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From experimental plots to experimental landscapes: topography, erosion and deposition in sub-humid badlands from Structure-from-Motion photogrammetry

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Abstract

In the last decade advances in surveying technology have opened up the possibility of representing topography and monitoring surface changes over experimental plots (<10 m^2) in high resolution (~10^3 points m^{-1}). Yet the representativeness of these small plots is limited. With 'Structure-from-Motion' (SfM) and 'Multi-View Stereo' (MVS) techniques now becoming part of the geomorphologist's toolkit, there is potential to expand further the scale at which we characterise topography and monitor geomorphic change morphometrically. Moving beyond previous plot-scale work using Terrestrial Laser Scanning (TLS) surveys, this paper validates robustly a number of SfM-MVS surveys against total station and extensive TLS data at three nested scales: plots (<30 m^2) within a small catchment (4710 m^2) within an eroding marl badland landscape (~1 km^2). SfM surveys from a number of platforms are evaluated based on: (i) topography; (ii) sub-grid roughness; (iii) change-detection capabilities at an annual scale. Oblique ground-based images can provide a high-quality surface equivalent to TLS at the plot scale, but become unreliable over larger areas of complex terrain. Degradation of surface quality with range is observed clearly for SfM models derived from aerial imagery. The modelling findings of James and Robson (2014) are proven empirically as a piloted gyrocopter survey at 50 m altitude with convergent off-nadir imagery provided higher quality data than an UAV flying at the same height and collecting vertical imagery. For soil erosion monitoring, SfM can provide comparable data to TLS only from small survey ranges (~ 5 m) and is best limited to survey ranges of ~10-20 m. Synthesis of these results with existing validation studies shows a clear degradation of root-mean squared error (RMSE) with survey range, with a median ratio between RMSE and survey range of 1:639, and highlights the effect of the validation method (e.g. point-cloud or raster-based) on the estimated quality.

Keywords: badlands; terrestrial laser scanning (TLS); Structure from Motion (SfM); topographic survey; sediment budget.

1. Rationale

Badlands can be described as well-dissected areas of unconsolidated sediment with sparse or absent vegetation that are unable to support agriculture (i.e. Bryan and Yair, 1982). These highly erodible landscapes make disproportionate contributions to catchment scale sediment budgets (e.g. García-Ruiz et al., 2008; López-Tarazón et al., 2012), control downstream processes in river-channels (e.g. Buendia et al., 2013) and, ultimately, can cause negative consequences to downstream infrastructure (e.g. reservoir siltation; Avendaño et al., 2000). Erosion risk maps and models (e.g. PESERA; Kirkby et al., 2004) can provide a broad-scale assessment of soil erosion rates, but any such models require calibration and validation using observed soil erosion rates under different environments (e.g. climatic conditions) and over representative (large) spatial scales (e.g. catchment scale). New techniques of topographic data acquisition have the potential to deliver this data. This study validates topographic data derived from Structure from Motion photogrammetry at three nested scales to assess the scale at which it can be applied in studies of soil erosion.

1.1. Measuring erosion in dynamic landscapes

A number of different methods of measuring and monitoring erosion exist. Erosion pins are used commonly to measure the erosion and deposition directly through observed changes in surface level at a given point (e.g. Clarke and Rendell, 2006; Della Seta et al., 2009; Francke, 2009). Despite the observed spatial variability in badland erosion rates (e.g. Kuhn and Yair, 2004; Solé-Benet et al., 1997), the point measurements are typically interpolated, but only over relatively small areas. Over similar-sized areas (up to ~10 m downslope length), bounded plots with sediment collectors catch exported sediment directly (e.g. Lázaro et al., 2008). Again, extrapolation of such plots is problematic (see Boardman, 2006; Boix-Fayos et al., 2006), collectors can fill up rapidly in highly erodible landscapes (Vericat et al., 2014), and data integrate all upslope processes at a single point. Sediment flux is often measured at gauging stations through continuous turbidity records (e.g. Cantón et al., 2001; Mathys et al., 2003) and at larger spatial and temporal scales still, repeat bathymetric surveys of reservoirs or check dams can provide estimates of sediment yield (e.g. de Vente et al., 2005; Batalla and Vericat, 2011). This indirect morphometric approach can also be applied to eroding surfaces at multiple spatial and temporal scales. Repeat topographic surveys have been used to measure soil loss volumes both at plot scales using microprofile meters (e.g. Descroix and Claude, 2002; Sirvent et al., 1997) and at large scales using Terrestrial Laser Scanning (TLS) (e.g. Vericat et al., 2014) or even larger by means of aerial photogrammetry (e.g. Ciccacci et al., 2008).

Each technique has different strengths and weaknesses, and each one may measure the result of different processes. Discrepancies between these methods have been noted previously (Poesen and Hooke, 1997). Nadal-Romero et al. (2011, 2014) compile sediment yield measurements over 87 study sites of eroding Mediterranean badlands and found statistically significant differences in sediment yield measurements obtained from different methods. Yet since no single method covers all spatial scales it is possible that the reported differences in sediment yield between methods actually reflect the different processes that operate at different catchment sizes. At larger scales, footslopes and concavities and other sediment sinks become incorporated into the study area. Sediment connectivity becomes an important factor as the entire range of catchment processes is studied rather than just interrill erosion (Faulkner, 2008; Godfrey et al., 2008; Bracken et al., 2014).

Clarification of such scale dependencies requires the application of a single method of monitoring erosion over a wide range of spatial and temporal scales. A substantial advantage of the morphometric method (i.e. comparing topographic models obtained at different periods) is that sub-catchments, discrete areas, or even single grid cells of a large study area can be isolated and examined at no extra field cost. Airborne LiDAR has been already applied to examine the topographic structure of badland areas (Bretar et al., 2009; Lopez-Saez et al., 2011; Thommeret et al., 2010), while Vericat et al. (2014) recently presented the use of TLS to produce a fully distributed morphometric sediment budget of a small (36 m^2) eroding badland area.

The challenge of using topographic survey techniques for erosion monitoring is to design and apply a methodology that provides meaningful and high-quality data over a range of spatial scales. Structure-from-Motion with Multi-View Stereo (SfM-MVS) offers a potential solution to the problem of acquiring such high resolution topographic data over a wide range of scales; however, validation of this technique at multiple scales is in its infancy.

1.2. Validation of Structure-from-Motion

Using a number of standard camera images of a single scene, Structure-from-Motion (SfM) can reconstruct simultaneously camera pose, scene geometry and internal camera parameters. Full details of different steps of the SfM-MVS workflow can be found in Lowe (2004), Snavely et al. (2008), Furukawa and Ponce, (2010) and James and Robson (2012). In short, features in each image are identified and matched. A bundle adjustment algorithm is used to produce jointly optimal estimates of 3D structure and viewing parameters (Triggs et al., 2000). This SfM sparse point cloud has been used as an end point in itself (e.g. Fonstad et al., 2013). However, SfM is often paired with multi-view stereo (MVS) which use the known camera locations to reconstruct a denser point cloud (see Furukawa and Ponce, 2010). Finally, the resultant dense point cloud must be given a scale and georeferenced using ground control points visible in images or point clouds. All

SfM-derived data products herein are technically SfM-MVS data, though, following the emerging convention, simply ‘SfM’ is also used as shorthand.

In combination, SfM-MVS provides high-resolution topographic data which, in recent years, has been applied and tested in a range of geomorphological settings including volcanic bomb hand samples (e.g. James and Robson, 2012), agricultural fields (e.g. Ouédraogo et al., 2014; Eltner et al., 2014), eroded gullies (e.g. Castillo et al., 2012; Frankl et al., 2015), exposed bars of braided rivers (e.g. Javernick et al., 2014), high water marks of recently flooded ephemeral rivers (e.g. Smith et al., 2014), submerged gravel bed rivers (e.g. Woodget et al., 2014), eroding cliffs (e.g. James and Quinton, 2013), alluvial fans (e.g. Micheletti et al., 2014), lava flows (e.g. Tuffen et al., 2013), glacial moraines (e.g. Westoby et al., 2012; Tonkin et al., 2014), landslide displacements (e.g. Lucieer et al., 2013), and volcanic craters (e.g. James and Varley, 2012).

Sub-grid data products extracted from point clouds are utilised increasingly in geomorphology (see Smith, 2014 for a review). Moreover, topographic change detection protocols, as described by Wheaton et al. (2010), utilise sub-grid roughness as an error term to determine the minimum level of detection of topographic changes estimated by differencing digital elevation models (DEMs) obtained at different periods. Thus, a thorough validation of the capability of SfM-MVS surveys to replace existing survey methods requires a detailed analysis of the precision of this approach at the scale required for a particular application.

Errors in SfM-MVS surveys are related to a number of factors, including the camera used (Micheletti et al., 2014), number and resolution of images acquired, distribution of perspectives in those images (James and Robson, 2014), processing software (particularly the number of parameters used in the camera model; James and Robson, 2012; Ouédraogo et al., 2014) and the distribution and quality of ground control points used for georeferencing (James and Robson, 2012). However, although the source of error is variable, it appears that the range at which the pictures are acquired is a particularly important factor in determining the resultant errors, with sub-m range surveys (i.e. <10^0 mm/pixel photography) exhibiting sub-mm errors and km-range surveys (i.e. > 10^1 mm/pixel) exhibiting m-scale errors. Clearly, the survey range achievable logistically is controlled by the spatial coverage of the surveys.

Overall, SfM has substantial potential to revolutionise the acquisition and accessibility of high resolution topographic data, potentially permitting the study of erosion rates over a range of spatial scales with a single technique. With a nested survey design and three scales of enquiry, ranging from experimental plots to experimental landscapes, this paper makes a substantial contribution to the validation of this approach. The aim of this study is to provide a detailed examination of the ability of SfM-MVS to represent topography and roughness and to detect reliably small topographic changes in a complex badland setting. To achieve this, the most extensive and detailed repeat TLS survey of an eroding badland conducted to date is used as a reference dataset.

Four specific objectives achieve this aim:

(1) To provide a robust validation of the capability of SfM-MVS as a high resolution topographic survey technique through quantitative analysis of standard derived topographic data products including (a) topography (DEMs); (b) sub-grid surface roughness; and (c) distributed topographic changes (erosion and deposition, i.e. sediment budgets);
(2) To examine the effect of survey range and extent on the results of (1);
(3) To examine the effect of the type of validation dataset on the results of (1);
(4) To integrate these findings with those of existing SfM-MVS validation studies to elucidate the scale-effects limiting the accuracy of SfM-MVS surveys.

The paper is structured as follows: the experimental badland is described in section 2. Field data collection is described in section 3.1. The post-processing steps are then described in section 3.2. Validation of topography is presented both for point-based total station data (section 4.2) and TLS-based DEMs (section 4.3). The latter is then used as a benchmark dataset against which to test the ability of SfM-MVS to represent sub-grid roughness (section 4.4) and topographic change (section 4.5). Finally, a synthesis of these results with those of recent SfM-MVS validation studies is presented in section 5.

2. Study Area

Eroding badlands provide an appropriate location validation of a topographic survey technique due to the complexity of their surfaces (e.g. slopes, aspect, dissection) and the variability of surface deformation rates (e.g. rill formation, head-cutting, deposition). A series of highly erodible badlands located at the Upper River Cinca (Central Pyrenees, Iberian Peninsula, Ebro Basin) were chosen for this study (Figure 1). The badlands are located at an average altitude of 600 m.a.s.l. and the local relief can be more than 15 m. The site has a Continental climate with an annual rainfall around 700 mm. Maximum rainfall is observed during spring and autumn. The average temperature is 11℃. Temperatures below freezing are often registered in winter when freeze-thaw is a fundamental process controlling the erosion and transfer of sediment.

The selected badlands present steep slopes (near vertical in places) and a high degree of dissection. The presence of vegetation is limited: isolated shrubs are observed in gentle slopes while boxwoods and relatively young pines are present on low gradient upper surfaces (Figure 1C). The badlands are composed of highly erodible Eocene marls and sandstones. A sequence of marls with different degree of compactness is observed. Therefore, erosional processes are hypothesized to be highly complex and spatially variable. The study is focused in three embedded scales as can be seen in Figure 1: (i) plots (5 in total and between 8 and 30 m^2) located within (ii) a small catchment (4710 m^2) (Figure 1C) which in turn is located within (iii) a larger landscape-scale (~1 km^2; Figure 1B).

The study landscape is rapidly eroding relative to other hillslopes in the area; however, the magnitude of the topographic change observed is small in comparison with that reported in gravel bed rivers or in areas subjected to landslides, for which morphometric sediment budgets are typically calculated. Therefore, the relatively low magnitude of the surface change represents a deliberately challenging test for SfM-MVS.

3. Methods

3.1. Field Data Collection

Two field campaigns were undertaken with an 11 month survey interval. The first survey took place over the 27th and 28th June 2013. The second took place over the 27th and 28th May 2014. A summary of the main methods used at each scale of enquiry is provided in Table 1. Two main data sets were obtained: (a) a series of photographs to derive point clouds by means of SfM; and (b) a series of validation data sets based on Terrestrial Laser Scanning and Total Station (TS) surveys. Details of the methods applied to obtain the data are provided in the following sections.

3.1.1. SfM-MVS image acquisition

To quantify robustly the typical errors observed with SfM, a number of separate image sets were acquired from different platforms and at different altitudes (Table 1). A number of sources of error can be identified for SfM-MVS including the number of images used and their overlap, errors associated with processing (software and algorithms), imaging geometry, the characteristics of the camera used and the quality of the lens model. However, the focus herein is on the effect of survey range (i.e. altitude from where the pictures are taken); a fundamental issue for assessing the broader applicability of SfM in geomorphology since it determines indirectly the maximum capability of survey coverage and data resolution (i.e. closer-range images cover smaller areas for a given camera). The errors associated with range will determine the appropriate scales at which SfM can be deployed to investigate scale-dependent processes and, consequently, address geomorphological questions.

In 2013 two sets of ~350 images were taken (Table 1) at the small-catchment scale (Figure 1C). The first was ground-based, utilising only oblique photographs taken from around the perimeter and hillcrests of the badland. Ground-based surveys are referred to as ‘Oblique’ surveys in the results. A Panasonic DMC-TZ65 (focal length 4 mm which is a 35-mm equivalent of 25 mm; 10 Mpx) was used in this campaign. The second sequence of pictures was taken aerially from a UAV; a remote controlled hexacopter DJI F550. In this case, a Ricoh CX5 (focal length 5 mm which is a 35-mm equivalent of 28 mm; 10 Mpx) camera was suspended from underneath the UAV with a vertical viewing angle. These two cameras are very similar; the key difference was that the Ricoh camera had an intervolemeter. The mean flying height was 47 m above ground. The camera was set up to take a picture every 5 seconds (interval timer, auto shooting). This survey is referred to as the ‘UAV’ survey in the results.

In 2014 a different set of images was obtained for each of the three study scales: plot, small-catchment and landscape. Five plots were imaged from the ground at around 5 m range (between 25 and 33 oblique images taken by hand). The same Panasonic DMC-TZ65 was used for this image set. Four independent sets of images were obtained at the small catchment scale (Table 1). First, the oblique survey of 2013 was repeated taking imagery along exactly the same route and using the same camera as in 2013. In addition, three aerial surveys were conducted at different altitudes. Images were taken from on-board a piloted AutoGiro (or gyrocopter). Off-vertical images were taken to avoid the doming effect described in James and Robson (2014). Flight paths were a sequence of parallel flight strips (previously designed based on flight altitude and camera specifications) spaced ~70 m apart, with ~3 additional perpendicular strips added to maximise the coverage and overlap between pictures. Images in a flight strip were ~ 10 m apart. Target flying heights of 50 m, 150 m and 250 m were designed for the three surveys; however, owing to the topographic variability of the ground, each survey contained a range of viewing heights. Final mean flying heights were 70 m (SD = 16 m), 170 m (SD = 25 m) and 270 m (SD = 19 m) respectively. Finally, to obtain the images required for the landscape scale study, the two AutoGiro flights at 150 m and 250 m above the ground were extended to cover an area of around 1 km x 1 km (Figure 1B). The 50 m altitude AG survey resulted in 149 images of the small catchment while the 150 m and 250 m altitude AG surveys of the 1 km^2 area resulted in 527 and 138 images respectively. With the camera operator taking images manually, a heavier camera could be used than from the

UAV; however, previous camera intercomparison experiments (Thoeni et al., 2014; Micheletti et al., 2014) show little difference between compact cameras and DSLRs. All images taken from the AutoGiro were obtained by means of a Nikon D310 SLR (focal length 55 mm which is a 35-mm equivalent of 25 mm; 14 Mpx). The improved image resolution of the Nikon was considered necessary to support the 250 m altitude surveys and locate GCPs. These surveys are referred to as 'AutoGiro' (AG) surveys in the results and the altitude of each is also stated to distinguish the data sets (e.g. AG 250 m).

A primary control network based on 4 benchmarks was established. Coordinates were obtained by means of a Leica Viva GS15 GNSS base station and post-processed using Rinex data from 5 stations of the Spanish National Geographic Institute (IGN) and the Spatial Data Infrastructure of Aragon (SITAR). The data quality of the coordinates of the benchmarks (3d quality) was, on average, 0.006 m, with a standard deviation of 0.0017 m. This primary network was used to register all surveys conducted in 2013 and 2014 to the same coordinate system.

Three different secondary networks of Ground Control Points (GCPs) were set up in relation to the scale of the study. Five 200 x 200 mm red targets with a central 50-mm diameter disk-mark were used for the plot scale and surveyed by means of a Total Station (TS). For the small-catchment scale, in both 2013 and 2014, a network of 30 GCPs was surveyed with a Leica Viva GS15 RTK-GPS. In this case, black 1 m x 1 m targets with a yellow cross were laid in a grid over the full catchment, similar to those used by Vericat et al. (2009) and Westoby et al. (2012). A local GPS base was set up at one of the benchmarks transmitting corrections to the RTK-Rover system. Small catchment GCPs were surveyed with 3d qualities between 0.009 and 0.014 m. Finally, at the landscape scale, the 200 x 200 mm red targets were used. The size and colour of the targets were chosen based on an experiment to determine the minimum target size that could be resolved using the Nikon D3100 camera from 250 m above the ground. A total of 80 GCPs were placed throughout the 1 km^2 badland area and surveyed with a Leica Viva GS15 RTK-GPS (3d qualities < 0.05 m).

3.1.2. Validation Datasets

Validation datasets were based on TLS and TS topographic surveys. A Leica ScanStation C10 TLS was used to provide high resolution topographic data across the field site in both 2013 and 2014. The C10 uses a 532-nm pulsed laser with stated precisions of 6 mm for position, 4 mm for distance, and 60 μrad for angles (one standard deviation; Leica Geosystems, 2011). The maximum data acquisition rate is 50000 points per second while the maximum survey range is 300 m. Although the reported minimum point spacing is < 1 mm, the laser point spread function is 4 mm over a range of up to 50 m. The small catchment area was surveyed from 12 different stations to minimise and eliminate gaps caused by occlusion. For consistency, survey markers were placed at each station to ensure that the same locations were used for the TLS surveys in each year. Plots were also surveyed and were positioned close to TLS stations. A target-based registration was performed using a floating network of tripod-mounted Leica targets (i.e. 6" circular tilt and turn blue/white targets). This floating network was registered using the primary control network described above. The coordinates of the targets were obtained by means of a reflectorless Leica TPS1200 Total Station. All TS surveys were performed by averaging 10 consecutive measurements with standard deviations always < 0.004 mm. The mean absolute scan registration errors were 3 mm and 2 mm in 2013 and 2014 respectively. All topographic data were georeferenced to a geographic coordinate system (ED50 UTM31N) using the primary control network.

The 2014 TLS dataset is used to validate SfM-MVS surveys, conducted concurrently. In addition, as an independent dataset to provide an additional validation, 515 points within the small catchment and 215 across the landscape-scale area were also surveyed with the reflectorless TS. Errors on the TS surveys were in the sub-centimetre range.

3.1.3. Validation metrics

Differences between SfM-derived topographic data and the validation datasets were investigated using the following metrics: (i) mean error (ME); (ii) mean absolute error (MAE); (iii) root mean squared error (RMSE); and (iv) standard deviation of error (SD).

3.2. Post-Processing

3.2.1. Obtaining SfM and TLS-based point clouds

Photographs were inspected manually and any blurred images were deleted. The remaining photographs were imported into Agisoft Photoscan Professional 1.0.4. This software package identifies keypoints using an algorithm based on the Scale Invariant Feature Transform (SIFT) object recognition system outlined in Lowe (2004). Once the SfM process was complete, estimated camera positions were inspected for misalignment and any misaligned images were removed. Such images typically resulted from insufficient overlap with other photographs, from objects that were not static during the image acquisition (e.g. vegetation, moving shadows), or from approximations in the keypoint matching process. GCPs were then identified in the image set and their GPS coordinates were imported. A linear similarity transformation was performed to scale and georeference the point clouds and the transformation was then optimised; a process where camera parameters and 3D points are adjusted to minimize the sum of the reprojection error and the georeferencing error (Agisoft, 2012; Javernick et al., 2014). A MVS dense reconstruction was then performed to produce the final SfM-MVS point clouds.

TLS point clouds obtained from the 12 stations were registered using Leica Cyclone 8.0. Both TLS and SfM point clouds were cropped to include only the area of interest. Specifically, at the plot scale, surveyed areas were limited to mostly bare soil, but any small shrubs were removed manually. At the small catchment scale, large trees and shrubs were also removed from the point clouds manually. In addition, a mosaicked orthophoto of the small catchment was derived from the AutoGiro flight at 50 m altitude. This orthophoto was extracted by means of Agisoft Photoscan Professional 1.0.4 after scaling and georeferencing. From this orthophoto (Figure 1C), polygons were defined manually to mask out areas of vegetation which were excluded from analysis. At the landscape scale, no such data cleaning took place as the TS validation was limited to bare areas and, consequently, was unaffected by vegetation.

3.2.2. Extracting ground surface and sub-grid topographic statistics

The open-source topographic point cloud analysis toolkit (ToPCAT) was used to unify point densities, extract ground-elevations and, consequently create DEMs from georeferenced 3d point clouds. Brasington et al. (2012) and Rychkov et al. (2012) give a full description of this intelligent decimation method and provide several examples of its application. While developed originally for use with TLS data, it has been used with SfM-MVS datasets previously (Javernick et al., 2014; Smith et al., 2014). ToPCAT was run to extract sub-grid topographic statistics at a 0.1 x 0.1 m resolution in case of the plot and small catchment scales. Several statistics (mean elevation, minimum elevation, maximum elevation, etc.) of the point clouds were obtained within each 0.1 x 0.1 m grid cell. Owing to the large area under investigation, the landscape-scale point clouds were post-processed at 1 x 1 m resolution. In each case, the mean elevation of each grid cell was used to generate a DEM.

Additional sub-grid scale statistics were also calculated using ToPCAT. For each cell, a neighbourhood triangular tessellation based on mean elevation in each cell was used to construct the local surface and detrend all points within the central grid cell (see Brasington et al., 2012). The detrended standard deviation of elevations σ_d was then calculated in each cell. Given the proliferation of use of σ_d as a roughness metric across the Earth Sciences (Smith, 2014), σ_d is an appropriate choice of roughness metric for this study.

3.2.3. Comparing DEMs and assessing a minimum Level of Detection (minLoD)

DEMs of the small-catchment were compared to investigate erosion and sedimentation patterns, and assess the net topographic change during the 11 months between surveys (as a proxy of the sediment yield). Three independent estimates were calculated: (i) differencing TLS-based 2013 and 2014 DEMs; (ii) differencing oblique, ground-based SfM DEMs from 2013 and 2014; and (iii) differencing SfM-based DEMs from the lowest aerial surveys (50 m flying altitude, see Table 1). To calculate topographic changes between the two survey periods the old DEM was subtracted from the new DEM to create a DEM of Difference (DoD) where negative values indicate a lowering of topography (erosion) and positive values represent sedimentation. The significance of these changes will be controlled by the errors and topographic uncertainties in each DEM. In the case of this study, following the approach described by Brasington et al. (2000), a threshold minimum level of detection was applied to distinguish between real topographic change and artefacts arising from errors/uncertainties in the two DEMs (see also the more recent studies of Brasington et al., 2003; Wheaton et al., 2010; Vericat et al., 2014). The minimum level of detection for real topographic change (i.e. minLoD), was calculated as:

$$minLoD = t[\varepsilon_{DEM1}^2 + \varepsilon_{DEM2}^2]^{0.5}$$

where *t* is the critical *t* value for a given confidence interval and ε_{DEMi} the errors associated to the new (*i* = 1) and old (*i* = 2) DEMs. Using the 90% confidence interval, *t* = 1.65. For each DEM the sub-grid roughness value σ_d was applied to represent ε_{DEMi} as the sub-grid topographic variability in the point cloud may be the largest source of uncertainty in the ground estimate. This technique yields a spatially distributed threshold minimum level of detection based upon local topographic roughness where small changes can be resolved more reliably on smooth surfaces than rough surfaces. Observed changes below the minLoD were filtered out of each DoD and considered unreliable.

4. Results

Results are divided into 5 sections: section 4.1 outlines the errors involved in registering and georeferencing TLS and SfM-based datasets. Validation of both 2014 TLS and SfM-derived topographic models (DEMs) with point-based measurements acquired through a TS survey is presented in section 4.2. The TS point measurements are considered to represent the true ground elevation. The validation is performed for the 2014 datasets over the three study scales to assess the role of survey range on survey quality. In section 4.3, TLS and SfM-based DEMs obtained in 2014 are compared at plot and small-catchment scales. In this case the TLS model is considered to represent the true ground surface estimate. The sub-grid scale topographic variability (i.e. roughness) of TLS and each SfM-based point cloud obtained for the 2014 datasets at the plot and small-catchment scales are compared in section 4.4. Finally, a demonstration of the change detection capabilities of TLS and SfM at the small-catchment scale is presented in section 4.5 through differencing of the DEMs obtained in each year.

4.1. Registration and georeferencing of point clouds

In both 2013 and 2014, a total of 12 TLS scans were merged to create the full topographic model at the small catchment scale using a target-based registration as explained above. Average registration errors were 3 mm (2013) and 2 mm (2014) (Table 2). The georeferencing error of the targets was < 2.2 mm. Both TLS point clouds contained over 300 Mn points resulting in an average point density of >6.7 points per cm^2.

SfM surveys at the small-catchment scale typically employed around 20 GCPs. Reported 3d errors range from 0.06 m to 0.21 m. The relatively high errors reported in the oblique (i.e. ground-based) 2014 survey reflect poor matches in the upper catchment, which was excluded from analysis owing to a low point density and presence of unreliable mismatched imagery. Excluding GCPs from the upper catchment reduces this error to 0.109 m. Relatively high georeferencing errors were also reported in the higher altitude AutoGiro (AG) surveys; however, for these surveys additional targets distributed over the 1 km^2 landscape-scale were used for georeferencing. Using only GCPs over the catchment-scale reduces this 3d error. At the plot scale, much lower 3d errors were reported. In this case 5 targets were used to georeference each plot survey with one target in each vertex of the plot and one extra GCP for redundancy. Such a perimeter-distribution was one of the optimal distributions observed by Vericat et al. (2009) when georeferencing aerial imagery.

The ability to georeference such surveys accurately is a fundamental aspect of an examination of SfM to produce reliable change detection estimates; however, it has the potential to affect greatly the comparison of topographic models in section 4.5 (see Micheletti et al., 2014). As such, topographic data products were produced for each survey to check for any systematic misalignment against the TLS datasets that would dominate results. Aspect and flow accumulation rasters were compared and no systematic georeferencing problems were observed (with a 0.1 m grid size).

4.2. SfM and TLS validation based on Total Station Surveys

External validation of both TLS and SfM-based surveys obtained in 2014 is provided by 515 TS survey points within the small-catchment, and an additional 215 points distributed over the landscape scale area. The plot scale SfM surveys (gridded at 0.1 x 0.1 m) were validated against TS point-based surveys (Table 3). No TS validation points were located within Plot 5. Plot-scale MAE values were in some cases an order of magnitude lower than those observed for the results from the aerial surveys (i.e. AG) and in all but one case, lower than the reported errors for the TLS survey (Table 2). This close fit is also reflected in the RMSE values (see Table 3; Figure 3A).

The distributions of errors for each small-catchment scale survey are displayed in Figure 2 and the errors for all surveys at each scale are summarised in Table 3 and Figure 3A. At the small catchment scale, the MAE between the gridded TLS DEM and the TS survey points was 0.03 m. In comparison, the reported MAE for the SfM surveys increased with survey altitude ranging from 0.07 m (AG50 m) to 0.18 m (AG250 m). The oblique survey demonstrated a higher MAE than the lowest aerial survey with a large number of points surveyed as being considerably lower than the validation dataset (Figure3A). From visual inspection of the oblique SfM DEM, a patch where images were matched incorrectly can be observed (also seen in Figure 4A). Other error metrics follow a similar pattern (Table 3).

Finally, the 1 m resolution AG150 m and AG250 m landscape-scale DEMs were validated against all 730 TS survey observations. Errors are increased substantially; while this increase may reflect greater unreliability of the SfM surveys outside of the small catchment, it also reflects the greater grid size used to produce the DEM. This issue is discussed further in section 5, and highlights the need for a robust validation of SfM surveys against co-incident TLS-derived point clouds.

4.3. SfM validation based on TLS Digital Elevation Models

Differences between each SfM-based DEM and the DEMs produced from the TLS datasets are summarised in Table 4 and Figure 3b. Differences between SfM and TLS-based DEMs (i.e. $DoD_{SfM\text{-}TLS}$) at the plot scale were very small, with generally sub-centimetre MAE. RMSE values between the cells of the plot scale data are all <0.02 m. These values are an order of magnitude lower than those found at the small catchment-scale (Table 4). Again, the lowest altitude (~50 m) SfM aerial survey showed the lowest errors when compared against the concurrent TLS data (MAE = 0.055 m; RMSE = 0.080 m). All error metrics increased with the altitude at which pictures were taken. Finally, the oblique ground-based SfM survey exhibited intermediate error metrics (Table 4). Notably, the UAV survey in 2013 exhibits much greater errors (MAE = 0.218 m, RMSE = 0.308 m) than the 50 m survey which was at a similar height and indicates a clear systematic error with this SfM model (Figure 4E).

In common with the TS validation (section 4.2), the distribution of errors for the Oblique SfM survey (Figure 5a) reveals a large area where the SfM DEM was lower than the TLS DEM in the stretching of positive errors. Examination of the spatial pattern of these differences (Figure 4A) identifies several areas of strong positive errors (i.e. SfM DEM is lower than the TLS DEM) mostly in the upper part of the catchment, but also with clear patches in the centre of the study area. The lowest altitude SfM aerial survey also underestimates terrain height over most of the catchment (Figure

4B), but this difference is relatively minor (see histogram). The survey overestimates the height of some thalwegs in the catchment, suggesting that the model is least reliable here.

The models obtained with pictures taken from the AutoGiro at 150 m and 250 m altitude overestimate the terrain height across much of the study area (Figure 4C−D; Table 4). Examination of the spatial distribution of errors (Figure 4C−D) highlights clearly a strong spatial pattern that appears related to the topographic variability, particularly in the lower parts of the study catchment. A profile taken over this area of pronounced topographic variability (i.e. high local relief) clarifies the nature of these errors (Figure 5).

While at first, the patterns in Figure 4D appear to resemble georeferencing errors in a zone of steeply sloping terrain, Figure 5 demonstrates that the models are well aligned. The AG50 m DEM corresponds closely with the TLS survey, as is also the case for the oblique survey, though clear areas of underestimated terrain height can be seen in the latter (e.g. at around 4 m on the profile). The higher SfM-based data are not able to represent fully the range of elevations, underestimating ridge elevations and overestimating thalweg elevations (despite an estimated pixel size of the images at around 0.025 m at the highest flying altitude). The increased variability in mean elevation in each grid cell with flying height is also pronounced (e.g. at 15 m in Figure 5). Such a loss of precision is investigated in section 4.4.

4.4. Differences in sub-grid topographic variability

An increasing number of studies are utilising the sub-grid variability of topography, or roughness, to infer process or as error terms in the case of change detection (as demonstrated in section 4.5). Thus, it is instructive to compare the topographic variability within each grid cell, specifically the detrended standard deviation taken as a metric of roughness. Increased sub-grid topographic variability will reflect either real surface roughness or the survey precision; the two components are combined in a sub-grid roughness metric (on a flat surface, sub-grid roughness would reflect instrument precision alone). The assumption here is that where real surface roughness has been captured by the higher precision instrument (i.e. the TLS) higher roughness values obtained with different survey methods broadly (though not directly) indicate survey precision. The distribution of roughness values in each survey is summarised in Table 5 along with summary statistics of cell-by-cell differences between TLS and SfM-based surveys at the plot and small-catchment scales. The spatial and statistical distributions of small catchment scale roughness values is displayed in Figure 6A-D and Figure 6E-H while cell-by-cell differences between each SfM-based survey and the TLS survey are presented in Figure 6I-K.

At the plot scale, sub-grid roughness in the TLS and SfM surveys are comparable. SfM surveys more frequently exhibit smaller roughness values overall which may indicate higher precision of the data set (or may alternatively reflect smoothing as part of the MVS algorithm). Indeed, the distribution of plot-scale TLS roughness contains a small number of cells with high roughness values which are not observed with SfM and could indicate the presence of ‘mixed pixels’.

At the small-catchment scale, both the mean and standard deviation of sub-grid roughness in TLS 2014 and AG50 m surveys are comparable and only marginally higher in the oblique SfM survey. Figure 6 demonstrates that the distributions of these values are similar. The spatial patterns of roughness in Figure 6A-D indicates that the TLS and AG50 m SfM surveys are picking out similar patterns, while the oblique survey exhibits additional patches of high roughness values. These high roughness patches are broadly co-incident with the areas of mean elevation understimation (Figure 4A) in the oblique survey, and are a consequence of mismatched imagery creating two surfaces at the same location at different elevations, increasing the range of elevations (and thus the sub-grid roughness) while lowering the mean elevation value used to derive the DEM. Despite being acquired from a similar survey range to the AG50m data, the 2013 UAV data is much rougher than the concurrent TLS data.

Figure 6D shows that the distribution of sub-grid roughness is clearly different for the higher altitude SfM aerial surveys with much higher values reported (Table 5). It should be noted that only grid cells with >3 survey points were included in the roughness analysis. This criterion limited the number of cells included from the AG150 m and AG250 m surveys. Nervertheless, it is clear from Figure 6D that the populated roughness values are much higher than observed by the TLS and so are likely to be dominated by a reduction in precision of the SfM point cloud even at 150 m altitude, particularly in the topographic lows, as seen in Figure 5. With only 102 sufficiently populated cells for roughness analysis, the distributions of roughness for the AG250 m SfM survey are not presented in Figure 5.

Cell-by-cell comparisons (Figure 6I-K) show considerable scatter at lower roughness values for both TLS and SfM-based surveys, suggesting that no agreement exists between the TLS and SfM data sets. The lack of agreement may reflect the uncertainty of the data sets which is relevant at such small sub-grid scales. Where higher sub-grid roughness is observed (~0.2 m) agreement can be seen, though this breaks down with increasing altitude.

4.5. Topographic change detection

The ability of SfM-MVS surveys to detect topographic change is compared against TLS-based results (i.e. $DoD_{TLS2014\text{-}TLS2013}$). While relatively large in comparison with other hillslope areas, the typical topographic changes observed over 11 months in a rapidly eroding badland are moderate in comparison with more dynamic higher-energy systems (e.g. gravel-bed rivers) to which this morphometric method is more often applied (e.g. Wheaton et al., 2013).

For TLS data, the number of cells above the minLoD is relatively low indicating that most topographic changes between surveys are in the range of the uncertainty of the surveys. The final DoDs created from the TLS data demonstrate relatively small areas of detectable topographic change focused in the thalwegs and flow lines of the small catchment (Figure 7A). This extensive TLS-derived morphometric sediment budget covers an area over 100 times larger than that presented previously by Vericat et al. (2014). Volumetrically, erosion was twice than deposition, with a catchment average topographic change of -1.44 mm a^{-1} (Table 6). As expected, much of this change is dominated by relatively small topographic differences between the two models, particularly in areas of deposition, which tend to be less pronounced but more widespread.

The magnitude of the measured topographic change increases when SfM-based surveys are used to estimate the morphometric sediment budget. While the overall catchment average topographic change calculated from ground-based SfM might at first appear to be reasonably accurate (-2.19 mm a^{-1}, Table 6), examination of the volumes of estimated erosion and deposition reveals that both figures are largely overestimating the real changes, resulting from insufficient accuracy. Similar overestimates are evident for the aerial surveys, which is to be expected given errors reported in the earlier topographic validation.

There is little relation between the TLS-derived DoD and the SfM-derived DoDs with considerable reconstruction error observable throughout the study area. Clear patterns of systematic error can be seen through the catchment. Quantitative comparison of the DoD derived from oblique ground based imagery (Figure 7B) with the DoD derived from TLS surveys reveals a ME of -38.97 mm, a MAE of 158.28 mm, an RMSE of 301.93 mm and a SDE of 299.41 mm. In comparison, the DoD derived from the aerial image at 50 m above the ground (Figure 7C) demonstrated much lower error metrics of ME = 2.51 mm, MAE = 134.54 mm, RMSE = 194.35 mm and SDE = 192.72 mm. Comparison of Figures 7C and 4E identified the 2013 UAV survey as the source of this error. For both datasets, these errors are too large to resolve annual topographic changes associated with badlands at this scale, though two datasets of the same quality as the AG50m imagery would enhance the ability of aerial imagery to resolve changes of <0.1 m.

5. Discussion

As a survey method, SfM-MVS can be implemented easily across a particularly wide range of scales (see Figure 8). This capability offers the potential for relatively standardised measurements of topography over a range of spatial and temporal scales. The validation study presented herein, aimed to clarify typical errors expected from SfM-MVS surveys, by conducting multiple nested surveys of the same area at a number of scales and over a number of platforms. Repeat TLS surveys covering a catchment of over 4000 m^2 and the derived spatially-distributed morphometric sediment budget offered an ideal and unique data product with which to validate both plot scale and small catchment SfM surveys. This was supplemented further with total station surveys for independent validation.

5.1. Quality of SfM-based topographic surveys: scale dependence

At the plot scale (here ~10 m^2), sub-centimetre mean absolute differences between SfM-MVS DEMs and TLS-derived DEMs are observed. In some cases, the detectable differences are sufficiently small that there is no reason to necessarily prefer the TLS survey as the reference dataset owing to: (i) the increased point density of the SfM-MVS point clouds over these plots; (ii) the generally lower sub-grid roughness (i.e. inferred higher precision) of SfM-MVS data sets and; (iii) the greater range of perspectives offered by SfM-MVS (causing fewer shadows). This finding is line with that of James and Robson (2012) who observed sub-millimetre errors when surveying a hand sample from an even shorter range. Given the high resolution of topographic data achievable at the plot scale with individual clasts being clearly observable, SfM-MVS is well capable of detecting topographic changes and, sediment budgets, at the plot or even slope scale, and is likely to be an improvement on many existing methods. Errors are well within those of the TLS sediment budget presented in Figure 7A. The visual nature of the method even indicates that the movement of individual clasts could be tracked in three-dimensions, permitting new inferences in the study of sediment transport connectivity (e.g. virtual travel velocity). Tuffen et al. (2013) applied such an approach to estimate the velocity of lava flows. Further work is required to demonstrate this convincingly.

Scaling up SfM-MVS using oblique ground-based imagery to small catchment scales (~0.5 ha in this example) becomes problematic, especially in a complex, heavily dissected environment as surveyed here. In some areas, the closer range yielded a dense point cloud and a close fit to the TLS-reference dataset (see profiles in Figure 5); however, the keypoint matching and camera pose estimation proved unreliable in parts of the survey area. While image pose estimation was examined visually before implementing the dense cloud reconstruction process, relatively small mismatches proved undetectable. Moreover, many images were rejected by the software and were not included in the reconstruction, resulting in a large part of the upper catchment where more vegetation is present (see Figure 1C) being excluded from oblique surveys. Matching ground-based imagery over relatively large scales is a demanding task for SfM software. Yet, mismatched patches are particularly problematic as these issues are not apparent during the field survey, and only arise during post-processing. The results herein suggest that, beyond plot sizes of ~ 100 m^2, there is a preference for aerial imagery for SfM-based point cloud generation.

Aside from large volumetric changes as seen with gully network expansion (e.g. d'Oleire-Oltmanns et al., 2012; Frankl et al., 2015), results herein suggest that SfM-MVS is only suitable as a method of monitoring soil erosion from ranges of < 50 m and possibly < 10 m. This would restrict applications to relatively small areas (<1 ha) as has been demonstrated by Eltner et al. (2014). Yet, errors observed even at the landscape scale are likely to be similar if not smaller than existing morphometrically-derived sediment yield estimates covering the largest areas which were estimated using DEMs created from historical aerial imagery (Ciccacci et al., 2008). Using an AutoGiro (or gyrocopter) as an aerial platform has advantages over UAV platforms allowing coverage over larger areas in a single survey, with longer flight times and the flexibility and stability that comes with hand-held shooting (permitting slightly oblique convergent photography). Comparison of the UAV and AutoGiro data acquired at the same altitude demonstrates this clearly, as UAV data exhibit a MAE four-times greater than the AutoGiro study. This result provides the first empirical confirmation of the modelling findings of James and Robson (2014) that off-vertical imagery in convergent pairs (taken for the AutoGiro survey) coupled with distributed ground control can reduce doming effects arising from vertical image sets (taken for the UAV survey) and inaccurate camera models. Further quality improvements can be made as camera technology develops; for example, full-frame FX sensors are now available for DSLRs which provide finer detail and capture larger image areas.

As reported in Vericat et al. (2014) in the case of sub-humid badlands, morphometric sediment budgets also require differentiation between topographic changes caused by erosion/deposition and surface shrinking/swelling which requires additional datasets (e.g. deep-anchored ground control points combined with trail cameras). Also, the masking out of observed changes that are below the minimum level of detection (and deemed unreliable) can potentially underestimate topographic change. However, as such changes are, by definition, minimal, this effect would not introduce a large bias in estimated sediment yield.

The potential cost and time savings achievable using SfM-MVS in place of other high-resolution survey methods (e.g. TLS or airborne LiDAR) are noteworthy (see Castillo et al., 2012). There was little difference in survey time required for each camera platform (all ~ 10-15 minutes) and while UAV purchase costs are the greatest expense (~<£1,000) this was balanced by the cost of the gyrocopter hire (~£150). Greater errors from larger survey ranges are likely to be acceptable for other applications (e.g. terrain analysis) or for monitoring change on more dynamic systems (e.g. gravel bed rivers). From 50 m survey range, changes of ~ 0.1 m will be detectable. Surface models derived from 150 m elevation imagery (e.g. the TIN of Figure 1B) are certainly comparable to those derived from airborne LiDAR. For the first time, this study has shown that the spatial distribution of sub-grid roughness can be reproduced with SfM from 50 m survey range meaning that the survey precision is similar to that of TLS, although systematic errors may be present in the data. Further developments using camera phones and freely available online processing software (e.g. 123D Catch) (Micheletti et al., 2014) increase the accessibility of SfM-MVS as a survey method and indicate serious potential for widespread utilisation of the technique in the Geosciences and beyond.

The TLS-derived morphometric sediment budget displayed in Figure 7A covers a much larger area than previous data sets presented in eroding badlands. Such a dataset is extremely valuable for the development of improved understandings of sediment connectivity (see Bracken et al., 2014). Further work is required to understand the topographic and meteorological controls on this erosion. Embedded event-scale repeat SfM surveys at the plot or slope scale can add value to such annual sediment budgets owing to the reduction in survey time and resources required to undertake such work regularly. In this manner, SfM can add value to longer-term morphometric monitoring with more conventional means.

5.2. Synthesis of SfM-validation: key findings and issues

This study contributes to the emerging body of literature that aims to validate SfM robustly in that it has increased substantially the amount of available validation data points to date. Multiple SfM surveys from a range of survey heights and over a wide range of scales are validated with both point-based total-station data and through a comparison of SfM and TLS DEMs (gridded data). In each case the same software was used; however, a range of alternative SfM programs are available and used in existing literature (e.g. Mic Mac, Visual SfM). Combining the findings of this study with other reported validation studies yields important insights into the overall accuracy achievable with SfM-MVS. While several studies report mean error (e.g. Fonstad et al., 2013; Woodget et al., 2014), RMSE is commonly cited as a metric of surface quality, while MAE provides an indication of non-directional elevation errors and provides a natural and comparable measure of model performance (Willmott and Matsuura, 2005). In total, 50 SfM validation points have been compiled.

Figure 9 plots both RMSE and MAE against survey range both for data sets presented in this paper and existing studies that report each validation metric. Data points are broadly separated into: (i) those that compare SfM-derived rasters (i.e. DEMs) with point topographic data (e.g. from RTK-dGPS or Total Stations) (‘point-to-raster’); (ii) those that compare SfM-DEMs with equivalent raster-based data products derived from another survey technique such as TLS (‘raster to raster’); and (iii) those that compare two point clouds directly (‘point to point’). As might be expected, RMSE at a given range decreases from (i) to (iii) (Figure 9A). Comparison of points with rasters is also dependent on raster grid size; this effect can be seen directly in Figure 3A as the error metrics for the AG150 m and AG250 m surveys increased between the small-catchment (0.1 x 0.1 m DEM) and landscape scales (1 x 1 m DEM) which were derived from the same point cloud. Direct comparison of two DEMs or two point clouds seem to be the fairest tests of SfM as comparable data-products are being evaluated. However, applications of SfM data typically derive DEMs as a final processing step, thus it could be argued that a raster-based comparison is most representative of real errors in final data products.

A linear degradation in precision with survey range is expected theoretically, is well established for traditional stereo photogrammetry and has been observed previously for SfM (James and Robson, 2012). However, the majority of existing validation studies report RMSE and not SD. With a greater synthesis of data points, over a wide-range of terrain types, a power-law relating RMSE and survey range provides the best fit to the data between survey ranges of <1 m and 1000 m (Figure 9A). The exponent of this relationship is 0.88 which is close to linear ($R^2 = 0.80$, $n = 43$). Combining all SfM validation points, a median ratio of RMSE : survey range of 1:639 is observed, which is very similar to the ratio of 1:625 reported by Micheletti et al. (2014). Since RMSE reflects overall model accuracy and not precision, the ratio is well below the 1:1000 ratio between precision and range reported by James and Robson (2012). RMSE reflects more than the expected linear degradation in precision; although a linear relationship between RMSE and survey range might be also expected, the summary in Figure 9A reflects a number of factors that seem to limit the practically-achievable accuracy of SfM. Camera platform, camera sensor, weather, georeferencing method, validation method, number of images and their geometry, distribution of GCPs, terrain type and processing software will all influence the final model quality to some extent and may be responsible for the observed non-linear trend. Certainly, survey range is not the only variable to be altered between the points in Figure 9A which compiles results from a wide range of studies. While Figure 9A gives a useful indication of the relationship between RMSE and survey range, there is a clear need for a systematic validation of SfM to determine the effect of each of these factors on data quality.

MAE is reported less frequently; Figure 9B compiles 28 reported values. Again, raster-based comparisons yield a lower error metric at a given range. Again a power law best fits the data (R^2 = 0.69) with a lower exponent of 0.57. Using just the raster-based validation data (n = 8) increases the exponent to 0.78 and improves fit substantially (R^2 = 0.97) (dashed line in Figure 9B).

From Figure 9A and considering both the RMSE : range ratio of 1:639 and degree of scatter around the trend line, at 10 m range, around 10−15 mm errors can be achieved which would be suitable for the majority of applications. Inspection poles provide ideal viewing angles at that range and could replace the need for UAVs over the small catchment scale presented here. Such inspection poles allow remote triggering of elevated cameras and achieve a compromise between the close-range imagery available from oblique ground-based surveys, and the more reliable surfaces generated from airborne surveys. Over larger areas (i.e. the landscape-scale surveys presented here) a larger range is required (>100 m) for a manageable survey; this increases anticipated errors by an order of magnitude. Thus, synthesis of extant literature suggests that, for soil erosion applications, SfM should only be applied where survey ranges ~ 10 m can be achieved.

6. Summary and Conclusions

Structure-from-Motion with Multi-View Stereo can be used to generate high resolution topographic data products at a wide range of scales. For the first time, this study presents a robust validation of SfM using multi-scale nested surveys and a distributed morphometric sediment budget over an area >4000 m^2 derived using TLS. Validation reveals that data sets of a sufficient quality for soil erosion monitoring and comparable with TLS can be obtained at the plot or hillslope scale. With a 0.1 x 0.1 m grid size, sub-grid roughness parameters similar to those from TLS can be derived even from ranges of ~ 70 m. However, the suitability of using SfM for topographic change detection at this scale is limited to rapidly changing landforms and environments (e.g. gravel bed rivers). For larger areas of more complex topography, aerial images from piloted gyrocopters are preferable for reliable image matching, but with increasing survey height, surface precision decreases. Sub-centimetre errors are achievable at ~10 m range as might be provided by a camera inspection pole. Errors increase approximately linearly with survey range and ratios of RMSE : survey range of 1:639 are observed. Despite these errors, landscape-scale DEMs can be derived rapidly and at minimal expense and are likely to have a considerable impact of the future trajectory of geomorphology as a discipline.

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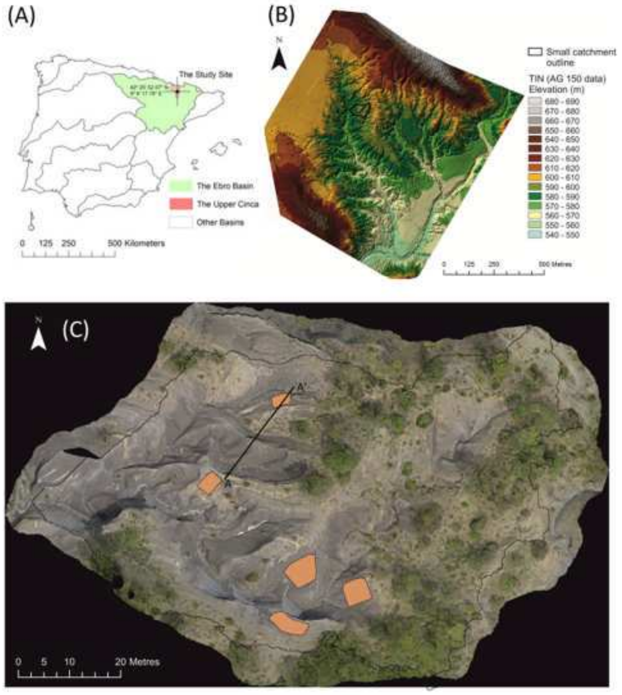


Figure 1. (A) Location of study site in the Upper River Cinca (Central Pyrenees, Iberian Peninsula, Ebro Basin); (B) topographic model of the landscape-scale (1 km^2) study area derived from SfM; (C) orthophoto of the small-catchment (4710 m^2) which is the main focus of this paper. Plot outlines (< 30 m^2) and the location of the profile AA' in Figure 5 are shown in (C).

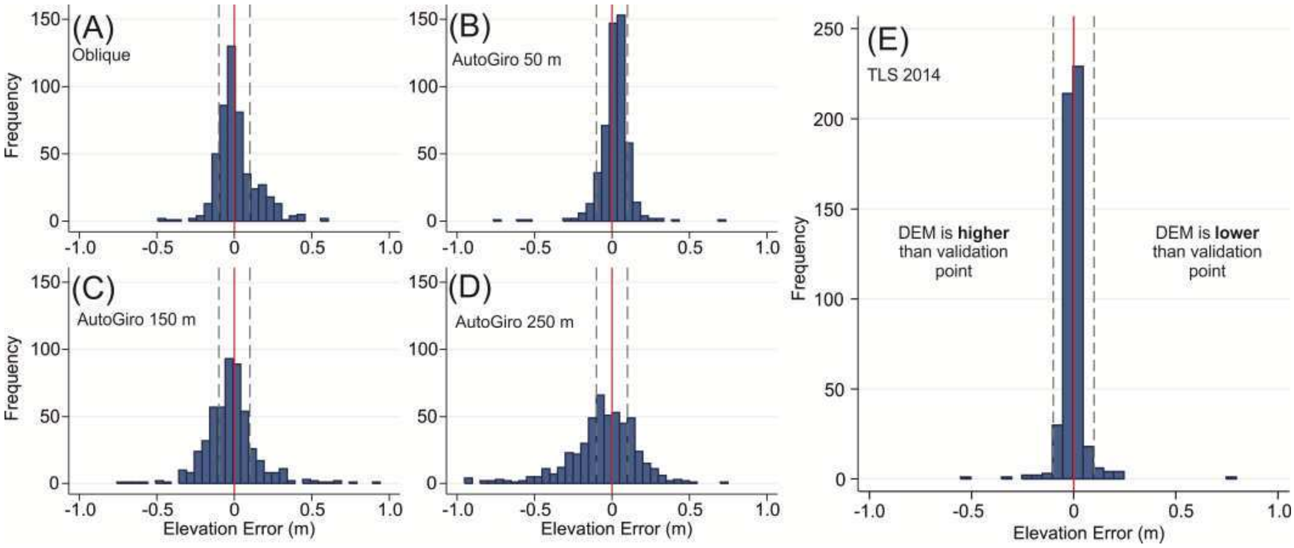


Figure 2. Distribution of errors in the total station validation of SfM-MVS surveys (A−D) and the TLS 2014 survey (E) at the small catchment scale. Dashed lines indicate ±0.1 m.

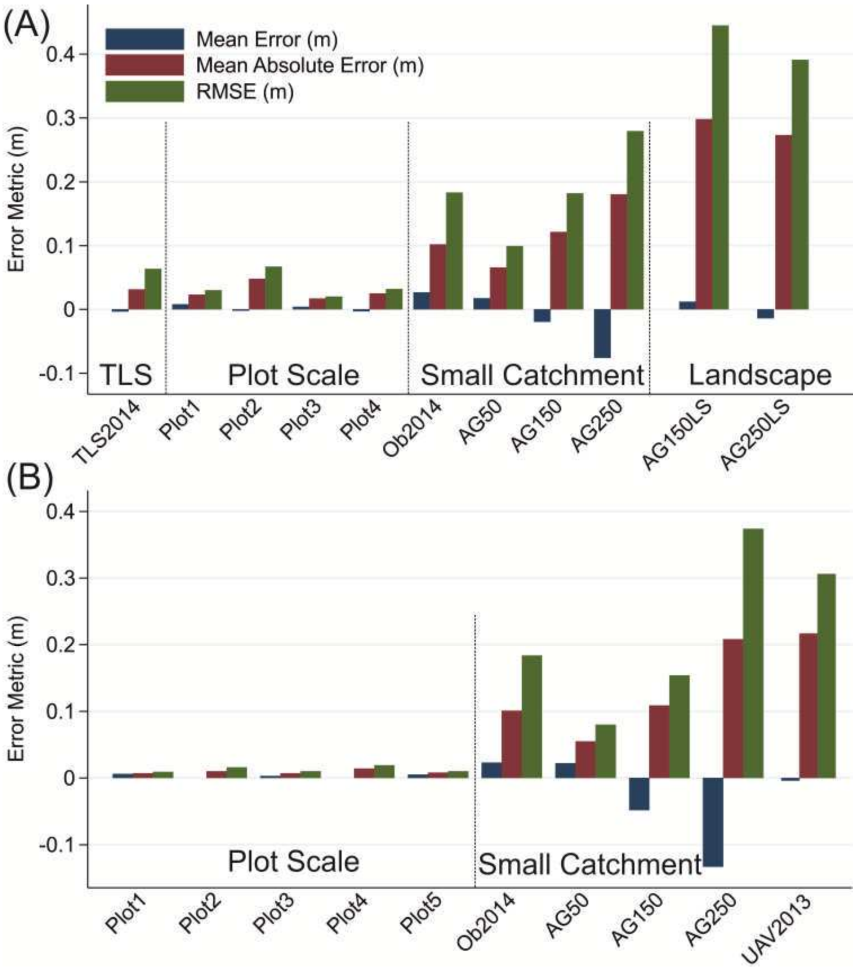


Figure 3. Summary of errors in topographic validation at three different scales using (A) total station data; and (B) using TLS data.

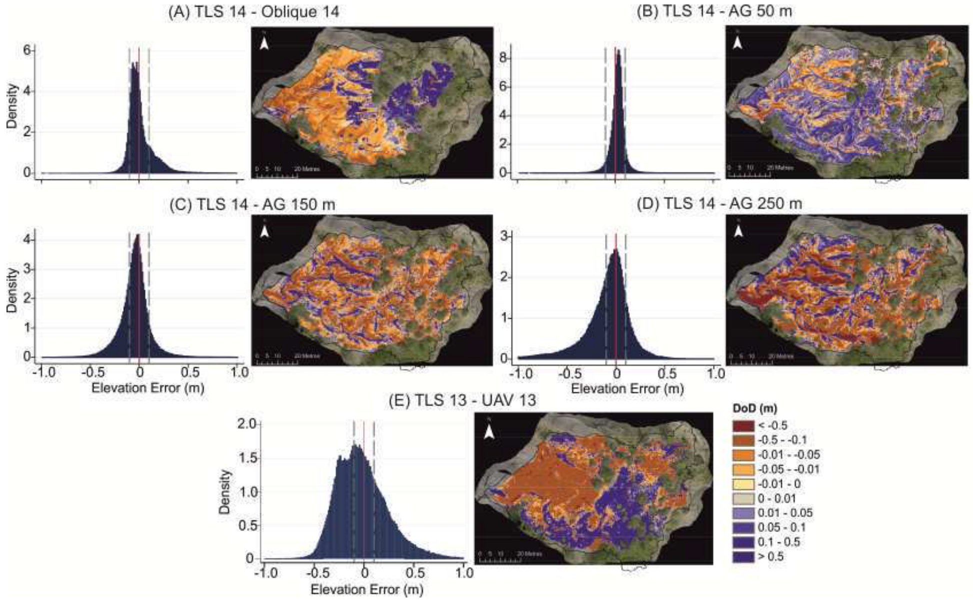
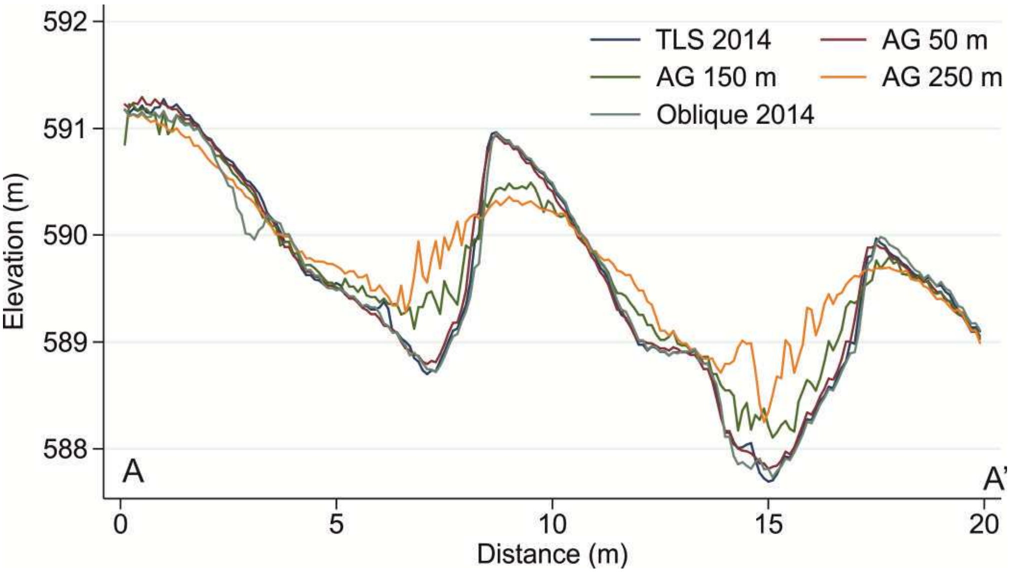


Figure 4. Distribution of errors in the TLS validation of SfM-MVS surveys and the spatial pattern of the errors across the small catchment (TLS survey – SfM surveys). Dashed lines indicate ±0.1 m.



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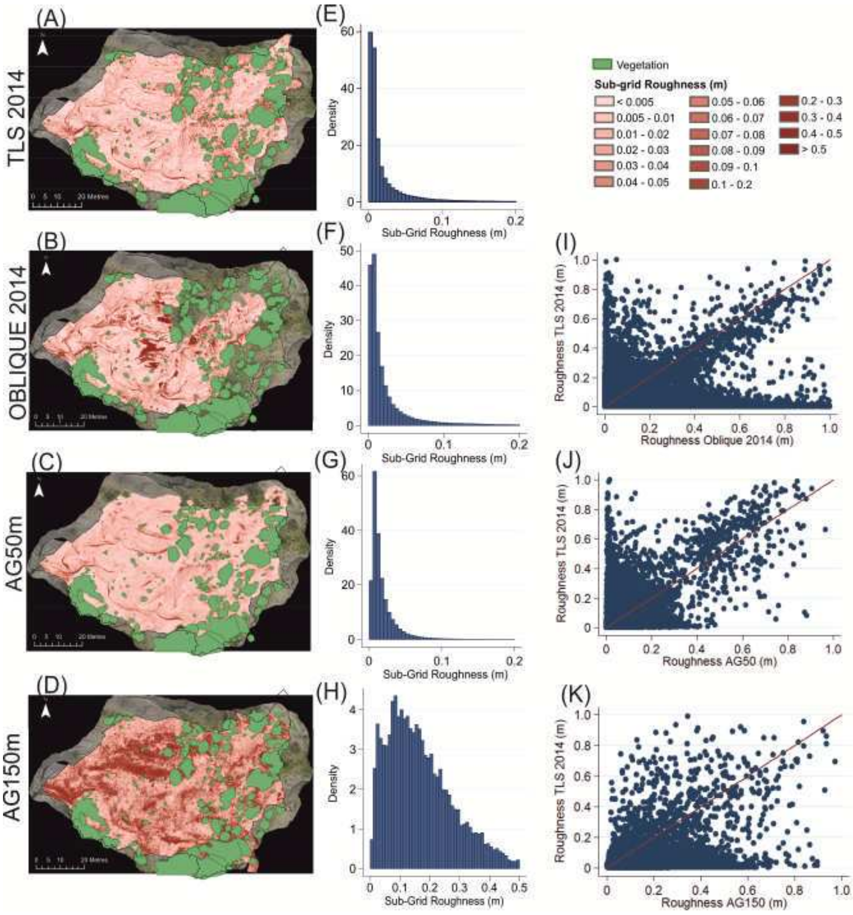

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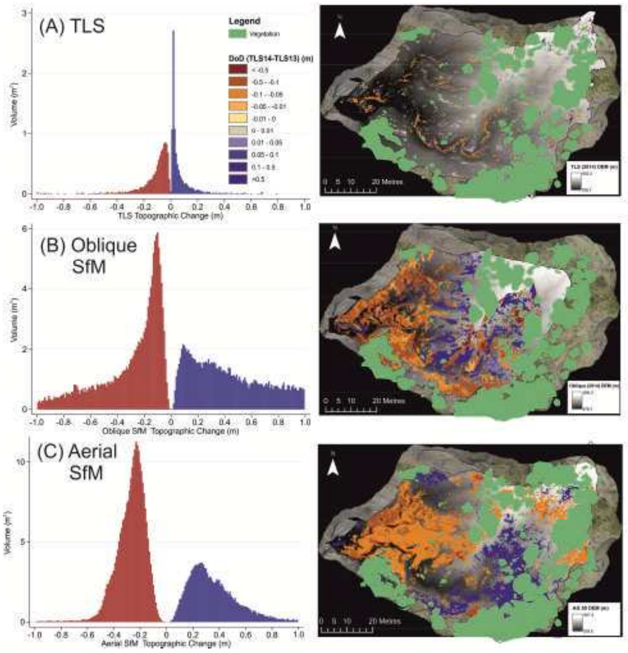

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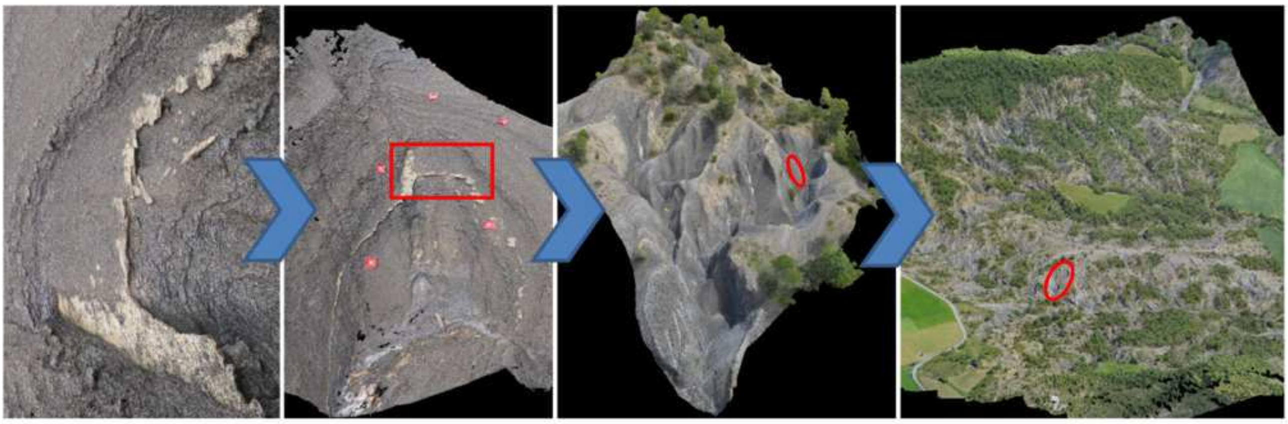

Figure 8. SfM-derived photorendered point clouds of the study badlands over a variety of scales (left to right): from plot (~0.0001 ha) to slope (~0.01 ha), to small catchment (~1 ha) to landscape (~100 ha).

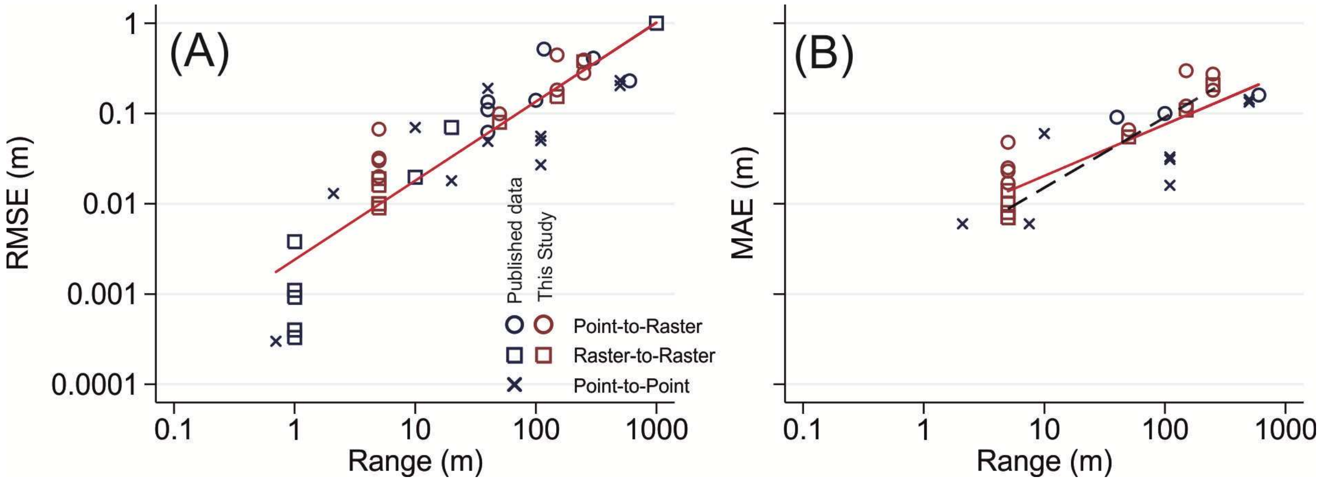

Figure 9. Synthesis of existing SfM validation studies (navy) with data points generated in this study (maroon) examining the effect of survey range against (A) RMSE and (B) MAE. Dashed line in (B) summarises only raster-based validation data. Data extracted from: Favalli et al. (2012), Harwin and Lucieer (2012), James and Robson (2012), Mancini et al. (2013), James and Quinton (2014), Javernick et al. (2014), Lucieer et al. (2014), Micheletti et al. (2014), Ouédraogo et al. (2014), Ruzic et al. (2014), Smith et al. (2014), Thoeni et al. (2014), Tonkin et al. (2014), Stumpf et al. (2015), subaerial data from Woodget et al. (2014) and an unpublished result by the authors on ice surface plots.

Tables

Table 1. Overview of field data obtained at each study scale. Note that plot and landscape scale surveys were not conducted in 2013.

	Plot Scale	Small Catchment Scale	Landscape Scale
2013 survey	–	- SfM: ground-based oblique photography - SfM: aerial photography from a UAV (50 m altitude) - TLS	–
2014 survey	- SfM: ground-based oblique photography - Terrestrial Laser Scanning (TLS) - Total Station (TS)	- SfM: ground-based oblique photography - SfM: aerial photography from a manned AutoGiro (50 m altitude) - SfM: AutoGiro at 150 m altitude - SfM: AutoGiro at 250 m altitude - TLS - TS	- SfM: AutoGiro at 150 m altitude - SfM: AutoGiro at 250 m altitude - TS

Table 2. Summary of registration (i.e. MAE of targets) and georeferencing errors (i.e. RMSE on control points) for 2013 and 2014 surveys. For the landscape-scale surveys (AG150m and AG250m) values in parentheses indicate errors using GCPs over sub-catchment area only. For the Oblique 2014 survey, values in parentheses indicate errors using GCPs in the lower catchment only.

TLS-based Surveys				
Survey	Year	Points	Registration Error (m)	Georeferencing Error (m)
TLS 2013	2013	351 Mn	0.003	0.002
TLS 2014	2014	317 Mn	0.002	0.002
SfM-MVS-based Surveys				
Survey	Year	Points	GCPs	Georeferencing Error (m)
Oblique 2013	2013	30.3 Mn	20	0.062
UAV 2013	2013	9.6 Mn	16	0.100
Oblique 2014	2014	99.4 Mn	21 (15)	0.210 (0.109)
AG50 m 2014	2014	2.4 Mn	29	0.086
AG150 m 2014	2014	717,000	110 (29)	0.100 (0.070)
AG250 m 2014	2014	313,000	75 (29)	0.150 (0.092)
Plots (5) 2014	2014	3.6−20 Mn	5	<0.01

Table 3. Summary of errors in the total station (TS) validation of SFM-MVS surveys and the TLS 2014 survey at three different scales. Note: no TS validation points overlapped with Plot 5.

Survey	Validation points	ME (m)	MAE (m)	SDE (m)	RMSE (m)
Plot Scale (0.1 x 0.1 m grid)					
Plot 1	9	0.008	0.023	0.031	0.030
Plot 2	18	-0.002	0.048	0.069	0.067
Plot 3	12	0.004	0.017	0.020	0.020
Plot 4	36	-0.003	0.025	0.032	0.032
Small Catchment Scale (0.1 x 0.1 m grid)					
TLS 2014	515	-0.003	0.031	0.063	0.064
Oblique 2014	504	0.027	0.102	0.181	0.183
AG50 m	515	0.018	0.066	0.098	0.099
AG150 m	515	-0.020	0.121	0.181	0.182
AG250 m	515	-0.076	0.181	0.269	0.279
Landscape Scale (1 x 1 m grid)					
AG150 m	730	0.012	0.298	0.446	0.445
AG250 m	730	-0.014	0.273	0.391	0.391

Table 4. Summary of errors in the validation of SfM-MVS surveys with the TLS surveys at the plot and small-catchment scales (comparison of gridded data).

Survey	Validation points	ME (m)	MAE (m)	SDE (m)	RMSE (m)
Plot Scale (0.1 x 0.1 m grid)					
Plot 1	808	0.006	0.007	0.007	0.009
Plot 2	2829	0.000	0.010	0.016	0.016
Plot 3	2238	0.003	0.007	0.010	0.010
Plot 4	2040	0.000	0.014	0.019	0.019
Plot 5	1149	0.005	0.008	0.009	0.010
Small Catchment Scale (0.1 x 0.1 m grid)					
Oblique 2014	277,000	0.023	0.101	0.183	0.184
AG50 m	333,000	0.022	0.055	0.077	0.080
AG150 m	327,000	-0.048	0.109	0.146	0.154
AG250 m	328,000	-0.133	0.208	0.349	0.374
UAV (2013)	331,293	-0.004	0.218	0.308	0.308

Table 5. Summary of: (i) sub-grid roughness statistics and (ii) cell-by-cell differences between TLS and SfM sub-grid roughness for each plot and small catchment scale survey.

Survey	**Summary of sub-grid roughness (mm)**			**Summary of Sub-grid Roughness Differences (TLS – SfM) (mm)**			
	n	Mean	SD	ME	MAE	RMSE	SDE
Plot 1							
TLS	1017	9.08	10.50	1.22	4.37	10.11	10.04
SfM	1017	7.85	6.21				
Plot 2							
TLS	2830	18.35	33.22	3.23	11.35	32.60	32.44
SfM	2830	15.12	16.78				
Plot 3							
TLS	2816	5.82	4.50	-0.53	2.70	4.48	4.45
SfM	2816	6.35	5.12				
Plot 4							
TLS	2442	11.60	20.60	2.10	7.94	21.11	21.01
SfM	2442	9.50	6.40				
Plot 5							
TLS	2047	8.82	12.67	-3.85	7.74	14.05	13.51
SfM	2047	12.67	12.54				
Small Catchment							
TLS (2013)	582591	30.84	92.92	-			
UAV (2013)	332269	104.07	111.87	-73.34	96.24	145.23	162.49
TLS (2014)	324940	21.76	47.37	-			
Oblique (2014)	264528	38.98	98.35	-19.18	34.28	101.17	99.33
AG50 m	241103	19.90	31.73	2.81	18.95	38.98	38.88
AG150 m	13100	176.46	126.36	-133.64	148.14	189.41	134.23
AG250 m	102	181.73	159.74	-141.39	163.99	227.41	179.03

Table 6. Sediment budgets at the small catchment scale derived from TLS data, ground-based oblique SfM surveys and repeat aerial SfM surveys (at ~ 50 m altitude).

Survey	Total Erosion (m^3)	Total Deposition (m^3)	Net (m^3)	Catchment Average Topographic Change (mm a^{-1})
TLS	-12.63	6.40	-6.24	-1.44
Oblique SfM	-153.62	144.16	-9.46	-2.19
Aerial SfM (50 m)	-258.72	136.35	-122.37	-28.34