provides the best reconstructions?
- What strategies work best when reconstructing sandbars?
- How will sandbars reconstruct from blurry images taken downstream?

The next series of vignettes (~5) will feature the reconstruction process and output of the remaining 35 sandbars. Findings and new strategies will be highlighted. Another step is comparing Photoscan results to open source ‘SfM’ software reconstructions.

Lastly, the Photoscan manual recommends image acquisition techniques (Figure 4). Although sandbar image sets are reconstructing in Photoscan, more robust image acquisition techniques will be tested in Logan.
Figure 4. Suggested image capture techniques from the Agisoft manual.

IF YOU HAVE ANY SUGGESTIONS IN THESE EARLY STAGES OF MODEL RECONSTRUCTIONS PLEASE TELL ME ASAP.
A.4 A Brief SfM Image Acquisition Investigation: Adjustments in Camera Angle and Pole Height

With minimal time to test image acquisition techniques with a pole mounted camera before fieldwork in Grand Canyon, most images were captured along coarsely defined transects that followed sandbar features (e.g., sandbar crest). At each camera location along the transect four images were collected with a T4i Canon Rebel digital camera (18 mm focal length/oblique angle) after turning the pole every 90 degrees. This technique was thought to maximize the view of the scene.

The sandbar images collected during the upstream survey (Lees Ferry to Phantom Ranch/ 0 – 88 RM) in late September/ early October 2014 poorly aligned (<20% of images aligned) in both the commercial (Photoscan Professional) and open source (Visual SfM-CMVS/PMVS2) ‘SfM’ software. Poor alignment results in poor surface coverage. Even small chunk reconstructions provided minimal coverage for DEM production. Similar alignment issues with the same image sets in two different workflows ruled out a software problem.

After investigating image acquisition techniques back in the lab, the method used in Grand Canyon was completely different than techniques in the literature. Oblique images were captured to converge on the surface/feature of interest (e.g., James and Robson 2012). The Agisoft manual also specifically suggests against using the method we used (oops). In conclusion, more tests are necessary to refine the image acquisition techniques for collecting sandbar images in Grand Canyon. This vignette unwraps answers to the following questions:

1.) Will images collected with a 16 ft pole height and wide focal lengths (18-21 mm) align?
2.) What distance between images equates to “enough” overlap for ‘SfM’ reconstructions?
3.) Are there benefits of a higher pole height (i.e., 21 ft)?
4.) Do image sets collected at varying heights (i.e., 16 ft and 21 ft) align in ‘SfM’ software?

Note: the original camera pole mount design used in Grand Canyon limited the camera to an oblique angle on top of the pole (Figure 1A). Camera geometry and overlap are two key elements for ‘SfM’ image acquisition. The camera lens in this investigation is even more oblique, approximately perpendicular to the feature of interest or facing straight down (Figure 1B).
Figure 1. A. Oblique pole camera mount angle used in the Sept./Oct. 2014 fieldwork in GC. B. Oblique pole camera mount angle used in this investigation.

**IDEA**

The camera angle adjustment will maximize surface area coverage and minimize holes in the scene similar to aerial imagery and images collected facing perpendicular to bluffs/cliffs. This adjustment will also aid in increasing overlap between images.

**METHODS**

On January 1st, three image sets were collected around a concrete driveway (~3,000 square feet in area) using a T4i Rebel Canon digital camera. Magic Lantern firmware was previously installed on the camera’s memory card and allowed automatic image capture every 10-15 seconds. The area was chosen out of convenience and for its pathetic topography (probably the biggest “hill” in Salisbury, Maryland). Images were taken between 10 AM and noon with 30% cloud cover; tall pine trees introduced stark shadows. My dad, whose 60th birthday was on Jan. 1st, rigged a telescoping pole with 21 ft maximum extension with a welded, inverted camera mount (Figure 2). The mount allowed for greater flexibility in obtaining an oblique angle nearing 90 degrees.
Figure 2. Dave’s camera mount creation. The removable plastic lid served to protect the camera.

The first image set was collected with a 21 mm focal length at a 16 ft pole height. This height was used for collecting most of the pole images in Grand Canyon. After marking the ground area of one photograph (~12 ft x 20 ft), I decided to collect images 10 ft apart along transects that were 6 ft apart (Figure 3A) for the first survey.

Figure 3. Image acquisition grids for all three surveys (arrows indicate the direction images were taken along the transects). A. Images taken with 16 ft pole 10 ft apart along transects that were 6 ft apart. B. Images taken with a 16 ft pole 4 ft apart along transects that were 4 ft apart. C. Images taken with a 21 ft pole 10 ft apart along transects that were 8 ft apart.
The first image set was tested in Photoscan Professional. After poor image alignment, I decreased the distance between each image and transect to 4 ft (Figure 3B) and slightly widened the focal length to 18 mm to maximize overlap (>60%). A taller pole height of 21 ft was used at one sandbar in the Grand Canyon. To mimic this GC survey, our pole was extended to 21 ft to collect images for the third survey (18 mm focal length). The distance between images was increased with the idea that more surface area is captured with a higher camera and would allow for fewer images with wider spacing (10 ft; Figure 3C).

All three images sets were processed with the commercial Photoscan Professional software (Agisoft) and the open source VisualSfM/CMVS/PMVS2 workflow (Changchang Wu and Yasutaka Furukawa). Medium accuracy settings were used for both sparse and dense point cloud generation in Photoscan. Image alignment was considered “successful” if >80% of the images aligned. The images collected at 16 ft and 21 ft were then combined in the ‘SfM’ software to see if the commonly held assumption that unordered images at varying heights, angles, and focal lengths provide a more representative/ dense point cloud (James and Robson 2012, Fonstad et al. 2012).

**FINDINGS**

Table 1 below summarizes image and software information from this investigation. PS = Photoscan Professional; VSfM = Visual SfM. Blank slots indicate no data.
Similar to attempted reconstructions of sandbars in Grand Canyon, the images in Survey 1 did not successfully align in both software (Photoscan = 26%; Visual SFM = 12%). After decreasing the distance between images to 4 ft and adjusting the focal length to 18 mm in Survey 2, there was 100% image alignment in both software (Figure 4).

**Figure 4.** Sparse point clouds for Survey 2 images with 16 ft pole height, 4 ft x 4 ft image distance, and 18 mm focal length (top image = Photoscan Professional; bottom image = Visual SFM). The camera positions are represented by blue squares in the Photoscan reconstruction and colored triangles in the Visual SFM reconstruction.
The extended height of 5 ft for Survey 3 provided successful image alignment in both software (Photoscan = 97%; Visual SfM = 90%) using less images (Photoscan = 60 images; Visual SfM = 56 images). More time was spent collecting images 4 ft apart, but the overlap guaranteed a 100% image alignment. Although the 21 ft pole height decreased the amount of images needed for successful alignment, our rigged pole was unwieldy (Figure 5). Perhaps an 18 ft pole is ideal for time and pole stabilization issues.

Figure 5. The weight of the camera at a 21 ft height made surveying slower and unwieldy.

The Photoscan software also takes less time to generate dense point clouds with more points/surface representation than those generated in Visual SfM.

Images collected from the 16 ft and 21 ft heights and slightly different focal lengths (18 mm and 21 mm) aligned in both software (Figure 6).
CONCLUSIONS / FUTURE WORK

This investigation answered my questions, revealed additional limitations, and developed new curiosities.

1.) Image sets that will successfully align can be acquired with a 16 ft pole, 18 mm focal length and more oblique camera mount angle. The adjustments made in this investigation provide better images for reconstructions than the images acquired in Grand Canyon.

2.) The distance of 4ft by 4ft between images provided the best overlap (>60%) for the 16 ft pole height and 18 mm focal length. Is this distance overkill? Exact distances with varying focal lengths and pole heights need to be constrained in future investigations.

3.) The 21 ft pole used in this investigation was a rigged pole used for power washing. There are sturdier telescoping pole options (locking segments) that can accommodate the weight of the T4i Rebel Canon digital camera in addition to lighter weight point-and-shoot cameras. Ideally, the higher camera height requires less images (faster processing)
and greater distances in between images (less survey time). More investigations are also needed to determine if the 16/21ft poles are high enough to capture highly defined topographic, sandbar features.

4.) This finding was a bit of a relief. Most ‘SfM’ literature claims that images from varying heights and positions add to the surface or feature reconstruction. This was not the case with the Grand Canyon images. This investigation also proves that images collected from different heights, positions, and slightly different focal lengths (18/21 mm) enhance reconstructions by adding more points to both the sparse and dense point cloud. More tests are needed to confirm if the drastic differences in camera positions collected throughout the varying survey types in Grand Canyon caused unsuccessful image alignment.

Moving forward, I propose we purchase a 25 ft telescoping/ pole with locking segments from http://geodatasys.com/pole3.htm ($350) for future data acquisition investigations in more representative terrain. Future work entails finding the ideal height (s), focal length (s), camera mount angle (s), and distance (s) between images to best reconstruct sandbars in Grand Canyon.

REFERENCES


A.5 Collecting Sandbar Imagery with an Unmanned Aerial Vehicle in Marble and Grand Canyons

DESCRIPTION

The purpose of this research is to develop a sandbar surveying methodology that is more time and cost efficient than the traditional, Northern Arizona University (NAU) survey. We propose to collect aerial imagery of sandbars within Marble and Grand Canyon with an unmanned aerial vehicle (UAV). The UAV will also allow for potential extension of the sandbar survey outside of the traditional sites. Upon future implementation of this method, citizen scientists (i.e., river guides) will collect sandbar images with the most time and cost efficient, image acquisition platform. Our objectives for UAV imagery collection of sandbars in Marble and Grand Canyon are threefold: 1.) test the feasibility of the UAV for collecting sandbar images in a harsh and remote environment, 2.) create 3D sandbar reconstructions and digital elevation models from sets of overlapping 2D aerial images using emergent ‘structure-from-motion’ (SfM) photogrammetry techniques, 3.) examine changes in sandbar topography between high flow experiments released from Glen Canyon Dam.

BACKGROUND

The traditional NAU sandbar survey occurs annually and collects topographic data using labor intensive methods (i.e., total station survey). The topographic data is used to calculate sandbar volumes and understand erosion and deposition processes driven by Glen Canyon Dam operations. Our SfM photogrammetry method has similar aims, but measures topography with oblique, overlapping images acquired from a digital camera. We are also interested in aeolian processes that contribute to archaeological site preservation. The SfM photogrammetry techniques have been proven to collect accurate, topographic data (James and Robson 2010; Westoby et al. 2012; Fonstad et al. 2013; Javernick et al. 2014). Our proposed method is potentially more cost and time efficient, only requiring a consumer grade digital camera, 2-3 surveyors, and overlapping image sets. 3D, topographic sandbar reconstructions (Figure 1) are created from the 2D image sets with robust pixel-matching algorithms in SfM software.

Limitations exist with any image acquisition platform. We previously collected image sets in Grand Canyon last fall with a pole-mounted camera (Figure 2). The 16 ft height of the pole was a limiting factor in image collection. The field of view was a limiting factor, and prominent topographic features were challenging to capture with overlapping images. At one site, we used a higher pole (21 ft), which captured wider views and greater overlap. The image sets collected with the higher pole produced more robust sandbar reconstructions, but the maneuverability of a high pole became unwieldy. We hypothesize that the UAV imagery will provide 1.) the best, vertical image coverage with the least amount of holes (i.e., created from obstructions in line of sight), 2.) the fastest surveying platform, 3.) less impact to the sandbar surface (i.e., foot traffic). GPS and environmental conditions specific to Marble and Grand Canyon will affect the UAV, and we need to test the limitations of this method to determine if and to what extent the UAV can be used to collect aerial imagery of sandbars.
Figure 1. Preliminary SfM results from images collected at a sandbar site (070R) during the 2014 September/October NAU sandbar survey trip. The orthophoto over hillshade shows the 3D reconstruction of the site, and the original digital elevation model (DEM) is on the far right.

Figure 2. Pole-mounted camera (21 ft) used for image collection during the 2014 September/October NAU sandbar survey. Notice the difficulty in maneuvering the pole.
METHODS

On June 10th to 26th (2015) we propose to collect aerial imagery with citizen scientists (i.e., youth) on the Grand Canyon Youth rafting trip. The second UAV survey will occur during the NAU sandbar survey trip in late September to early October 2015. We propose to fly a UAV similar to the DJI Phantom II in Figure 3 to collect aerial imagery at a minimum of 20, representative (i.e., variety of topography, vegetation, surface texture, and location) sandbars (Table 1) in Marble and Grand Canyon. The UAV has a Gopro camera that captures several images per second. A transmitter attached to the unit communicates with a ground receiver that streams the aerial imagery. The video monitor (Figure 4) displays height, azimuth, distance from pilot, and speed, which will be kept constant. We will fly the UAV at times during the day with the lowest, rafter visibility and audibility. Table 1 lists alternative sandbar sites in the case of high wind conditions or overlap with other rafting trips. We plan to fly two repeat surveys at each sandbar, totaling 40 image sets. Depending on sandbar size, two repeat surveys will take a maximum of 30 minutes of time in the air at each sandbar. We will manually fly the UAV directly over the surface of the sandbar at an approximate height of 70 ft along flight path transects; we will avoid flying over the river. Lastly, Figure 5 displays an example of an aerial image of a gravel bar collected with the DJI Phantom II in Logan, UT at approximately 100 ft height.

Figure 3. Potential UAV platform. The UAV, camera, GPS, and gimble mount weigh approximately 2 lbs.
Table 1. 20 proposed sandbars (2 archaeological sites*) for aerial imagery collection (subject to change to the listed alternate sites).

<table>
<thead>
<tr>
<th>Preferred Sandbar (RM)</th>
<th>Alternate Site (RM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cathedral Wash (03L)</td>
<td>-</td>
</tr>
<tr>
<td>Badger (08L)</td>
<td>Hot Na Na Camp (17L)</td>
</tr>
<tr>
<td>Nine Mile (09L)</td>
<td>Sand Pile (31R)</td>
</tr>
<tr>
<td>South Canyon (32R)</td>
<td>-</td>
</tr>
<tr>
<td>Buck Farm (41R)</td>
<td>-</td>
</tr>
<tr>
<td>Eminence Break (44.5L)</td>
<td>Willie Taylor Camp (45L)</td>
</tr>
<tr>
<td>Saddle Canyon (48R)</td>
<td>Dinosaur (50R)</td>
</tr>
<tr>
<td></td>
<td>Carbon Creek (65R)</td>
</tr>
<tr>
<td>Fifty-One Mile (51L)</td>
<td>-</td>
</tr>
<tr>
<td>Tanner (68R)</td>
<td>-</td>
</tr>
<tr>
<td>Basalt* (70R)</td>
<td>-</td>
</tr>
<tr>
<td>Above Trinity (92R)</td>
<td>-</td>
</tr>
<tr>
<td>Emerald (104R)</td>
<td>-</td>
</tr>
<tr>
<td>Big Dune (119L)</td>
<td>122 Mile (123R)</td>
</tr>
<tr>
<td>Upper Forster (123L)</td>
<td>Below Mohawk (173L)</td>
</tr>
<tr>
<td>Football Field (138L)</td>
<td>-</td>
</tr>
<tr>
<td>Above Olo (146L)</td>
<td>-</td>
</tr>
<tr>
<td>Below Chevron (183R)</td>
<td>Hualapai Acres (195L)</td>
</tr>
<tr>
<td>202-Mile (202R)</td>
<td>220-Mile (220L)</td>
</tr>
<tr>
<td>Pumpkin Springs (213L)</td>
<td>-</td>
</tr>
<tr>
<td>Fossil*</td>
<td>-</td>
</tr>
</tbody>
</table>
Figure 4. Video monitor that displays live video from the UAV and flight information (e.g., height, azimuth, and speed).

Figure 5. Example of aerial imagery collected with our DJI Phantom II of a gravel bar from an approximate height of 100 ft.
CONCLUSION

Aerial imagery collected by a UAV will potentially result in a more cost and time efficient method to survey sandbars and archaeological sites in Marble and Grand Canyon. Although limitations (e.g., environmental conditions and UAV visibility/audibility) exist with a UAV surveying platform, advantages and disadvantages accompany all surveying methods. The two proposed surveys will test the feasibility of sandbar imagery collected with a UAV.

REFERENCES CITED


A.6 2015 Grand Canyon Youth Trip Proposal: Youth Collecting Sandbar Data for ‘Structure-from-Motion’ Methodology

05/08/2015

1. INTRODUCTION

Citizen science is critical to the implementation of a new time and cost efficient sandbar surveying method in Marble and Grand Canyons. Our primary work plan goal is to develop a rapid, low-cost image collection survey using emerging ‘Structure-from-Motion’ (SfM) techniques that will produce 3D, sandbar reconstructions and digital elevation models (DEMs). If our SfM surveying method is successful and straightforward, it may be feasible to train citizen scientists, such as recreational river runners, to acquire imagery of sufficient quality to support expanding the spatiotemporal scope of ongoing sandbar monitoring in Grand Canyon. The Grand Canyon Youth trip is an excellent opportunity to involve youth in collecting imagery and testing the feasibility of a future SfM sandbar surveying protocol. I propose to collect sandbar images with the help of youth on the 2015 Grand Canyon Youth (GCY) trip from June 10th to June 26th. Our objectives include 1.) exposing youth to emerging scientific surveying methods and geomorphic processes in Marble and Grand Canyons, 2.) collecting overlapping, oblique imagery with consumer grade digital cameras from and in close proximity to selected, Northern Arizona University (NAU) sandbar monitoring sites, and 3.) collecting ground control data on sandbars with a total station.

On the 2015 GCY trip, we will refine the SfM image acquisition techniques used during the NAU sandbar survey in September and October 2014 (i.e., fall 2014 trip). During the fall 2014 trip, we collected sandbar images, detailed observations, and ground control data for proof of concept of the SfM method in Marble and Grand Canyons. Thirty-seven sandbar sites (mostly NAU sandbar sites) were surveyed with SfM techniques between Lees Ferry (RM 0) and Diamond Creek (RM 225) in Marble and Grand Canyons (Figure 1; Table 1). Professional surveyors collected ground control points with the traditional total station setup. Most images were taken with an EOS Rebel T4i SLR camera set on autofocus and mounted on a 16 ft pole. Three other pole heights (8, 12, and 21 ft) were used for experimental purposes. We also used the 21 ft pole to maximize the field of view (FOV) at an archaeological site. The remaining images were taken from ground level with an EOS Rebel T4i digital SLR and various point and shoot (P&S) cameras (Sony, Panasonic, Canon). To capture the widest FOV, the camera lens was fixed at 18 mm, and the camera mount angle was fixed at an oblique angle. We collected images with five distinct survey types (Table 2; Figure 2) to capture a range of images with different heights, angles, and perspectives. Several survey types were used in combination at multiple sandbars to fully capture the sandbar features in the scene. Due to camera visibility and pole stability, image collection was limited to dry weather and low wind speeds.
Figure 1. Sandbar sites (yellow triangles) surveyed with SfM techniques in September/October 2014. Modified from Hazel et al. (2010).
Table 1. Thirty-seven, sandbar sites surveyed with SfM techniques in September/October 2014.

<table>
<thead>
<tr>
<th>Site Name</th>
<th>River Mile and Side</th>
<th>Site Name</th>
<th>River Mile and Side</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cathedral Wash</td>
<td>2.5L</td>
<td>Trinity</td>
<td>91.8R</td>
</tr>
<tr>
<td>Badger</td>
<td>8.1L</td>
<td>Granite</td>
<td>93.8L</td>
</tr>
<tr>
<td>9-Mile</td>
<td>8.9L</td>
<td>104-Mile</td>
<td>104.4R</td>
</tr>
<tr>
<td>Hot Na Na</td>
<td>16.6L</td>
<td>Big Dune</td>
<td>119.4R</td>
</tr>
<tr>
<td>22-Mile</td>
<td>22.0R</td>
<td>122-Mile</td>
<td>122.7R</td>
</tr>
<tr>
<td>Sand Pile</td>
<td>30.7R</td>
<td>Upper Forster</td>
<td>123.3L</td>
</tr>
<tr>
<td>South Canyon</td>
<td>31.9R</td>
<td>Football Field</td>
<td>137.7L</td>
</tr>
<tr>
<td>Redwall Cavern</td>
<td>33.3L</td>
<td>Above Olo</td>
<td>145.8L</td>
</tr>
<tr>
<td>Nautiloid</td>
<td>35.1L</td>
<td>Lower National</td>
<td>167.2L</td>
</tr>
<tr>
<td>Buck Farm</td>
<td>41.4R</td>
<td>Below Mohawk</td>
<td>172.6L</td>
</tr>
<tr>
<td>Anasazi Bridge</td>
<td>43.4L</td>
<td>Below Chevron</td>
<td>183.3L</td>
</tr>
<tr>
<td>Eminence</td>
<td>44.6L</td>
<td>Hualapai Acres</td>
<td>194.6R</td>
</tr>
<tr>
<td>Willie Taylor</td>
<td>45.0L</td>
<td>202-Mile</td>
<td>202.3R</td>
</tr>
<tr>
<td>Lower Saddle</td>
<td>47.6R</td>
<td>Pumpkin Springs</td>
<td>213.3L</td>
</tr>
<tr>
<td>Dinosaur</td>
<td>50.2R</td>
<td>220-Mile</td>
<td>220.1R</td>
</tr>
<tr>
<td>51-Mile</td>
<td>51.0L</td>
<td>225-Mile</td>
<td>225.5R</td>
</tr>
<tr>
<td>Kwagunt Beach</td>
<td>56.6R</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crash Canyon</td>
<td>62.9R</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Carbon</td>
<td>65.2R</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basalt</td>
<td>70.1R</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grapevine</td>
<td>81.8L</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 2. Top pane: images collected with survey types A-D at an assortment of sandbar sites. Bottom pane: locations for each survey type and ground control points (GCPs) at RM 41.4R.

Table 2. Description of Survey Types for SfM Image Collection

<table>
<thead>
<tr>
<th>Survey Type</th>
<th>Camera Position</th>
<th>Collection Method</th>
<th>Camera Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>16 ft pole (other: 8/12/22 ft)</td>
<td>remote shutter/intervalometer (2 sec)</td>
<td>digital SLR</td>
</tr>
<tr>
<td>B</td>
<td>higher elevation above bar</td>
<td>handheld</td>
<td>digital SLR/P&amp;S</td>
</tr>
<tr>
<td>C</td>
<td>higher elevation on opposite bank</td>
<td>handheld</td>
<td>P&amp;S</td>
</tr>
<tr>
<td>D</td>
<td>rafting alongside sandbar</td>
<td>handheld</td>
<td>P&amp;S</td>
</tr>
</tbody>
</table>

Post-processed sandbar image sets show the reconstruction and georeferencing capabilities of the SfM method for a diverse set of sandbar topography, surface texture, and
vegetation. Figure 3 shows raw DEM and orthophoto outputs from the SfM software (Agisoft Photoscan Professional) for a sandbar at river mile 50R.

Figure 3. Reconstructed, georeferenced sandbar topography and DEM outputs using SfM surveying methodology and post-processing workflow with images collected from the September/October 2014 rafting trip.

2. METHODS

Our main goals for the June 2015 GCY trip are to refine our image acquisition techniques and to collect images and ground control points with the help of youth. We propose a surveying design that will maximize our time for data collection on the GCY trip. We will thoroughly survey a minimum of 14 representative (i.e., variety of spatial location, topography, vegetation, and surface texture) sandbars between Lees Ferry and Diamond Creek. We plan to survey one sandbar each day with a minimum of 6 sandbars between Lees Ferry and Phantom Ranch (“upstream”) and 8 sandbars between Phantom Ranch and Diamond Creek (“downstream”; Figure 4; Table 4). Table 4 also lists some alternate sandbar survey sites with similar characteristics for logistical reasons (e.g. not enough time or inconvenient to stop at preferred site).
Figure 4. Preferred and alternate sandbar sites for the 2015 GCY trip. Modified from Hazel et al. (2010).

Table 4. List of preferred and alternative sandbar sites for the 2015 GCY trip. *Time permitting.

<table>
<thead>
<tr>
<th>UPSTREAM</th>
<th></th>
<th>DOWNSTREAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preferred Site</td>
<td>Alternate Site</td>
<td>Preferred Site</td>
</tr>
<tr>
<td>Name</td>
<td>RM</td>
<td>Name</td>
</tr>
<tr>
<td>1 Badger</td>
<td>8.1L</td>
<td>Hot Na Na</td>
</tr>
<tr>
<td>2 Sand Pile</td>
<td>30.7R</td>
<td>9-Mile</td>
</tr>
<tr>
<td>3 South Canyon</td>
<td>31.9R</td>
<td>Big Dune</td>
</tr>
<tr>
<td>4 Buck Farm</td>
<td>41.4R</td>
<td>Tanner</td>
</tr>
<tr>
<td>5 Eminence</td>
<td>44.6L</td>
<td>Willie Taylor</td>
</tr>
<tr>
<td>6 Dinosaur</td>
<td>50.2R</td>
<td>Lower Saddle Carbon</td>
</tr>
<tr>
<td>7 Basalt*</td>
<td>70.1R</td>
<td>202-Mile</td>
</tr>
<tr>
<td>8 Grapevine*</td>
<td>81.8L</td>
<td>Pumpkin Springs</td>
</tr>
</tbody>
</table>
We will survey the 14 sandbars with pole-mounted (~16 ft height) digital point and shoot (P&S) and SLR cameras (i.e., survey type A; Table 2), and with survey types B-D (Table 2) where applicable. We will also conduct repeat, type A surveys at each bar to test consistencies between image sets. Pole-mounted (~21 ft height) camera surveys for comparison of previous datasets will focus on the sandbar and archaeological site at RM 70.1R with time permitting. All digital P&S and SLR cameras for survey type A will be fixed on an 18 – 21 mm focal length, set on automatic settings, and programmed with Magic Lantern intervalometer capabilities. Survey type A images will be collected with a pole height of 16-21 ft along transects spaced 4-6 ft and 8-10 ft apart. For survey types B and C we will collect images at higher elevations behind sandbars with accessible slope or rock outcrops and from across the river. For survey type D we will collect images from the boat as we approach or depart the sandbar site. We will evenly distribute and survey 10 – 30 ground control points at each sandbar site with a total station for georeferencing capabilities. Youth will also measure distances between GCPs to help scale the 3D reconstructions, and create GCP reference maps. Suggested equipment is listed in Table 5.

Table 5. Suggested equipment list for GCY trip.

<table>
<thead>
<tr>
<th>Equipment</th>
<th>Quantity</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital SLR Canon Cameras</td>
<td>2</td>
<td>T4/3i Rebel w/ Magic Lantern Firmware installed Extra batteries/camera charger</td>
</tr>
<tr>
<td>Digital Point and Shoot Cameras</td>
<td>5</td>
<td>SfM software installed Charger/extra batteries</td>
</tr>
<tr>
<td>Field Laptop</td>
<td>1</td>
<td>Field note template</td>
</tr>
<tr>
<td>Ground Control Targets</td>
<td>50 -100</td>
<td></td>
</tr>
<tr>
<td>Ipad</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Write in the Rain Field Notebooks</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Writing Utensils</td>
<td>10</td>
<td>Pencils/sharpies</td>
</tr>
<tr>
<td>Tape Measure/String</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Poles</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Camera Mounts</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Surveying Equipment</td>
<td>1</td>
<td>Total station setup</td>
</tr>
</tbody>
</table>

The trip starts on June 10th, and I will introduce the methodology, explain the 3D sandbar reconstruction process, and assign tasks and youth teams primarily based upon the youth’s interests and abilities. I also plan on practicing data collection techniques with the youth on June 10th. The goal is to survey 1 sandbar site each day, starting with the first group of youth on June 10th, and ending on June 16th. The second group of youth will be introduced to the method on June 17th and survey 1 sandbar site each day until June 25th. Table 6 summarizes the data.
collection tasks and time frames that could occur at a sandbar site. The establishment of the control network for the total station survey will need to take place before the youth arrive at each site. Youth will rotate taking Type D images upon arrival at each sandbar site with a handheld camera. Upon arrival, all of the youth will evenly distribute ground control targets on the sandbar surface. Then the 8 to 10 youth will be broken up into four teams to simultaneously survey ground control points, conduct two repeat Type A surveys, and conduct Type B and C surveys. If feasible, the Type B and C surveys will require the help of a supervisor. The Type C survey will require a boatman and supervisor to assist the youth across the river. Ideally, I plan to spend 2 hours to complete all the surveys at each sandbar site.

Table 6. Potential Data Collection Schedule at a Sandbar Site

<table>
<thead>
<tr>
<th>Task</th>
<th>Time (min)</th>
<th>Time Frame</th>
<th>Team #</th>
<th># of Youth</th>
<th>Equipment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collect Type D Images</td>
<td>15</td>
<td>10:45 - 11:00</td>
<td>All</td>
<td>8-10</td>
<td>Waterproof P&amp;S Cameras</td>
</tr>
<tr>
<td>Place Ground Control Targets</td>
<td>20</td>
<td>11:00 - 11:20</td>
<td>All</td>
<td>8-10</td>
<td>Ground Control Targets</td>
</tr>
<tr>
<td>Survey Ground Control Targets</td>
<td>40-60</td>
<td>11:20 - 12:00</td>
<td>1&amp;2</td>
<td>6</td>
<td>Survey Rods</td>
</tr>
<tr>
<td>Measure Distances Between GCPs</td>
<td>40</td>
<td>11:20 - 12:00</td>
<td>1&amp;2</td>
<td>6</td>
<td>Measuring Tape; Notebook; Writing Utensil</td>
</tr>
<tr>
<td>Collect Type A Images</td>
<td>30-60</td>
<td>11:30 - 12:30</td>
<td>1</td>
<td>3</td>
<td>Pole-mounted camera; Notebook; Writing Utensil</td>
</tr>
<tr>
<td>Collect Type A Images</td>
<td>30-60</td>
<td>11:30 - 12:30</td>
<td>2</td>
<td>3</td>
<td>Pole-mounted camera; Notebook; Writing Utensil</td>
</tr>
<tr>
<td>Collect Type B Images</td>
<td>60</td>
<td>11:30-12:30</td>
<td>3</td>
<td>2</td>
<td>Camera; Notebook; Writing Utensil</td>
</tr>
<tr>
<td>Collect Type C Images</td>
<td>60</td>
<td>11:30-12:30</td>
<td>4</td>
<td>2</td>
<td>Camera; Notebook; Writing Utensil</td>
</tr>
</tbody>
</table>
participating in citizen science has widen my perspective and understanding of Grand Canyon and why it is vital to protect it.”

-Grand Canyon Youth
Earlier this summer, Utah State University graduate student Becca Rossi rafted and surveyed sandbar topography along the Colorado River with a group of youth citizen scientists from the Grand Canyon Youth program. Her team for this trip consisted of 24 youth, 2 youth coordinators, 6 river guides, and 2 other scientists.

During the two weeks of surveying, the group rafted over 225 river miles of canyons in the Grand Canyon National Park (GCNP) to collect data. Both USU and the Grand Canyon Monitoring and Research Center (GCMRC) will use this data to monitor and record changes in size and stability of sandbar deposits along the Colorado River downstream of Glen Canyon Dam. Sandbars provide habitat for terrestrial and aquatic species, campsites for river rafters and scientists, and an aeolian sediment source for the preservation of archaeological sites.
The Glen Canyon Dam Adaptive Management Program has monitored sandbar depletion for more than twenty years through GCMRC. Within the past twenty years annual topographic monitoring has focused on sandbar response to high flow experiments at 45 sites throughout GCNP. The Paria and Little Colorado Rivers are the two main sand sources downstream of the dam. High flow experiments (HFEs) are released at the end of the monsoon season. With enough monsoonal rain, tributary sand is stored on the channel bed and is then mobilized downstream by the HFEs. These environmental flows aim to maintain and build sandbars within GCNP. Annual monitoring campaigns survey sandbar topography using a total station setup and repeatable control network.

There are roughly 500 large sandbars distributed over the 225 miles of the Colorado river throughout GCNP. The question remains if the 45 sandbar monitoring sites are representative of the total sediment budget in response to modified dam operations.

Map of the Colorado River downstream of Glen Canyon Dam with locations of the 45 annual sandbar monitoring sites (red triangles)
Sandbar site extension provides an option to test the representation of the 45 monitoring sites, but is costly and time-consuming with the current surveying method. 'Structure-from-motion' photogrammetry (SfM) is a new surveying method that will potentially provide a cheaper and faster way to extend the topographic sandbar survey in GCNP. The method consists of collecting overlapping, oblique imagery with consumer grade cameras mounted on 16 ft poles. To ensure repeatability of the survey, 10-50 ground control points are surveyed across the sandbar surface with a total station. Post-processing of the data consists of creating 3D models of the surface topography using robust pixel-matching algorithms.
The team collected data at 12 different sandbar sites distributed across Marble and Grand Canyons. Images were taken every 10-15 feet along upstream, downstream, and circular transects on the sandbar surface. Repeat surveys were used to test the variability in camera angle and image spacing between youth crews. While in the field, youth were able to see 3D visualizations of the sandbars they surveyed with the SfM software Photoscan Professional. The youth also collected ground control point data with the help of a surveyor, and handheld images from across, behind, and in front of the sandbars.
In addition to teaching the youth emerging scientific survey methods, Becca’s research goals included teaching them about fluvial geomorphology in Grand Canyon, and the impacts of Glen Canyon dam on the downstream environment and sand resources. She also hopes to evaluate the feasibility of using citizen science in future monitoring of sandbars. This is the second of three field work trips that Becca will conduct in GCNP during her time at USU to develop and implement a SfM surveying protocol.

One of the youth on the trip said “participating in citizen science has widen my perspective and understanding of Grand Canyon and why it is vital to protect it.” He especially enjoyed the scientists, saying that “they knew how to have fun and to get the projects done,” and that he “really enjoyed learning about the software that would create the beach models.”

Becca is currently working on her Master’s degree in Watershed Sciences with Dr. Joseph Wheaton, Dr. Paul Grams (GCMRC), Dr. Daniel Buscombe (GCMRC), and Dr. Jack Schmidt (USU). At USU, she is specializing in fluvial geomorphology. This interest has brought her to Utah and specifically the Colorado River downstream of Glen Canyon Dam where she is currently working on a thesis investigating sandbar dynamics in response to high flow experiments in Marble and Grand Canyons using emerging ‘structure-from-motion’ photogrammetry techniques.

Of her experience, Becca says, “the public is often disconnected to science and its importance, and citizen science is a way to bridge this gap. Citizen science is especially important for protecting environments from negative anthropogenic impacts. This experience has not only aided the progress of developing an SfM surveying protocol, but has aided me to contextualize my research into the bigger picture of disseminating scientific knowledge to the public, and more importantly to youth.”

Related links:
- Ecogeomorphology and Topographic Analysis Lab (ET-AL)
- USU Watershed Sciences
- U.S. Geological Survey
- Grand Canyon Youth

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A.8 2016 AGU Abstract

From Hype to an Operational Tool: Efforts to Establish a Long-Term Monitoring Protocol of Alluvial Sandbars using Structure-from-Motion Photogrammetry

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Despite recent advances in the use of Structure-from-Motion (SfM) photogrammetry to accurately map landforms, its utility for reliably detecting and monitoring geomorphic change from repeat surveys remains underexplored in fluvial environments. It is unclear how the combination of various image acquisition platforms and techniques, survey scales, vegetation cover, and terrain complexities translate into accuracy and precision metrics for SfM-based construction of digital elevation models (DEMs) of fluvial landforms. Although unmanned aerial vehicles offer the potential to rapidly image large areas, they can be relatively costly, require skilled operators, are vulnerable in adverse weather conditions, and often rely on GPS-positioning to improve their stability. This research details image acquisition techniques for an underrepresented SfM platform: the pole-mounted camera. We highlight image acquisition and post-processing limitations of the SfM method for alluvial sandbars (10s to 100s m$^2$) located in Marble and Grand Canyons in a remote, fluvial landscape with limited field access, strong light gradients, highly variable surface texture and limited ground control. We recommend a pole-based SfM protocol and evaluate it by comparing SfM DEMs against concurrent, total station surveys and TLS DEMs. Error models of the sandbar surfaces are developed for a variety of surface characteristics (e.g., bare sand, steep slopes, and areas of shadow). The Geomorphic Change Detection (GCD) Software is used to compare SfM DEMs from before and after the 2014 high flow release from Glen Canyon Dam. Complementing existing total-station based sandbar surveys with potentially more efficient and cost-effective SfM methods will contribute to the understanding of morphodynamic responses of sandbars to high flow releases from Glen Canyon Dam. In addition, the development and implementation of a SfM-based operational protocol for monitoring geomorphic change will provide a methodological foundation for extending the approach to other fluvial environments.
The following vignette aims to provide a revised set of instructions and explanations for scientists performing SfM sandbar surveys on the Upper Half of the fall 2015 sandbar monitoring trip.

Objectives for the fall 2015 SfM sandbar survey include:

- Refine image acquisition techniques to improve surface reconstructions and DEMs by taking images along several different transect types.
- Collect repeat survey data from previously reconstructed sandbar sites (Upper Half: 50R Dinosaur, 65R Carbon, and 70R Basalt arch site) for geomorphic change detection.
- Test two different cameras (Canon Rebel T4i DSLR vs. Canon Powershot D30) and corresponding intervalometer and wired trigger image collection methods.
- Identify and describe surface textures that correspond to erosional, depositional, and stable topographic sandbar features pre-HFE.

### METHODS

#### 1. FALL 2015 SANDBAR SURVEY SITE SELECTION

#### 1.1 Image Acquisition Styles

SfM image acquisition is dependent on four main factors:

1. Sandbar topography
2. Sandbar size
3. Surface texture
4. Line of site obstructions (e.g., vegetation and boulders)

**Table 1** rates each sandbar site on the upper half based upon these four factors. The rating values equate to image acquisition “success”. In other words, how easy or difficult will it be to acquire overlapping images from a camera mounted on a 16ft pole along transects that results in successful reconstructions (i.e., alignment and coverage) of surface topography and ultimately DEMs? The value of 1 translates to easier image acquisition and occurs at sandbars with flat topography, small sandbar size, and few line of site obstructions. The value of 2 translates to increased difficulty for image acquisition that occurs at sandbars with complex surface topography/obstructions to line of site (steep slopes/cut banks), homogeneous surface texture, and vegetation ≤16ft pole height. The value of 3 translates to difficult image acquisition that occurs at sandbars with discontinuous survey areas (i.e., multiple line of site obstructions), and large sandbar size. “Must get” survey sites (designated by a * in Table 1) on the upper half are selected based upon a representative sample of all three image acquisition ratings.

**Table 1.** Fall 2014 survey sites, image acquisition ratings, and previous survey information. *must get sites, **repeat survey sites (fall 2014/2015), green=easy image acquisition, yellow=medium difficulty image acquisition, and orange=difficult image acquisition. For “Past Data Collection”, A= images collected on surface of bar (mostly 16ft pole), B= images collected from above/behind bar, C= images collected from across river, D= images collected in boat – “drive-by”, E= images collected perpendicular to bank face, A Repeat = repeat survey A, AA = concentric ring survey. “Extra” listed under camera types means conduct one survey with the Canon D30 if you have time.
## 1.2. Repeat Surveys for Geomorphic Change Detection

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### Image Acquisition Rating

- **A**: Very Poor
- **B**: Poor
- **C**: Average
- **D**: Good
- **E**: Excellent
Table 1 also lists three repeat sandbar sites/areas from the fall 2014 trip (designated with a **) that will potentially be used for geomorphic change detection of sites on the upper half. The list below describes the locations of the fall 2014 surveys, previous transect designs, and approximate GCPs and locations. More repeat surveys will be conducted on Lower Half sites that have better reconstructions. Also refer to section 3. Image Acquisition Site Supplement on how to resurvey these sites on the fall 2015 trip.

1.) 50R Dinosaur – Last fall images were collected at the upstream and downstream end of the separation bar with a 12ft pole and T4i/clicker. Only the downstream end of the separation bar reconstructed (Figure 1).

![Figure 1](image1.png)

**Figure 1.** Reconstructed downstream end of separation bar at 50R Dinosaur. The sandbar was reconstructed with 129 images (spaced 1-3 m apart; blue rectangles) along 2 transects (spaced ~6 m apart) with the sensor pointed in the downstream direction, and 8 GCPs (flags).

2.) 65R Carbon – Images were taken with a 16ft pole every 2 seconds along three transects defining the water edge, sandbar crest, and back of the reattachment bar. Images also included background and unwanted features, causing image alignment issues without mask implementation.

3.) 70R Basalt - Figure 2.
Figure 2. Reconstructed archaeological site at 70R Basalt. A 21 ft pole, T4i Rebel (intervalometer), 77 manually sorted images and 3 GCPs were used to reconstruct this area. The camera configurations are shown by the blue rectangles.

2. FALL 2015 IMAGE ACQUISITION DESIGN

2.1. Image Acquisition Types (IAT) for Pole Surveys

To account for sandbar surface topography, size, texture and line of site obstructions, I have developed three different Image Acquisition Types (IAT) for pole surveys. The three defined IAT are represented by scaled image acquisition maps of 03L Cathedral, 30R Sand Pile, and Buck Farm 41R in Figures 3, 4, and 5. Of the nine “must get*” sites on the Upper Half, the three IAT are generally applicable when surveying all sandbar sites with some exceptions described in section 3. Image Acquisition Site Supplement:

IAS #1: 03L Cathedral, 08L Badger, 32R South Canyon, 33L Redwall Cavern, 44L Anasazi Bridge, 56R Kwagunt Beach, 62R Crash, and 68R Tanner.


IAS #3: 16L Hot Na Na, 35L Nautiloid, 41R Buck Farm, and 44L Eminence.

The three maps also include approximate GCP counts and locations, approximate number of images based upon sandbar size/transect numbers, and transect descriptions.

2.2. Camera Comparison

Table 1 also lists camera types that will be used for two different pole mounted camera surveys at the nine “must get” sandbar sites. Two different camera setups will test tradeoffs in image acquisition times, resolutions, focus/exposure quality, and trigger mechanisms. The first camera (Canon Rebel T4i DSLR) setup is designed to capture complete coverage of the sandbars by collecting images along transects every 2-3m based upon time intervals. This camera setup and intervalometer trigger mechanism will allow for rapid image collection of the sandbars in a semi-gridded fashion. The second camera (Canon Powershot D30) setup has been previously used to allow for triggering the point and shoot sensor remotely with a wired trigger mechanism. Unlike the DSLR, the shutter click for the D30 point and shoot cannot be heard or felt when mounted 16 ft in the air. The implementation of the wired remote trigger allows for slightly less rapid image collection, but also allows for more control and less blurry images. I recommend taking two different surveys with both camera/mechanism setups along similar transects with similar transect/camera spacings (2-3m). If this is taking too long, I would increase the transect/camera spacing of the D30 camera survey to 5m.

I WOULD ALSO TEST THE MAXIMUM RESOLUTION (18MP) OF THE T4i REBEL AT 30 MILE TO TEST ANY DIFFERENCE IN HIGHER RESOLUTION CONTRIBUTING TO BETTER RECONSTRUCTION OF HOMOGENOUS BARS WITH STEEP SLOPES.

3. IMAGE ACQUISITION SITE SUPPLEMENT

3.1. Transect Descriptions

Collect images spaced 2-3m apart along transects also spaced 2-3m apart with the sensor consistently pointed in the same direction along each type of transect. I recommend against taking an upstream image and then immediately flipping the camera to take a downstream image at each point along the transect. Although this saves times, the sensor directions are not as consistent. I recommend placing pin flags to mark transects to return to for the second survey.
When collecting images along transects, start at the upstream end walk along the transect in one direction and then turn around and collect images along the same line in the opposite direction. Then start at the second transect...

1.) **Upstream**: Collect one image every 2-3m with the sensor pointed along the transect in the upstream direction.

2.) **Downstream**: Collect one image every 2-3m with the sensor pointed along the transect in the downstream direction.

3.) **Perimeter**: Collect one image every 2-3m around the perimeter of bar with the sensor direction pointed towards the center of the bar.

4.) **Lateral River**: Collect one image every 2-3m with the sensor direction pointed perpendicular to the river.

5.) **Lateral Back of Bar**: Collect one image every 2-3m with the sensor direction pointed perpendicular to the back of the bar.

*Only needed for IAT #2/3 with increased bar width.*

### 3.2 Additional Image Acquisition Site Instructions

1.) **03L Cathedral**:
   - Figure 3. No line of site obstructions; upstream, downstream and perimeter transects should be more than enough.

2.) **08L Below Jackass**:
   - Add circular transects around boulders and dense vegetation patches with the camera angled towards the obstruction. I don’t have an exact distance you should be away from the obstruction when you take these images, but I would recommend keeping a consistent distance away from the obstruction.

3.) **09L 9Mile**:
   - Collect two transects that are placed at the base of the steep slope and at the top of the steep slope/cut bank. I recommend “straddling” the steep slope/cut bank to acquire maximum image overlap across the feature. If you have them, I would place colored targets on the bar face to aid in reconstructing the homogeneous surface texture.

4.) **16L Hot Na Na**:
   - Inactive floodplain will be difficult to survey with continuous transects due to vegetation. As this site is “extra”, I would focus on surveying the active floodplain with the Canon D30.
5.) 22R 22-Mile:
   - See 9-Mile. Due to the large size of the bar, I would also add “Lateral River” and “Lateral Back of Bar” transects similar to those in Figure 4.

6.) 30R Sand Pile:
   - See Figure 4. I WOULD ALSO CONDUCT A THIRD IMAGE SURVEY WITH THE T4i REBEL WITH THE MAXIMUM RESOLUTION (18MP) AT 30 MILE TO TEST ANY DIFFERENCE IN HIGHER RESOLUTION CONTRIBUTING TO BETTER RECONSTRUCTION OF HOMOGENOUS BARS WITH STEEP SLOPES.

7.) 32R South Canyon:
   - As this site is “extra” and large, I would focus on surveying the active floodplain with the Canon D30 and avoid the upstream inactive, vegetated area near the debris fan.

8.) 33L Redwall Cavern:
   - The walls of the cavern reconstruct well, but the sand has a homogeneous surface texture of footprints, resulting in poor reconstructions. If you have time, try surveying this site with colored targets spread across the surface of the bar.

9.) 35L Nautiloid:
   - As this site is “extra”, large, and vegetated, I would focus on the downstream, elevated campsite area.

10.) 41R Buck Farm:
   - See Figure 5.

11.) 43L Anasazi Bridge:
   - I haven’t surveyed at this site.

12.) 44L Eminence:
   - See Figure 5. Divide the bar into two areas, 1.) along the bank, and 2.) directly behind the vegetation in the campsite area.

13.) 45L Willie Taylor:
   - See 9-Mile/Figure 4.

14.) 47R Lower Saddle:
   - See 9-Mile/Figure 4. As this site is “extra”, I would focus on surveying the active floodplain with the Canon D30 and avoid the upslope inactive, vegetated area.

15.) 50R Dinosaur:
   - See 9-Mile/Figure 4.

16.) 51L 51-Mile:
• See 9-Mile/Figure 4. As this site is “extra”, I would focus on surveying the active floodplain with the Canon D30 and avoid the upslope inactive, vegetated area.

17.) 56R Kwagunt Beach:
• There are few line of site obstructions at the narrow, downstream portion of this site. I would do upstream, downstream, and perimeter transects for the entire bar and add three lateral transects where the bar widens laterally upstream/upslope.

18.) 62R Crash:
• As this site is “extra”, I would focus on surveying the active floodplain with the Canon D30 around the gully near pull-in.

19.) 65R Carbon:
• See Figure 4. This site will probably have stark shadows and sand blowing around. I would keep the lighting as consistent as possible, and resume survey when wind stops. This is also a good bar to test out the effect of shadow. Angle the sensor to exclude background and unwanted features. The sandbar is narrow enough and has few line of site obstructions to omit lateral transects. Make sure to survey the steep cut bank as described at 9-Mile.

20.) 68R Tanner:
• As this site is “extra” and large, I would focus on surveying the active floodplain with the Canon D30 near Tanner Camp.

21.) 70R Basalt:
• As I was only able to reconstruct the arch site, I would focus on collecting images along ~3 parallel transects through the site and 2 transects along the top sides of the depression. Be sure to angle the camera to exclude sky/unwanted background features. As the arch site is small, you could try reconstructing all of these images on the tough pad. I would place control on the slopes of the depression, as the vegetation on the sides of the depression cover the targets. If you have time you could place more control and survey upslope.

22.) 81L Grapevine:
• This site has minimal line of site obstructions, but has a steep bank face (see 9-Mile).
Figure 3. General representation of Image Acquisition Type #1. The above bar (03L Cathedral) consists of 5 upstream and 5 downstream transects (red) totaling 132 images. The camera sensor is pointed along the transect/follows topography in the upstream direction rather than pointed in the upstream flow direction. The blue perimeter transect collects images with the sensor point towards the center of the bar. GCPs are first placed to constrain the survey area, and then sporadically placed inside the perimeter transect.
Figure 4. General representation of Image Acquisition Type #2. These are conservative transect spacings (2m), camera location spacings (2-3m), and GCP arrangement (45). If you were to survey upstream and downstream transects (red) with the above map you would take ~1000 images (500 upstream/500 downstream). As the surface topography flattens, the transect spacing can widen. This survey may require fewer closely spaced transects around the steep bar face. You may have to adjust to a more acute angle around the steeper bar face. I’d also try placing “texture targets” on the steep bank face to aid with homogeneous surface reconstruction. Due to the width of the bar, I’ve included green “lateral” transects, collecting a set of images upslope (perpendicular to the back of the bar) and a set of images downslope (perpendicular to the river) along the transects.
Figure 5. General representation of Image Acquisition Type #3. Sites similar to 41R Buck Farm will be difficult to continuously survey, so I recommend breaking up the survey areas and also overlapping the different survey areas (not show in figure). The active floodplains for sites like 41R Buck Farm will be easier to survey (similar to Image Acquisition Type #1), but the inactive floodplain surface is dissected with line of sight obstructions. I’ve included upstream/downstream transects (red) and upslope/downslope/lateral transects in green for the inactive floodplain area. I’m unsure of the best way to survey these types of floodplains if we want to come out with the most continuous surface with the least amount of gaps.

4. SFM SURVEY GEAR LOGISTICS
4.1. Cameras

4.1.1. CANON EOS REBEL T4i DSLR (8MP):

- Check for correct date & time settings, full battery life, and smudges on lens.
- Fix focal length to 18mm (secure lens with duct tape).
- Set to autofocus.
- Set intervalometer/CHDK settings to take an image every 2-3m, delaying the first shot to allow for elevating pole.
- If you need to change resolution quality settings, reference pictures below.
4.1.2. CANON POWERSHOT D30 (12MP):

- Check for correct date & time settings, full battery life, and smudges on lens.
- Turn off GPS settings to conserve battery life.
- Set to autofocus.
- Do not change focal length/zoom (automatically set to full zoom out when powered on).
- **MAKE SURE POWER SAVING MODE IS TURNED OFF IN MENU SETTINGS** (so camera will not shut off during survey)
- Set CHDK settings for remote trigger by:

1. Access CHDK settings.
3. Enable Remote.
4.2. Poles

4.2.1. ELEVATOR:

- Telescope to 16ft (extend all the way and then click into first notch)

4.2.1. BIG YELLOW

- Telescope to 15ft (each segment is ~5ft; the collapse button on one of four segments is jammed, but you only need three segments)

4.3. Mounts

4.3.1. ELEVATOR POLE:

- Pull back on gray lever to release flat, gray, platform and reset locking mechanism.
- Screw either camera onto gray, flat removable platform, and lock into black mount.
- Adjust angle with black knob to ~80 degrees.
  - Take an image and adjust camera angle to encompass mostly sandbar feature, eliminating background features:

- Screw black mount onto top of the Elevator Pole.
4.3.2. BIG YELLOW POLE:

- Screw either camera onto black circular mount.
- Fit rounded metal pieces together (see picture), and fit notch that correspond to ~80 degree angle.
- Take an image and adjust camera angle to encompass mostly sandbar feature, eliminating background/unwanted features.
- Secure two metal pieces with screw and washer (see picture).

4.4. Trigger Mechanisms

4.4.1. INTERVALOMETER → CANON T4i REBEL CAMERA:

- Set intervalometer/CHDK settings to take an image every 2-3 m, delaying the first shot to allow for elevating pole.

4.4.2. INTERVALOMETER → WIRED REMOTE TRIGGER → CANON POWERSHOT D30:

- Fully extend 16ft pole.
- Plug in mini USB to the USB port on the side of the Canon Powershot D30 camera.
- Wrap wire down pole and hold or secure black trigger box for surveying (see picture). If using duct tape, secure black trigger box with the button facing towards you (facing opposite of camera sensor).
- Switch black trigger box button “ON” and turn camera on.
- **FOCUS IMAGE BY 1st HOLDING DOWN RED BUTTON FOR 2-3 SECONDS AND 2nd RELEASE BUTTON TO TAKE IMAGE.**
- Take one image to test trigger before surveying.
4.5. Batteries/Chargers

- Charge camera batteries each night.

4.6. Toughpad

- Plug in USB adaptor into toughpad.
- Plug in keyboard, mouse, and, battery charger into toughpad.
- Run images in small chunks in Agisoft Photoscan Professional software.
  - By image chunk, I mean images that we think should easily align together. For example uploading all the images collected along transects with the sensor pointed in the upstream direction should correctly align in Photoscan on the toughpad quickly (low alignment setting).
- Organize images each night by site, transect number and camera sensor direction.

4.7. Ground Control Points (GCPs)

- Enlarge target numbers by re-writing the target number in the white panes of the target (as large as possible).
- Place 10-30 (depending on size of bar) checkerboard targets on sandbar (facing numbers in consistent direction).
  - Define survey area inside a perimeter of targets.
  - Randomly place remaining targets inside of target perimeter.
- Place colored targets near or on steep bank slopes.
- **DO NOT MOVE TARGETS ONCE IMAGE SURVEY HAS STARTED.**
- **NAME CENTER OF TARGET LOCATIONS AS CLOSE TO THE IMAGE SURVEY AS POSSIBLE.**
### 5. IMAGE ACQUISITION FIELD BOOK TEMPLATE

**Before each survey, take a picture of a piece of paper that has the site name and survey # (this will help with organizing images).**

#### GENERAL SITE INFORMATION

<table>
<thead>
<tr>
<th>Sandbar Name – River Mile – Date</th>
<th>Surveyor Name</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Start Time</td>
</tr>
<tr>
<td></td>
<td>End Time</td>
</tr>
<tr>
<td></td>
<td>Survey Duration</td>
</tr>
</tbody>
</table>

Environmental Conditions (EC): describe lighting, wind, precipitation conditions. If shadows occur during surveys, sketch out sandbar map with approximate locations of shadowed areas. Describe any changing environmental conditions during the survey.

Bar Vegetation (BV): describe/sketch out areas of vegetation.

Other surface characteristics (OSC): describe/sketch surface texture; estimate bank gradient.

### IMAGE ACQUISITION (always start image collection at upstream end of bar)

Survey #: I would always start with the Rebel survey (#1), and resurvey with the D30 (#2). The only survey #3 you should have is at 30-Mile if you do a third maximum resolution (18 MP) survey.

Camera Setup and Pixel Resolution; Focal Length: Rebel (8MP), PS (12MP), Rebel (18MP), or combination of both; 18mm (Rebel) and automatic zoom (D30).

Pole settings: name of pole, record height if other than 16ft (e.g., handheld).

Transects: sketch transects; ideally you would write down the image numbers corresponding to the different directional transects. Note if you deviate from the 2-3m transect/image spacing (e.g., changing angle for steep banks).

### GCPs (always place numbers on targets facing upstream)

Sketch GCP arrangement on bar surface.

Note any GCPs that you think were moved during the image survey.

### Other Notes:

- Transect #s and sensor directions
- GCP #s and arrangement
- Mapped surface textures
- Mapped areas of shadow
- Mapped areas of vegetation
- Mapped areas of steep slopes/cut banks

### Sandbar Sketch:

- Transect #s and sensor directions
- GCP #s and arrangement
- Mapped surface textures
- Mapped areas of shadow
- Mapped areas of vegetation
- Mapped areas of steep slopes/cut banks
APPENDIX B
POLE-MOUNTED SFM PROTOCOL FOR MONITORING ALLUVIAL SANDBAR TOPOGRAPHY

B.1 Introduction

The historical and current monitoring of alluvial sandbar topography in Marble and Grand Canyons has advanced the understanding of sandbar behavior in response to normal (e.g. hydropeaking) and experimental (e.g. high flow experiment: HFE) operations of Glen Canyon Dam (Howard, 1975; Schmidt and Graf, 1990). The closure of Glen Canyon Dam in 1963 eliminated the downstream sediment supply, negatively impacting sandbar building and dramatically altering the flow regime by increasing base flows and the range of daily fluctuations in addition to decreasing peak flows. Starting in the early 1970s, repeat topographic sandbar measurements were made along cross-sections at 20 sandbar sites (Beus et al., 1985). These repeat topographic measurements along with quantitative evaluations of sandbars directly before and after the 1983-1984 flood were used in a decadal sandbar change analysis (Beus et al., 1985). From this analysis, Beus et al. (1985) recognized the sandbar building capabilities of the 1983-1984 flood with sufficient riverbed sand. Using repeat aerial imagery, Schmidt and Graf (1990) identified patterns in sandbar aggradation and degradation from before and after the 1983 flood. A time-lapse camera system was
installed in 1990 at representative sandbar deposit types (Schmidt and Graf, 1990, i.e., reattachment, separation, margin;) to capture repeat images of rapid erosional events that were not capable of being topographically measured and to quantify rates of change in sandbar width and area. In 1996, the first HFE was released from Glen Canyon Dam as part of a resource management strategy to rebuild sandbars in Marble and Grand Canyons (Hazel et al., 1999; Melis, 2011). To detect changes in sandbar volume and area in response to HFEs, the Grand Canyon Monitoring Research Center (GCMRC) and Northern Arizona University (NAU) perform an annual topographic survey of sandbars at 45 monitoring sites along the Colorado River in Marble and Grand Canyons (Hazel Jr. et al., 2008).

‘Structure-from-Motion’ photogrammetry (SfM) with Multi-View Stereo (MVS), collectively referred to here as SfM, has recently become a popular, high resolution topographic (HRT) tool used for accurately mapping topographic features (Javernick et al., 2014; Mancini et al., 2013; Micheletti et al., 2015; Nouwakpo et al., 2016; Piermattei et al., 2015; Prosocimi et al., 2015; Woodget et al., 2015; Carrivick et al., 2016), hydrodynamic analysis (Javernick et al., 2014; Smith et al., 2014; Westoby et al., 2014), and morphologic monitoring/geomorphic change detection (Clapuyt et al., 2016; Dietrich, 2016b; Fonstad et al., 2013; Gómez-Gutiérrez et al., 2014; James and Robson, 2012; Lucieer et al., 2013; Smith and Vericat, 2015; Turner et al., 2015; Westoby et al., 2012). The SfM method is based upon traditional photogrammetry and consists of a field component in which overlapping images are collected from multiple camera perspectives without exact knowledge of camera parameters. The images are then post-processed with SfM and MVS algorithms, which automatically resolve camera parameters and orientations of the overlapping images, producing a 3D, topographic model (for reviews of SfM applications in geomorphology, survey techniques, algorithms, and software see A.1; Smith et al., 2016; Bartoš et al., 2014; Fonstad et al., 2013; James and Robson, 2012; Gomez et al., 2016; Carrivick et al., 2016). SfM techniques encourage faster, cheaper, and more accessible methods for accurately reconstructing 3D topography from overlapping images with consumer-grade cameras (James and Robson, 2012; Westoby et al., 2012; Fonstad et al., 2013). Fonstad et al. (2013)
and Westoby et al. (2012) have promoted SfM as the democratization of high-resolution topographic (HRT) data acquisition.

Given the recent appeal of SfM as a potentially cheap, fast, accurate and simple method to monitor HRT, GCMRC was interested in exploring its feasibility and developing a field survey and data post-processing protocol. The complimentary implementation of the SfM method could also provide a larger sandbar sample size. Although this thesis has determined the SfM method works to monitor sandbar topography in Marble and Grand Canyons, the SfM method is not necessarily cheaper, faster and simpler compared to the traditional, annual GCMRC/NAU topographic survey (reference 2-page memo). The purpose of this protocol is to provide a set of procedures for the field survey and data post-processing components of the SfM method. The protocol will explain the rationale for the presented procedures. The protocol can be used for monitoring alluvial sandbar topography in Marble and Grand Canyons and can also be used for other sand monitoring applications in Grand Canyon (e.g. aeolian sediment transport).

B.2 Part 1: Field Survey

Pole-Mounted Camera Platform

The most widely used image acquisition platform for the SfM method is the aerial, UAV platform (Harwin and Lucieer, 2012; Lucieer et al., 2013; Bemis et al., 2014; Lucieer et al., 2014; Ouédraogo et al., 2014; Tonkin et al., 2014; Vasuki et al., 2014; Puttock et al., 2015; Ryan et al., 2015; Smith and Vericat, 2015; Turner et al., 2015; Clapuyt et al., 2016). UAVs provide an advantageous aerial perspective which maximizes image overlap and coverage from the plot (Smith and Vericat, 2015, e.g.) to the landscape (Dietrich, 2016b, e.g.) scale. As of 2017, Grand Canyon National Park prohibits the use of UAVs for recreational and research purposes. Therefore a pole-mounted camera was chosen as the primary camera platform to collect images of alluvial sandbar topography in Marble and Grand Canyons. Table B.1 shows the specs for two different poles that were tested for collecting imagery of sandbar topography.

Rapidly collecting images with a camera pole held in the vertical position became
Table B.1 Comparison of Two Camera Poles for Sandbar Image Acquisition

<table>
<thead>
<tr>
<th></th>
<th>YoungBlood Elevator Photo Pole*</th>
<th>H-series Telescoping Pole**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Length (m)</td>
<td>2.4</td>
<td>1.9</td>
</tr>
<tr>
<td>Maximum Length (m)</td>
<td>4.9</td>
<td>9.1</td>
</tr>
<tr>
<td>Weight (kg)</td>
<td>4.5</td>
<td>2.9</td>
</tr>
<tr>
<td>Pole Material</td>
<td>Fiberglass and Aluminum</td>
<td>High Strength Fiberglass</td>
</tr>
<tr>
<td>Lock Material</td>
<td>Brass</td>
<td>Nylon</td>
</tr>
<tr>
<td>Price of Pole (US$)</td>
<td>275</td>
<td>430</td>
</tr>
</tbody>
</table>

*https://www.bhphotovideo.com/c/product/981652-REG/youngblood_the_elevator.html
**http://www.geodatasys.com/pole3.htm

cumbersome and inefficient with a pole length greater than 4.9 m. Therefore, the additional length of the H-series Telescoping pole was not needed. The YoungBlood Elevator pole comes with a fully adjustable and reliable camera mount that screws onto the top of the pole. The camera mount for the H-series Telescoping pole is an additional $36 and contains more rigid camera adjustment options. Also, the metal locking and stop mechanisms on the YoungBlood Elevator pole proved to be significantly more efficient after exposure to fine-grain sand and water. The H-series Telescoping pole weighs less, but proved unreliable after several parts of the pole (telescoping segments and plastic buttons) failed to function after exposure to water and fine-grain sand. For the previous reasons, the YoungBlood Elevator pole (4.9 m length) was chosen to maximize the ground footprint of the camera, while ensuring vertical stability of the pole and image capture of surfaces with low-lying and intermediate height vegetation.

**Camera Options**

In 2014, I collected images with a Canon T4i digital single lens reflex camera (8 MP, fixed focal length = 18 mm) mounted on a 4.9 m tall pole. Considering the accuracies of SfM DEMs from former studies (Micheletti et al., 2015) and the portability/durability of consumer grade cameras, during the 2015 trip, I also used the Canon D30 point and
shoot camera (12 MP, fixed focal length = 38 mm) in addition to the Canon T4i camera. I did not find the DEM error to be significantly different between the DEMs generated with the Canon D30 and T4i cameras. Therefore, I recommend using the D30 point and shoot camera because it is much more durable and weighs less on top of the pole. The size of the picture frame is less with the point and shoot camera, but more images can easily be acquired.

**Image Acquisition**

To guarantee sufficient image collection (i.e. enough overlap and less blurry images) and successful reconstructions in Photoscan, I recommend using 1.) a modified camera mount that extends the camera away from the pole to allow for a nadir perspective without the pole in the frame (see section A.4: Figure 1), 2.) an intervalometer camera setting to automatically collect images at specified time intervals, and 3.) grid-like transects that cover the sandbar. Compared to a nadir camera orientation, the low camera angle that I used to collect imagery (Figure C.1) caused narrower ground footprint size, but captured more sandbar area with less images. Ultimately, the camera angles of the additional sandbar images that I collected did not necessarily aid in successful reconstructions in Photoscan because of the low camera angle. Although more images will be collected to ensure enough overlap with a nadir camera perspective (without the camera pole in the frame), more successful reconstructions are guaranteed and will take significantly less time for the algorithms to process. The nadir camera perspective should also eliminate the capture of some background features (e.g. sky/water), which add noise to the SfM point clouds.

The Canon D30 can easily be programmed with the Canon Hacker Development Kit to collect images at specified time intervals. Unfortunately, the shutter click of the Canon D30 is difficult to hear, resulting in blurry images that are taken when the pole is moved abruptly. To ensure less blurry images, I recommend turning on the intervalometer setting and carrying the pole at a constant, slow rate without long pauses or dropping of the pole to the ground. The size of the ground footprint of a nadir image collected with the Canon D30 camera is smaller (about 0.9 x 1.2 m), and will require more images that overlap about
60% in all directions. I recommend practicing how many seconds it takes to collect images every 0.6 to 0.9 m at the slow walking rate to ensure roughly 60% image overlap. I do not recommend collecting images at sites that are covered in partial shade. Elevations that were collected in areas of dark shadow contained high error. There are certain sites that experience shadowing at specific types of the day, and image acquisition at those sites should be planned according to the lighting conditions. Also, to avoid blurry imagery, I recommend ending the survey before the evening hours (when the camera flash starts to come on). Lastly, to ensure coverage of the sandbar, I recommend collecting images along a grid-like pattern (see examples in section A.6: p. 161-163). The grid-like transect pattern will depend on the shape of each sandbar and generally will consist of a set of two groups of transects that are perpendicular to each other. The nadir camera angle will also eliminate walking up and down the same transect. Additional transects with images collected from other angles should be added (e.g. perimeter transects section A.6: p. 161-163). The multiple angles can be useful for the post-processing algorithms.

This research found that vegetated areas have high elevation uncertainty. To monitor sandbars using the SfM method, additional point measurements (collected with the TS) are needed to fill in gaps where the bare earth surface is not visible. For example, additional TS point measurements are needed to fill in gaps in densely vegetated areas larger than 2 m. TS measurements are also needed to acquire accurate elevation measurements offshore in deep, turbid water.

**Ground Control Points**

Ground control targets were distributed across the entire surface of each sandbar, approximately 10 m apart in a random grid pattern (e.g. section A.6: p. 161-163). This method of control target distribution worked well. The accuracy assessment of SfM points and DEM cell values did not show a spatial pattern in relationship to the ground control target locations. If a target moved during the survey, a high RMSE value was returned in the post-processing software. Thus, moved targets are easily identified outside of the field. The elevation discrepancy can also be visualized in Figure B.2. I recommend numbering the
Fig. B.1. The pole-mounted camera platform setup that I used in this study. A. The 4.9 m tall, pole platform with camera mount that I used to acquire the majority of sandbar images. B. Surveyor collecting images of a sandbar with the pole-mounted camera platform setup in Marble Canyon. C. Comparison of camera angle perspectives from the 4.9 m tall pole. I captured most of the images with a low-angle perspective from the pole. The square targets are 0.3 x 0.3 m for scale.
vinyl targets with large, visible numbers. This is extremely helpful for georeferencing the SfM point clouds in the post-processing steps. For the most part, the vinyl control targets held up to the wind conditions without having to puncture the surface of the sandbar and could be used for an entire trip. As part of the random grid of targets (spaced approximately 10 m apart), I recommend placing a set of targets around the perimeter of the survey. This can be difficult at the water’s edge, where the water level is fluctuating and can move targets. But the accuracy assessment showed the water’s edge, especially with shallow, clear water, to have lower elevation discrepancies. Thus, if a few targets placed at the water’s edge move, they can be discarded. I also recommend placing additional targets around steep or rough topographic features on bare/visible sand (e.g. around cut bank or patch of vegetation) to anchor the estimated elevations around the features that contain higher elevation uncertainty. The high accuracy of the TS measurements determined the high accuracy of the SfM sandbar point clouds and DEMs.

B.3 Part 2: Image Processing

B.3.1 SfM Workflow: Image Preparation

Image Removal

To prepare for the alignment stage in Photoscan, blurry images and images out of context should be removed. If the images are not removed they can 1.) significantly slow down alignment and/or 2.) produce less accurate points, both of which you dont want. Ive found the image quality feature in Photoscan, that supposedly detects blurry images, is not robust enough to remove all the blurry images. Also, the image quality algorithm does not remove images out of context and additional sorting is still necessary. I go through each image in the preview pane in file explorer (to quickly view the image) and drag the blurry/out of context images into a removed folder in file explorer.

Image Decimation

Most of our imagery was collected using an intervalometer camera script. Convergent images were collected every second to every five seconds along transects. Overlap is one
Fig. B.2. Example of how GCP accuracy affects elevation uncertainty. A. Orthomosaic of site 123L with inset map. B. Elevation uncertainty derived from residual analysis with incorrectly positioned GCP. C. Elevation uncertainty derived from residual analysis with correctly positioned GCP. Incorrect GCP located in black circle in panes B. and C.
of the most crucial criteria for successful and accurate alignments. But too much overlap
and redundancy can be just as bad as a lack of image overlap; redundancy and dense
image configurations will result in strange alignment artifacts (e.g. extraneous points that
misrepresent the surface) that will require additional correction steps (which may or may
not work). I simply decimate the image set by using every other image. I've decimated
every third image with extremely large image sets of several thousands of images. I only
decimate the dataset if there is enough redundancy; if there are only a few hundred images
I do not decimate the image set.

Image Masks

Due to the large number of images, I was unable to create masks for each image. Ideally
and often practiced in the literature, you would want to block out anything that is not the
feature of interest. This takes hours, and unlike previous literature, we have hundreds of
thousands of images across multiple sites. Future development of automated masking, such
as morphological snake algorithms, is needed to facilitate masking of large image sets. If you
need to mask the same region of a set of images, create a mask in Photoscan and re-import
the mask for the set of images. I previously recommended collecting nadir images; nadir
images will reduce the time it takes to mask each image.

B.3.2 SfM Workflow: Agisoft Photoscan Software (Version 1.2.4 build 2399
64-bit)

The following workflow has been refined after hundreds of post-processing runs in
Photoscan with my sandbar imagery. I think this workflow produces the most accurate,
successful, operational alignments and point clouds for the imagery I collected. All computer
systems are different and will yield different alignment solutions in Photoscan. Therefore, I
advise testing multiple settings through all stages of the workflow in Photoscan with future
imagery. The following settings and steps worked best on my system with the T4i Rebel
DSLR and the D30 point and shoot cameras with few handheld images and mostly pole
imagery at 4.9 m elevation above the surface.
I was also after the most operational workflow, meaning which settings and steps provided the best reconstructions in the least time. I did not think it was operational to run 2,000 images on a high alignment and high dense point cloud settings to obtain a final point cloud with 6,000,000 points that requires days to run. To then take that point cloud and interpolate to a 1 m DEM. I found it more operational to generate a sparse point cloud of around 500,000 points, and come out with a dense point cloud of around 1,000,000 points (still high resolution). I also had more than 30 sites to process, and perhaps if you only had one site you may have the time to adopt the higher settings. But I've found so far that higher settings and more points do not equate to higher accuracy and/or precision in the final DEM.

**Import Images and Separate Cameras**

As for the project organization within Photocan, I process one site per Photoscan project. Although there are benefits to having multiple sites in a Photoscan project, the project file can become extremely large and corrupted more easily. Also, I save my Photoscan projects with the image folders used in the project. I keep everything together by the site and the trip that I collected data. If you move your imagery around to different folders, the links will break in your Photoscan project. Of course, after each major run I save my work to an external hard drive. Do not run more than one project at a time.

Within the Photoscan project itself, I create a chunk that I rename Low Alignment. I add all prepared images for the site. If there are images collected with different platforms (e.g. handheld and pole) I create two camera groups and separate the images into each group. I then set the calibration settings to recognize and calibrate the two different image sets as two different cameras. This calibration step will allow for more successful alignment as the two image sets vary in camera angle, height to feature, and/or lighting conditions to name a few. This step can help to avoid having to align the two image sets separately and then merge the two together.

**Low Alignment**

For image sets with greater than 1000 images, I use the low alignment setting, which
downsizes the pixels in the original imagery (2-3 hours post-processing time). For image sets with less than 1000 images, I use the medium alignment setting, which uses the actual size of the original image pixels (2-3 hours post-processing time). I use the disabled pair preselection setting that takes longer to run but identifies more key points. Under advanced settings, I use a key point limit of 10,000 points and a tie point limit of 0. The key points are points that are identified with a variation of the scale invariant feature transform algorithm (SIFT) that identifies robust points in each image. You can watch the console to see how many key points are identified in each image and adjust the value accordingly. The tie points are the points matched between all the key points. I want as many tie points as possible so I set it without a limit (0). If you created masks, make sure to check the constrain features by mask box in the advanced settings.

**Reset Cameras**

To be able to access the previous step, I duplicate the Low/Medium Alignment chunk, rename it Reset Cameras and work from it. The SfM literature fails to mention that the alignment stage (the most critical stage) in Photoscan often fails (i.e., not enough images align) or creates an incorrectly aligned point cloud. If the alignment fails, resulting in say less than 50% aligned images, there is most likely a problem with overlap. In other words, there are not enough images, or you need to increase your alignment settings to aim at generating more key points that can be matched to create tie points.

Incorrect alignments result in strange artifacts that look like planes of points coming out of the point cloud. To guide the software into generating a more correct solution, I reset incorrectly aligned cameras. To do this you can select the cameras that look like they are positioned incorrectly, or you can select the incorrectly aligned points themselves and reset cameras associated with those points.

**Realigned Cameras**

To be able to access the previous step, I duplicate the Reset Cameras chunk, rename it Realigned Cameras and work from it. After resetting incorrectly aligned cameras, I select those cameras with NA next to them and I realign them. I often select a handful at a
time to ensure they are correctly aligned. If any of the cameras result in incorrectly aligned points, I reset those cameras and realign.

**Realigned Cameras Optimized**

To be able to access the previous step, I duplicate the Realigned Cameras chunk, rename it Realigned Cameras Optimized and work from it. More than 80% of the cameras should be aligned at this point. Again, if your alignment falls below this, try using different point settings or adding more images if you have them. Under the reference tab, I optimize the camera calibration. The optimization corrects for multiple camera parameters including lens distortion.

**Manual Clip Optimized**

To be able to access the previous step, I duplicate the Realigned Cameras Optimized chunk, rename it Manual Clip Optimized and work from it. The area of interest with the most surface accuracy is going to be where the cameras are located. I clip my point cloud by drawing an outline around the cameras and clipping everything outside of that boundary. I then reoptimize the model.

**Reprojection Uncertainty Optimized**

To be able to access the previous step, I duplicate the Manual Clip Optimized chunk, rename it Reprojection Uncertainty Optimized and work from it. Even with what appears to be a successful alignment, there are points that create noise in the cloud. Ideally, you want those points removed before you georeference the model and generate a dense point cloud. To do so, I use the reprojection uncertainty gradual selection setting to select noisy points. I set the setting at level 20 and examine which points are selected. Level 20 selects around half of the points. If more points are removed, then some areas may be less represented. I've found this is a good level and that removing half of the sparse cloud still results in a dense cloud with at least 1,000,000 points if not more. With our image sets we often come out with a sparse point cloud that I would term dense, which results in a dense cloud post-processing nightmare that can take 48 hours or more to create. In other words, the program is designed to take a truly sparse cloud and turn it into a dense one, not a
dense cloud to a dense cloud. After I removed the noisy points, I optimize the point cloud.  

**Manual Clean Optimized**

To be able to access the previous step, I duplicate the Reprojection Uncertainty Optimized chunk, rename it Manual Clean Optimized and work from it. After using reprojection uncertainty, I manually remove any other points that are outside the feature of interest. For example, I will remove vegetation, people or boats once instead of masking each individual image at the beginning. After I remove the points, I optimize the point cloud.

**Georeference**

To be able to access the previous step, I duplicate the Manual Clean Optimized chunk, rename it Georeference and work from it. I import my ground control points from a .txt file with x, y, z, label fields into Photoscan. I set the coordinate system (e.g. ESPG 26949) and the marker accuracy. I select yes to all to create a coordinate/marker from each row of the .txt file. I look at the model and select the points around a GCP with the circle selection tool. I right click and select filter photos by points. I then go through each of the images and mark the center of the GCP. I only mark GCPs that are visibly clear, and I leave the rest untouched (the marker stays gray). I do this two more times for two additional GCPs. Then, I refresh the coordinates and an error value pops up (you need at least three GCPs). Also, all the other coordinates are visibly located on the model if they are checked in the reference pane. The other markers are now automatically placed but need to be adjusted. I now repeat the process for each additional GCP, making sure the GCP Im working with is selected in the reference pane. As you click through each image, the viewer will shift to where the GCP is you are currently marking. After marking each additional GCP, I update the error values.

**Georeference Optimized**

To be able to access the previous step, I duplicate the Georeference chunk, rename it Georeferenced Optimized and work from it. After georeferencing the model, I optimize the point cloud.

**Lowest Dense Point Cloud**
To be able to access the previous step, I duplicate the Georeference Optimized chunk, rename it Lowest Dense Point Cloud and work from it. As I mentioned previously, the image sets we collected resulted in sparse point clouds with higher point counts. This may not be the case with your data. I used the lowest dense point cloud setting because our sparse point clouds were already dense and mild depth filtering. This results in at least a dense cloud of 1,000,000 points that takes around an hour to run.

B.4 Post SfM Processing (DEM Generation)

After generating the dense point clouds, I exported the XYZ and RGB values from Photoscan as a .txt file to clean the point clouds. Although I saved time by not masking individual images in Photoscan, more time was spent filtering additional noise from the exported dense point clouds. I used a python script to filter some of the dense points by color. Ultimately, the most effective cleaning method was to manually remove points in CloudCompare. I removed noisy edges of the surveys (e.g. deep, turbid water), and I only included points along the edges in shallowly inundated areas with clear water. I was unable to visually remove all surface roughness, and therefore surface roughness persists in the dense point clouds (e.g. low-lying vegetation on steep bank).

As I needed to quickly generate multiple SfM DEMs and DEM products (e.g. slope and roughness rasters) from dense SfM point clouds to quantify DEM uncertainty, I used ToPCAT (Brasington et al., 2012; Javernick et al., 2014; Smith and Vericat, 2015) and a custom python script to batch decimate the SfM point clouds and generate SfM DEMs, respectively. I decimated each cleaned, dense point cloud with ToPCAT using a 10 cm moving window with a minimum of four points per window (Passalacqua et al., 2015) to calculate the minimum elevation (i.e. $Z_{\text{min}}$; Brasington et al., 2012; Javernick et al., 2014)). After examining the results of a 10 cm, 50 cm, and 1 m ToPCAT window size, I determined that the 10 cm moving window size was best for preserving the variability in topography, while maintaining reasonable post-processing times. I then used the $Z_{\text{min}}$ SfM point cloud from ToPCAT as an input into the python script that batch generates SfM DEMs with any specified grid resolution and extent. I used a 10 cm resolution for the SfM DEMs because
the high $Z_{\text{min}}$ SfM point cloud density supported this resolution (Passalacqua et al., 2015). Although other interpolation techniques (e.g. triangular irregular network: TIN) have been used to generate SfM DEMs (e.g. Javernick et al., 2014), I used a nearest neighbor method because a.) I could not implement a batch TIN script and b.) the point density is high enough in the $Z_{\text{min}}$ SfM point clouds to directly convert from $Z_{\text{min}}$ point cloud elevations to grid node elevations in the DEM. To average/ smooth out the SfM DEM elevation estimates to provide a more representative DEM, I also used inverse distance weighting, where the weight = $1.0 / \text{distance}^2$, to average up to 100 $Z_{\text{min}}$ SfM point cloud estimates per grid node. The nearest neighbor, inverse distance weighting method alone did not introduce high interpolation error going directly from the $Z_{\text{min}}$ SfM point cloud to the SfM DEM. However, I did interpolate up to 2 m across the holes in each SfM DEM that were caused from cleaning the cloud. For example, in areas (<2 m wide) where I manually removed equipment that protruded from the ground in the SfM point cloud, I interpolated over the hole up to 2 m with the elevation value of the nearest neighbor because I was confident the elevation remained constant across the hole. I assigned nodata values to areas with large holes (e.g. areas of dense vegetation) in the SfM DEMs.

B.5 Protocol Summary

I’ve presented several modifications to my original field and post-processing workflow. Namely, the collection of images with a camera mount that accommodates nadir imagery without the pole in the image frame. Also, the collection of the nadir imagery at a much slower walking rate with no repeated transects. I also strongly recommend against taking imagery that contains dark shadows with unresolvable pixels. These image acquisition modifications will guarantee better image alignments in Photoscan and significantly reduce post-processing times. When post-processing imagery, image sorting and decimation can save time and will result in more successful image alignments. Medium resolution settings in Photoscan are a good tradeoff between post-processing time and point resolution. Although the lowest settings take less time to process, they result in less accurate point clouds. The original ground control distribution worked because of the well-established TS ground
control network. If using the SfM method for geomorphic change with densely vegetated areas, supplemental TS measurements are needed to fill in SfM data gaps.
APPENDIX C
MEMORANDUM

To: Glen Canyon Dam Adaptive Management Work Group
From: Rebecca Rossi
Subject: Monitoring Topographic Sandbar Change in Marble and Grand Canyons Using ‘Structure-from-Motion’ Photogrammetry

The historical and current monitoring of alluvial sandbar topography in Marble and Grand Canyons has advanced the understanding of sandbar behavior in response to normal (e.g. hydropeaking) and experimental (e.g. high flow experiment: HFE) operations of Glen Canyon Dam (Howard, 1975; Schmidt and Graf, 1990). The closure of Glen Canyon Dam in 1963 eliminated the downstream sediment supply, negatively impacting sandbar building and dramatically altering the flow regime by increasing base flows and the range of daily fluctuations in addition to decreasing peak flows. Starting in the early 1970s, repeat topographic sandbar measurements were made along cross-sections at 20 sandbar sites (Beus et al., 1985). These repeat topographic measurements along with quantitative evaluations of sandbars directly before and after the 1983-1984 flood were used in a decadal sandbar change analysis (Beus et al., 1985). From this analysis, Beus et al. (1985) recognized the sandbar building capabilities of the 1983-1984 flood with sufficient riverbed sand. Using repeat aerial imagery, Schmidt and Graf (1990) identified patterns in sandbar aggradation and degradation from before and after the 1983 flood. A time-lapse camera system was installed in 1990 at representative sandbar deposit types (Schmidt and Graf, 1990, i.e. reattachment, separation, margin;) to capture repeat images of rapid erosional events that were not capable of being topographically measured and to quantify rates of change in sandbar width and area. In 1996, the first HFE was released from Glen Canyon Dam as part of a resource management strategy to rebuild sandbars in Marble and Grand Canyons (Hazel et al., 1999; Melis, 2011). To detect changes in sandbar volume and area in response to HFEs, the Grand Canyon Monitoring Research Center (GCMRC) and Northern Arizona University (NAU) perform an annual topographic survey of sandbars at 45 monitoring sites.
along the Colorado River in Marble and Grand Canyons (Figure C.2; Hazel Jr. et al., 2008).

‘Structure-from-Motion’ photogrammetry (SfM) has recently become a popular, high resolution topographic (HRT) tool used for accurately mapping topographic features (Javernick et al., 2014; Mancini et al., 2013; Micheletti et al., 2015; Nouwakpo et al., 2016; Piermattei et al., 2015; Prosdocimi et al., 2015; Woodget et al., 2015; Carrivick et al., 2016), hydrodynamic analysis (Javernick et al., 2014; Smith et al., 2014; Westoby et al., 2014), and monitoring (Clapuyt et al., 2016; Dietrich, 2016b; Fonstad et al., 2013; Gómez-Gutiérrez et al., 2014; James and Robson, 2012; Lucieer et al., 2013; Smith and Vericat, 2015; Turner et al., 2015; Westoby et al., 2012). The SfM method is based upon traditional photogrammetry and consists of a field component in which overlapping images are collected from multiple camera perspectives without exact knowledge of camera parameters. The images are then post-processed with SfM and multi-view stereo algorithms, which automatically resolve camera parameters and orientations of the overlapping images, producing a 3D, topographic model (Figure C.3; for reviews of SfM applications in geomorphology, survey techniques, algorithms, and software see A.1; Smith et al., 2016; Bartoš et al., 2014; Fonstad et al., 2013; James and Robson, 2012; Gomez et al., 2016; Carrivick et al., 2016). SfM techniques encourage faster, cheaper, and more accessible methods for accurately reconstructing 3D topography from overlapping images with consumer-grade cameras (James and Robson, 2012; Westoby et al., 2012; Fonstad et al., 2013). Fonstad et al. (2013) and Westoby et al. (2012) have promoted SfM as the democratization of high-resolution topographic (HRT) data acquisition (Figure C.4).

Given the recent appeal of SfM as a potentially cheap, fast, accurate and simple method to monitor topographic features, the Grand Canyon Monitoring and Research Center (GCMRC) was interested in exploring its feasibility and developing a field survey and data post-processing protocol. The complimentary implementation of the SfM method could also provide a larger sandbar sample size. A 3-year project was funded by GCMRC in partnership with Utah State University to answer the following questions:
1.) Does the SfM method work to monitor sandbars (cell by cell topographic change) in Marble and Grand Canyons?

2.) If the SfM method works, is it feasible to extend the sandbar monitoring network with the SfM method?

3.) How does the SfM method compare to the traditional topographic survey? In other words, is the SfM method a cheaper, faster, and easier method according to recent finds in the scientific literature?

4.) If the method works, can it be used by citizen scientists to collect additional topographic data on river trips?

To answer these questions, I collected data with both the SfM method and the traditional TS method. Due to permitting restrictions, an unmanned aerial vehicle could not be flown in Grand Canyon. As such, I used a 4.9 m tall pole-mounted camera platform (Figure C.1) to collect overlapping images for 30 SfM surveys at 13 sandbar sites (Figure C.2) with variable sandbar size and surface conditions (i.e. vegetation and slope; Figure C.5). I collected data on two sandbar monitoring trips (2014 and 2015) to determine if the SfM method was a tractable method for determining cell by cell (1 m resolution) topographic change. This type of topographic change detection also required accounting for elevation uncertainty and propagating error estimates through time. I processed the images in the lab to obtain topographic sandbar surfaces. The traditional survey consisted of collecting individual point measurements on the surface of the sandbar with a total station instrument that has high accuracy 0.05 horizontal/vertical accuracy; Hazel Jr. et al. (2008). The center of 10 to 30 square targets were also surveyed with the total station to establish control for the SfM surveys.

I performed an accuracy assessment, where I differenced the values of the SfM elevation estimates with those of the traditional total station measurements. The accuracy assessment proves that the SfM method is a tractable method in certain areas of the sandbar. Those areas are bare and exposed sand with low to high surface gradients. The SfM method works in areas with vegetation at low to medium heights, but the elevation uncertainty increases
in these areas because the SfM method is unable to penetrate through the vegetation to obtain an elevation of the bare exposed surface. After quantifying elevation uncertainty for the 30 SfM sandbar surveys, I grouped the elevation uncertainty values by general surface cover types (Figure C.6). I used the value of 0.12 m as an acceptable uncertainty value for monitoring topographic sandbar change. From this plot, 62% of the 13 example sites which used the SfM method have acceptable amounts of elevation uncertainty to quantify cell by cell geomorphic change. The results suggest that the SfM method is a tractable method to extend to many other flat, bare sites to increase the sandbar sample size. But the SfM method is not tractable to extend to densely vegetated sites. As the upper portions of sandbars become topographically stable, the sandbar survey will also focus on the portions of the bar that are actively reworked and often bare sand where the SfM method works.

The SfM method turned out not to a cheaper, faster, and easier method compared to the TS survey for monitoring sandbar change. For other sandbar monitoring applications, such as wind-blown sediment studies, the high resolution of the SfM method may be more justified. To calculate cell by cell sandbar change, the TS and SfM surveys must be georeferenced to the Earth’s surface. This process requires the TS to survey ground control points for the SfM method. Therefore, both methods require the full TS setup, resulting in similar costs for both methods. A smaller crew could go out and survey sandbars with SfM (lower the survey cost), but they need a TS setup to acquire ground control for the SfM method. The SfM survey was faster than the TS survey at smaller bars, but again the ground control targets take time to survey for the SfM method. Also the image post-processing and high resolution products require expert knowledge of the software and an abundant amount of time (weeks to months) to process. Carrying the 4.9 m tall pole may have been harder for the surveyor to support while walking transects. Also, the surveyor collecting TS points can penetrate through the densely vegetated areas to fill in gaps in the sandbar topography. Even though data collection is easy and straight forward for the SfM method, citizen scientists need a total station and experienced surveyor to collect sandbar imagery for cell-by-cell topographic sandbar change.
RECOMMENDATIONS

1.) Use the SfM method to obtain topography of areas with bare sand, gravel, clay, and silt. Also if the sandbar sample size is expanded, sites that are bare and flat should be selected. Use the TS method to collect more measurements on the perimeter of the sandbar sites where there is more vegetation. Use the TS method for offshore points.

2.) The use of hard points as elevation control for the SfM method should be investigated. Hard points (e.g. boulders) are immobile elevation measurements that could be used as ground control. Hard points have limitations. For example, there are often fewer hard points near the active portion of sandbars. But, if hard point can provide some elevation control, then the TS is no longer a critical component and the SfM method. Therefore, citizen scientists can easily collect imagery without a paid surveyor.

SUMMARY

1.) Does the SfM method work to monitor sandbars (cell by cell topographic change) in Marble and Grand Canyons?

Yes. But the SfM method fails to capture in-channel/wet areas and struggles in vegetated areas.

2.) If the SfM method works, is it feasible to extend the sandbar monitoring network with the SfM method?

At this stage, while extending the sandbar monitoring network with the SfM method may be feasible, the SfM method does not appear cost effective and the traditional total station surveys are simpler, cheaper and more reliable.

3.) How does the SfM method compare to the traditional topographic survey? In other words, is the SfM method a cheaper, faster, and easier method according to recent finds in the scientific literature?

The SfM method compares favorably to the traditional total station survey where it works. However, the SfM method provides incomplete coverage of sites and really only speeds things up where the total station is already quick.
4.) If the method works, can it be used by citizen scientists to collect additional topographic data on river trips?

No. Too much expertise is required to make good use of the SfM-derived data. While SfM could be done from citizen science photographs, it would require exhaustive amounts of post-processing to produce an unideal output and therefore the SfM method is not work pursuing for producing a comparable product to the traditional total station surveys.
Fig. C.1. The pole-mounted camera platform setup that I used to collect images. A. The 4.9 m tall, pole platform with camera mount that I used to acquire the majority of sandbar images. B. Surveyor collecting images of a sandbar with the pole-mounted camera platform setup in Marble Canyon. C. Comparison of camera angle perspectives from the 4.9 m tall pole. I captured most of the images with a low-angle perspective from the pole. The square targets are 0.3 x 0.3 m for scale.
Fig. C.2. Map of the 45 sandbar monitoring sites and the 13 sandbar sites that I used to answer the questions in this memo (RKM are approximate locations). Figure contains a 10 m DEM basemap from GCMRC and is modified from (Hazel et al., 2010).

Fig. C.4. Example of the democratization of high resolution topography with the SfM method. Each colored point represents an XYZ data point of the River Cinca in Spain. https://www.youtube.com/watch?v=2Kd_fA-dLig.
Fig. C.5. Examples of typical sandbar site conditions from a variety of perspectives. Sites are named by river kilometer, and the site location on the left (L) or right (R) side of the river (oriented in the direction of channel flow). A, C, E, and G: Site view of sandbar sites 48R, 113R, 146R, and 343L. B, D, F, and H: view from the 4.9 m tall, pole-mounted camera platform used in this study of the same sites.
Fig. C.6. Elevation uncertainty grouped by general surface cover types. The plot shows acceptable amounts of elevation uncertainty for sandbar monitoring. Areas of sites with elevation uncertainty above the 0.12 m acceptance criteria line signify the SfM method is not tractable for quantifying cell by cell topographic sandbar change.