Digital close range photogrammetry for the study of rill development at flume scale

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ABSTRACT

Soil erosion is a continuous process of detachment, transportation, and deposition of soil particles. Obtaining accurate descriptions of soil surface topography is crucial for quantifying changes to the soil surface during erosion processes. The objective of this study was to develop an improved close-range photogrammetric technique to assess soil erosion under rainfall conditions. Based on high overlapping image acquisition, digital point cloud matching, digital elevation model (DEM) generation and soil erosion calculation, a digital close-range photogrammetric observation system was explored and established. The results showed that the established digital photogrammetric observation system could accurately calculate the digital point cloud from the underlying surface with a 2 min time interval and a 1.5 mm spatial resolution. In addition, based on the DEM generated from digital point clouds, the amount of soil erosion in different topographic positions within various time periods was calculated. The digital photogrammetric observation methods explored in our study provide a reliable way to monitor soil erosion processes, especially under rainfall conditions. This approach can accurately resolve the evolution of the underlying surface soil erosion, which is of great importance in understanding soil erosion mechanisms.

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1. Introduction

Soil erosion is an important environmental issue in many parts of the world. Detachment and transportation of soil particles during the erosion process can result in soil degradation, water pollution and damage to drainage networks (Morgan, 2005; Peter Heng et al., 2010). During an erosion event, the soil surface is continuously transforming. Depending on the volume of soil transported, erosion processes can result in considerable topographic variations that can have broad effects on agricultural practices (Liu et al., 2004; Peter Heng et al., 2010). Various technologies have been developed by soil and geomorphology scientists to acquire detailed information on the variation in the soil surface caused by erosion (Nouwakpo and Huang, 2012).

Contact techniques, such as the erosion pin and rillmeter, have long been used to understand changes in the soil surface during erosion (Elliot et al., 1997; Kronvang et al., 2012). Although the change in the length of the exposed part of the pin can be used to calculate the amount of erosion that has occurred after an erosion event, the accuracy of the erosion pin technique is limited by the low spatial coverage due to the small number of pins (Sirvent et al., 1997; Zhang et al., 2011). The rillmeter technique can acquire precise data for the measurements of soil surface geometry, but it can disturb the soil surface during the measurement process due to the contact between the rillimeter device and the soil surface (Elliot et al., 1997). As technology has become more robust and accessible in recent years, non-contact soil surface techniques, such as laser scanning and digital close-range photogrammetry, have been adopted to overcome the limitations of contact methods (Babault et al., 2004; Nouwakpo and Huang, 2012).

Both laser scanning and digital close-range photogrammetric techniques have been widely used to generate DEMs with sufficient resolution for micro-topographic analysis (Aguiar et al., 2009; Babault et al., 2004; Nouwakpo and Huang, 2012; Rieke-Zapp and Nearing, 2005). Comparatively, digital photogrammetry allows for faster data acquisition and a wider vertical range of the DEM (Aguiar et al., 2009; Rieke-Zapp and Nearing, 2005). In addition, a camera is easier to handle, and a digital photogrammetric system allows operators to scale according to their own requirements (Frankl et al., 2015; Rieke-Zapp et al., 2001). Therefore, digital photogrammetry enables the possibility of instantaneous data capture.

Previous investigations have proved the usefulness of high-resolution digital close-range photogrammetry in soil erosion studies. The experimental plots in those studies varied between 0.09 and 16 m², and the grid resolution of generated DEMs ranged from 1 to 15 mm (Abd Elbasit et al., 2009; Aguiar et al., 2009; Brasington and Smart, 2003; Peter Heng et al., 2010; Rieke-Zapp and Nearing, 2005).
However, none of the previous methods observed ongoing soil erosion processes during rainfall events, principally because the equipment was not waterproof. Consequently, understanding soil erosion during rainfall was not achieved (e.g., Rieke-Zapp and Nearing, 2005). Under natural rainfall conditions, soil erosion is a continuous process. To study the evolution of erosion, soil surface topography must be monitored at both fine temporal and spatial scales.

In addition, during an erosion event, when runoff accumulates and flows in narrow channels, it is difficult to obtain soil surface images of the inundated area, especially at the sidewall and bottom of the eroding rill. Obtaining soil surface information from the sidewall and bottom of the channel is another challenge when using the digital photogrammetry technique.

To address these issues, this study aims to (1) develop an improved photogrammetric approach for soil surface measurements that can monitor the soil erosion process at fine temporal and spatial scales and capture instantaneous images during ongoing rainfall and (2) assess the accuracy of the developed photogrammetric approach in detecting changes in soil erosion by comparing the amount of soil erosion calculated using the photogrammetric approach, laser scanning, and traditional runoff and sediment collection method.

2. Material and methods

2.1. Experimental design

All experiments were conducted in the State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau. We conducted two simulated rainfall experiments, the first on 19 July 2013 and the second on 4 July 2014 (Table 1). The dimensions of the experimental plots were 5.0 × 1.0 × 0.5 m³ steel soil bins set at a gradient of 15° to the horizontal (Fig. 1). Loess soil common in the area of Loess Plateau, China was used in the two experiments. The soil was first sieved through an 8 mm soil sieve then loosely packed in the soil bin. The soil surface was pre-wetted several times over a period of 5 days before the experiment, allowing the settlement of the loose soil surface (Gessesse et al., 2010). The total rainfall duration for the two experiments was 190 min and 150 min for the first and second experiments, respectively. To test the accuracy of the developed photogrammetry approach under various conditions, rainfall intensity and time intervals of image acquisition were designed differently according to previous rainfall simulation experiments (Berger et al., 2010; Rieke-Zapp and Nearing, 2005). In the first experiment, rainfall intensity during the first 60 min was 60 mm/h and increased to 90 mm/h during the final 130 min. Image acquisition was conducted at 30, 50, 70, 90, and 100 min, then every 10 min until 190 min. In the second experiment, rainfall intensity was 90 mm/h throughout the experiment and image acquisition was conducted every 10 min.

Pictures of the soil surface were obtained during rainfall using an industrial CCD (charge-coupled device) camera, which was hand controlled by the operator walking around the soil bin. Image collection frame rate was set to 15 frames/s, and the average distance of data acquisition to the surface was 80 ± 5 cm, resulting in a density of digital images of 150–170 frames/m². Image acquisition for the entire plot took approximately 2 min. Raw image data were captured in a waterproof high-speed hard disk drive, then transferred to a host computer and then further transferred to three parallel computers for analysis. Scale bars were placed around the bin and marked as white on a black background.

Before each rainfall experiment, we tested the precision of the developed photogrammetry approach by measuring the diameter of a selected spherical target 40 times. To test the accuracy of the digital photogrammetry, we compared this method with physical observations. Physical observations were conducted by placing cylindrical and rectangular objects of a known size in the steel soil bin before the rainfall experiment, and the digital photogrammetric observation method was used to measure and calculate their geometric size. We also collected all water and sediment samples for each rainfall experiment, followed by the collection of sediment, drying, weighing and processing to calculate the soil erosion volume. The surface terrain was simultaneously scanned using a Leica ScanStation 2 laser scanner while photogrammetric images were collected. To compare the observation precision of the laser scanning method and digital photogrammetric observation, digital point clouds were calculated from both the laser-scanned images and photogrammetric images.

2.2. Design of digital photogrammetric observation systems

The digital photogrammetric observation system was composed of two subsystems: the image acquisition subsystem and the image interpolating and calculation subsystem (Fig. 2). The image acquisition subsystem consisted of an industrial CCD camera, PICO machine, solid-state drive, touch control panel, DC (direct current) power supply, waterproof adapter and waterproof case. The image interpolating and calculation subsystem consisted of a data storage unit, a host computer and nine parallel computers. We wrote code for image acquisition, task assignment (assigning tasks to the parallel computers), sub-block division and matching, and soil erosion calculations. The code used in 3D point cloud reconstruction was available as part of the open source VLFeat library (www.vlfeat.org) and OpenCV (http://opencv.org/).

2.2.1. Image acquisition subsystem

Because raindrops affected the imagery during rainfall, we designed an industrial CCD camera with a waterproof housing to ensure reliability during rainfall conditions (Fig. 3a). The camera was hand controlled during the capture of soil surface information on the sidewall and bottom of the channel. We took photos at a close range (80 ± 5 cm) from the soil surface, which constrained the field of view and reduced raindrops passing through the view. The CCD camera has a matrix of 1624 × 1232 picture elements (pixels). The distance between two pixel centers was 0.004 mm. The collection frame rate of the CCD camera was 12–20 frames/s, which resulted in a minimum of 8-fold overlapping, that is, a feature point was found in at least 8 different images (Table 2).

The PICO machine controlled the acquisition system, which was responsible for command control, data reception and forwarding. System commands and data were transferred by a TCP/IP (Transmission Control Protocol/Internet Protocol) network and a gigabit ethernet hardware interface. Software parameters were adjusted during the acquisition process using the touch-control surface (Fig. 3b). Moreover, as the equipment was designed to be waterproof, real-time monitoring via the capture screen on the control panel was achieved.

2.2.2. Image calculation subsystem

The huge amount of images collected required sufficient storage data computational power to execute the large amount of computations. As off-the-shelf consumer computers were inadequate for

<table>
<thead>
<tr>
<th>Table 1</th>
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<tbody>
<tr>
<td>Experimental design and image acquisition.</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Experiment 1</td>
</tr>
<tr>
<td>Soil bulk density (g/cm³)</td>
</tr>
<tr>
<td>Rainfall intensity (mm/h)</td>
</tr>
<tr>
<td>After 60 min: 90</td>
</tr>
<tr>
<td>Image acquisition time interval (min)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Image acquisition frame rate (frame/s)</td>
</tr>
<tr>
<td>Image acquisition density (frame/m²)</td>
</tr>
</tbody>
</table>
image interpolation and calculation, we created a custom computer system consisting of a host computer and nine parallel computers. The host computer was responsible for assigning tasks to parallel computers, monitoring parallel computer processes, optimizing schedules on parallel computers, and collecting results from parallel computers. The software of the image calculation subsystem consisted of three modules. First, the parallel computing management and digital point cloud matching module, which divided all images within the observation area into sub-blocks, detected feature points, identified homologous points, calculated the point cloud, and collected the results. The second module, point cloud stitching, integrated the point clouds from each sub-block into a unified coordinate system according to the observation area. Lastly, the point cloud editing and DEM generation module edited the stitched point clouds, repaired errors in the point cloud, and generated a DEM to calculate surface soil erosion.

2.3. Image sub-block division

Each observational pass of the entire plot took approximately 2 min, and produced approximately 1200 images. And there were 14 and 15 passes in the two different rainfall experiments, respectively. Therefore, the associated calculation is huge. To process the large amount of images, all images in each individual observation were divided into 5 sub-blocks in this study (images can be divided into several different sub-blocks in different investigations depending on the number of images involved). Images were coded according to the image number, and then were divided into 5 sub-blocks according to those codes.

2.4. Three dimensional (3D) reconstruction

After sub-block division, digital point clouds were calculated using computer-visual identification and photogrammetric methods (extraction, recognition, and computing) to generate the 3D points in each sub-block. Feature points in each image were identified using the Scale-Invariant Feature Transform (SIFT) algorithm (Lowe, 2004), and mismatched pairs were filtered using the RANdom Sample Consensus (RANSAC) algorithm (Fischler and Bolles, 1981). Because images were obtained with a hand controlled camera, it was impossible to obtain pre-oriented images. Therefore, point cloud matching was carried out in image space alone. The interior orientation of the camera, exterior orientation of the images, and object coordinates of all measured points...
were solved using a free-net bundle adjustment (Luohmann et al., 2013). As highly overlapping images can provide a large amount of feature points, to avoid the noise caused by raindrops, only reliable homologous points were used in point cloud matching.

2.5. Sub-block registration

2.5.1. Defining the neighbourhood sub-blocks

In each single sub-block, the 3D points were numbered to get the ID (Identification) arrays for each single point. For example, the ID array of point A was described as: \( [(A_1, \ a_1), (A_2, \ a_2), \ldots, (A_n, \ a_n)] \), where \( n = 1, 2, 3, \ldots, N \), \( N \) is integer, which represented the number of original images that the 3D point A belongs to. \( A_n \) was the ID of 3D point A in the original image \( n \), \( a_n \) was the SIFT feature of point A in the original image \( n \). \( \{A_n, \ a_n\} \) is the ID tuple of point A. According to the ID arrays, the sub-blocks were registered.

To define the neighbourhood sub-blocks, homologous points in different sub-blocks were determined first. If at least one ID tuple existed in the intersection of ID arrays between two points, then they were considered homologous points. If the number of homologous points within two sub-blocks was \( > 10\% \) of the number of 3D point in each sub-block, they were defined as neighbourhood sub-blocks. The sub-block that had the most homologous points was selected as the primary block to match the sub-blocks.

2.5.2. Sub-block registration

To match images from different sub-blocks, we constructed edges from the homologous points (Fig. 4). For example, \( p_1 \) and \( p_2 \) belong to sub-block1, \( p'_1 \) and \( p'_2 \) belong to sub-block2, \( p_1 \) and \( p'_1 \) are homologous points, \( p_2 \) and \( p'_2 \) are homologous points, we constructed edge \( l \) from \( p_1p'_2 \) in sub-block1, and edge \( l' \) from \( p'_1p_2 \). Then we could get \( C_n^2 \) edges from each sub-block, \( n \) is the number of homologous points. According to Eqs. (2)-(4), we obtained \( C_n^2 \) of \( \lambda \) value. Then we used 3σ rule to detect the outliers of \( \lambda \) (Lehmann, 2013). When the outliers of \( \lambda \) were deleted, the reliable homologous points were used to match the sub-blocks.

\[
d_{p_1p_2} = \sqrt{(x_{p_1} - x_{p_2})^2 + (y_{p_1} - y_{p_2})^2 + (z_{p_1} - z_{p_2})^2}
\]

\[
d_{p'_1p'_2} = \sqrt{(x'_{p_1} - x'_{p_2})^2 + (y'_{p_1} - y'_{p_2})^2 + (z'_{p_1} - z'_{p_2})^2}
\]

where \( d_{p_1p_2} \) represents the distances between points \( p_1 \) and \( p_2 \), \( d_{p'_1p'_2} \) are the distance between points \( p'_1 \) and \( p'_2 \).

\[
\lambda = \frac{d_{p_1p_2}}{d_{p'_1p'_2}}
\]

As shown in Fig. 5, by using the homologous points \( a1 \) and \( a2 \) in coordinate systems 01 and 02, the rotation matrices \( R2 \) and \( T2 \) can be calculated, and according to the calculated \( R2 \) and \( T2 \), the three dimensional points in coordinate system 02 can be integrated into coordinate system 01. Likewise, by using the homologous points \( a2 \) and \( a3 \) in coordinate systems 02 and 03, the rotation matrices \( R3 \) and \( T3 \) can be calculated, and according to the calculated \( R3 \) and \( T3 \), the three dimensional points in coordinate system 03 can be integrated into coordinate system 02. From these relationships between homologous points, the coordinate system can be unified during cloud matching. The algorithm formula is depicted in Eq. (4):

\[
\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = R \begin{bmatrix} x \\ y \\ z \end{bmatrix} + T
\]

As the scale of the images during the free net bundle adjustment were not uniform (Fig. 6a), we designed a cross-shaped rod to fix the scale issues. When the point cloud registration was completed, a scaling factor was calculated by comparing the actual scale length to the model scale length. This scaling factor was then used to multiply the integrated point cloud coordinate to obtain the real coordinates of the measured object (Fig. 6b).

2.6. Point cloud reparation

When a soil erosion channel appears, runoff accumulates along the channel, making it difficult to capture images of the soil surface in the inundated area. Without information on the locations at the bottom of eroding rill, it is difficult to match the point cloud at those locations in the flow channel, resulting in a sparse point cloud. To resolve this issue, we repaired the point cloud in the flooded areas using the obtained sparse point cloud and variation in the terrain. Sparse matched point clouds occurred due to the rough and uneven surface of the channel bed. This condition resulted in sparse point cloud data in flooded areas for interpolation. However, as the terrain varied continuously, the

Table 2

<table>
<thead>
<tr>
<th>Camera specifications.</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image resolution</td>
<td>2 million pixels (1624 × 1232)</td>
</tr>
<tr>
<td>Pixel size</td>
<td>0.004 mm × 0.004 mm</td>
</tr>
<tr>
<td>Focal length</td>
<td>12 mm</td>
</tr>
<tr>
<td>Image scale (m)</td>
<td>1:67</td>
</tr>
<tr>
<td>Ground sampling</td>
<td>0.3 mm pixel⁻¹</td>
</tr>
<tr>
<td>Forward overlap of</td>
<td>90%</td>
</tr>
<tr>
<td>images</td>
<td></td>
</tr>
<tr>
<td>Sidelap</td>
<td>60%</td>
</tr>
<tr>
<td>8-folded overlapping</td>
<td>One single feature point can be found at least in 8 different images</td>
</tr>
<tr>
<td>Height above surface</td>
<td>80 cm ± 5 cm</td>
</tr>
</tbody>
</table>
elevation of neighboring points also varied continuously. Thus, a vacant point cloud can be interpolated according to the terrain variation. Based on this approach, we used inverse distance-weighted (IDW) interpolation to obtain the three-dimensional coordinates of objects in flooded or vacant areas (Fig. 7).

2.7. Soil erosion calculation

To calculate the soil erosion volume, digital point clouds were converted to a DEM. The DEM grid size represents the accuracy of terrain surface approximation from grid data, and the density of the digital point cloud represents how accurately the point cloud describes the terrain. Thus, the density of points in the cloud determines the size of the DEM grid. To calculate soil erosion volumes, differences between two DEMs at two time points were calculated. The DEM surface of \( t - 1 \) (\( DEMt - 1 \), reference surface) was used as an input to estimate the surface at point \( t \), and the soil erosion was calculated by subtracting the ranges of the DEM (\( DEMt - n \)) from this reference surface. In the calculation, the DEM grid was regarded as the differential unit, the area of the unit multiplied by its distance from the reference surface was the differential cylinder volume for the space, and the summary of all the differential elements was equal to the volume of the entire measurement area. The equations are expressed as follows:

\[
V = \iint_{D} e(x, y) \, dx \, dy
\]

where \( V \) is the volume of the reference surface, \( e(x, y) \) is the distance between grid (points) in the DEM and the reference surface, and \( D \) is the integral region.

As the DEM is composed of discrete data, in the practical calculation, the equation was expressed as follows:

\[
V = \sum_{i=m}^{i=n} \sum_{j=d}^{j=d} e(i, j) \cdot Ds
\]

where \( V \) is the volume of the reference surface; \( m \) and \( n \) are the line and column numbers, respectively, of the DEM; \( e(i,j) \) is the distance between the DEM point \((i,j)\) and the reference surface; and \( Ds \) is the area of the DEM grid.

3. Results

3.1. Spherical target test

To test the sensitivity of the digital photographic observation instrument, 40 diameter measurements of a selected spherical target were conducted (Fig. 8a). The result showed that the average diameter of the spherical target was 140.60 mm, mean deviation was 0.63 mm and the standard deviation was 0.74 mm (Fig. 8b). The histogram of spherical target diameter showed a normal distribution (skewness = –0.094, kurtosis = –0.764), indicating high precision of the designed observation instrument.

3.2. Physical observation and photogrammetric observation

A cylinder and two rectangular objects of known size were placed in the bins, and the digital photogrammetric observation method was used to measure and calculate their geometric sizes. The observation results showed a significant positive relationship between the photogrammetric observed value and the true value (\( Y = 1.0074x \), Fig. 4. Sub-block registration.

Fig. 5. Registration of homologous point cloud maps. a1, a2 and a3 are homologous points.
R² = 0.999). The maximum absolute error was 2.2 mm, while the minimum absolute error was 0. The maximum relative error was 2.1% (Table 3).

3.3. Runoff and sediment collection and photogrammetric observation

Results from photogrammetric observations and runoff and sediment collections showed significant positive relationships (first rain: Y = 0.99x + 0.81, R² = 0.999; second rain: Y = 0.98x − 0.53, R² = 0.985, Tables 4-5). This indicates that the digital photogrammetric observation method accurately observed the variation in soil loss during rainfall. In practice, due to the large amount of work, researchers generally collect only part of the runoff, inevitably resulting in errors caused by changes in the sediment concentration. In contrast, images for digital photogrammetric observation can be acquired at the relevant times and image processing and calculation can be carried out subsequently, thus making it convenient to operate.

During a rainfall event, soil erosion and changes in soil surface morphology became more significant with increased rainfall duration. In this case, the precision of photogrammetric observation also increased (Tables 4-5). The observational precision in the later stage of a rainfall event was higher than that in the earlier stage; this threshold in observational precision occurred during gully formation. In the present experiment, the rapid development of gullies occurred 50–60 min after the rainfall started. The relative error between the runoff and sediment collection method and the photogrammetric observation method was higher before the development of gully erosion than after; it varied from −44.64% to 0.21% in the first rain and from −81.49% to 1.55% in the second rain (Tables 4–5).

Table 6 shows the point cloud density and maps at different time intervals in the first rainfall experiment. According to the statistics from the matched point cloud maps obtained from the two rainfall experiments, the point cloud density is 0.8 ± 0.2/mm². High-density point clouds and DEM information allowed soil loss at defined times to be calculated and spatial soil erosion maps at corresponding times to be created. Thus, the soil erosion volume and spatial sources were determined simultaneously, as were the resolution of soil erosion events, such as gully formation, erosion across different gradients or different topographic positions, and sediment deposition.

![Fig. 6. Digital point cloud map (a) before and (b) after bundle block adjustment and scale constraints. The numbers from 1 to 6 indicate the positions of the ground control points.](image1)

![Fig. 7. Digital point cloud reparation at the bottom of the flow channel. Digital point cloud (a) before and (b) after the inverse distance-weighted (IDW) interpolation.](image2)
3.4 Laser scanning and photogrammetric observation

The photogrammetric technique matched many more points than laser scanning. As shown in Table 7, the number of point clouds obtained by photogrammetric images was 26% and 78.2% higher than those obtained by laser scanning in the first and second rainfall experiments, respectively. This finding indicated that the object size represented by each single point cloud was smaller from the photogrammetric observation method, therefore, this method can resolve the terrain more accurately. Fig. 9 shows the three-dimensional digital point cloud maps obtained from laser scanning and photogrammetric observation.

4. Discussion

4.1 The image acquisition system

A challenge for the application of digital close range photogrammetry on soil erosion experiments is that rain drops affect the imagery during rainfall. How to collect high quality images (less noise, less shadow) during rainfall conditions and remove noise caused by rain drops during image matching are the two main issues. In the present study, by constraining the field of view, raindrop interference during image acquisition was reduced. Furthermore, the high density of images obtained meant that points interrupted by raindrops could be eliminated while maintaining a large number of feature points for image matching.

4.1.1 Field of view

In traditional photogrammetry cameras are often mounted 1.9–4 m above the soil surface (e.g. Rieke-Zapp and Nearing, 2005; Peter Heng et al., 2010), which can limit the view of erosion banks and channel bottoms. However, the camera in this study was designed as hand controlled, which enabled soil surface information to be acquired from the sidewall and bottom of the water channel. Additionally, photos were taken at a closer range (20 ± 5 cm) from the soil surface and the camera movement was perpendicular to the surface during image acquisition, which constrained the field of view, so that less raindrops could pass through the view during imagery.

4.1.2 High speed image acquisition

Since the soil surface changes continuously during rainfall, real-time soil surface monitoring is needed to investigate the evolution of soil erosion. Since the collection frame rate of the CCD camera used was 12–20 frames/s, digital images were collected with a density of 120–240 frames/m² within 10 s. This high speed image acquisition on the one hand can reduce raindrops in the field of view due to the short time window. On the other hand, it provides a large number of high overlapping images. In the present study, image overlap reached a minimum of 8-fold, namely, one single feature point can be found at least in 8 different images (Table 2). The dense and high overlapping images provided sufficient reliable

Table 4

<table>
<thead>
<tr>
<th>Observation no.</th>
<th>Rainfall duration (min)</th>
<th>Runoff and sediment collection (cm³)</th>
<th>Photogrammetry (cm³)</th>
<th>Relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>30</td>
<td>56</td>
<td>31</td>
<td>-44.64</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>19,861</td>
<td>20,248</td>
<td>1.95</td>
</tr>
<tr>
<td>3</td>
<td>70</td>
<td>33,662</td>
<td>34,015</td>
<td>1.05</td>
</tr>
<tr>
<td>4</td>
<td>90</td>
<td>8598</td>
<td>8,637</td>
<td>0.45</td>
</tr>
<tr>
<td>5</td>
<td>100</td>
<td>38,379</td>
<td>38,118</td>
<td>-0.68</td>
</tr>
<tr>
<td>6</td>
<td>110</td>
<td>39,952</td>
<td>39,546</td>
<td>-1.02</td>
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<tr>
<td>7</td>
<td>120</td>
<td>52,604</td>
<td>52,714</td>
<td>0.21</td>
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<tr>
<td>8</td>
<td>130</td>
<td>65,869</td>
<td>68,050</td>
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<tr>
<td>9</td>
<td>140</td>
<td>70,334</td>
<td>72,989</td>
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<td>10</td>
<td>150</td>
<td>98,844</td>
<td>99,888</td>
<td>1.06</td>
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<td>11</td>
<td>160</td>
<td>108,884</td>
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<td>12</td>
<td>170</td>
<td>128,918</td>
<td>129,209</td>
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<tr>
<td>13</td>
<td>180</td>
<td>167,112</td>
<td>168,451</td>
<td>0.80</td>
</tr>
<tr>
<td>14</td>
<td>190</td>
<td>214,700</td>
<td>211,652</td>
<td>-1.42</td>
</tr>
</tbody>
</table>

Relative error = \( \frac{\text{measured value - true value}}{\text{true value}} \).
effort, therefore, we used parallel computing techniques to address these involved a large computing. The interior orientation of the camera, exterior orientation of the images, and object coordinates of all measured points were solved using a free-net bundle adjustment (Luhmann et al., 2013). These involved a large computing, the discrepancy between soil loss and sediment yield coincided. As shown in Tables 4 and 5 that the discrepancy between soil loss and sediment yield became less over time, and that only during the initial phase of the experiment, bulk density changes are important.

High speed image acquisition provides a reasonable observation time window and high overlapping images for soil surface monitoring, but the high overlapping image matching involves a large computing effort. Although methods and commercial packages for dense image matching (dense point-cloud generation) are available, they should be used carefully in consideration of image acquisition and parameter selection (Remondino et al., 2014). Working with a calibrated camera would make life much easier as there would be less parameters to solve for, and oriented imagery can be searched much faster based on epipolar constraints. However, in this study, it was impossible to obtain the pre-oriented images because the camera was hand controlled, point cloud matching was carried out in image space alone. The interior orientation of the camera, exterior orientation of the images, and object coordinates of all measured points were solved using a free-net bundle adjustment (Luhmann et al., 2013). These involved a large computing effort, therefore, we used parallel computing techniques to address this issue.

Table 5
Comparison between the runoff and sediment sampling methods and photogrammetric observation in the second rainfall experiment (conducted on 4 July 2014). Relative errors = (soil erosion volume measured by photogrammetry – volume measured by runoff and sediment collection) / volume measured by runoff and sediment collection).

<table>
<thead>
<tr>
<th>Observation no.</th>
<th>Rainfall duration (min)</th>
<th>Runoff and sediment collection (cm³)</th>
<th>Photogrammetry (cm³)</th>
<th>Relative error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>2059</td>
<td>2713</td>
<td>31.76</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>2978</td>
<td>2766</td>
<td>30.47</td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>5334</td>
<td>2334</td>
<td>56.24</td>
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<tr>
<td>4</td>
<td>40</td>
<td>10,860</td>
<td>2415</td>
<td>77.76</td>
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<tr>
<td>5</td>
<td>50</td>
<td>15,807</td>
<td>2926</td>
<td>81.49</td>
</tr>
<tr>
<td>6</td>
<td>60</td>
<td>26,217</td>
<td>30,614</td>
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<td>7</td>
<td>70</td>
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<td>41,093</td>
<td>9.56</td>
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<td>8</td>
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<td>49,834</td>
<td>53,994</td>
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</tr>
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<td>9</td>
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<td>63,184</td>
<td>64,363</td>
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<tr>
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<td>120,178</td>
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<td>140</td>
<td>133,425</td>
<td>127,564</td>
<td>4.39</td>
</tr>
<tr>
<td>15</td>
<td>150</td>
<td>150,099</td>
<td>138,739</td>
<td>7.57</td>
</tr>
</tbody>
</table>

Table 6
Results of the digital photogrammetric observation method at different time intervals in the first rainfall experiment.

<table>
<thead>
<tr>
<th>Duration of rainfall (min)</th>
<th>Number of point clouds (10⁴)</th>
<th>Density of point clouds (/mm²)</th>
<th>Digital point clouds</th>
</tr>
</thead>
</table>
| 30                         | 530.6                        | 1.06                          | 0.094, kurtosis = −0.764, indicating the high precision of the designed observation instrument. The precision of photogrammetric observation was also tested by sediment yield and laser scanner data. The relative error between the runoff and sediment collection method and the photogrammetric observation methods was higher before the development of gully erosion than after; it varied from −44.64% to 0.21% in the first rain and from −81.49% to 1.55% in the second rain (Tables 4–5). In this study the soil erosion was calculated from the changes in soil surface derived from the differences in the sequential DEMs. Calculation of soil loss from the 3D data may lead to inaccurate result because soil bulk density changes when rainfall was applied (Gessesse et al., 2010). Therefore, one should not assume volume loss and sediment yield coincide. As shown in Tables 4 and 5 that the discrepancy between soil loss and sediment yield became less with time. Our assumption was that rill erosion becomes significant over time, and that only during the initial phase of the experiment, bulk density changes are important.

4.2. Precision and accuracy

To test the precision of the digital photographic observation instrument, we measured the diameter of a spherical target for 40 times. The histogram of spherical target diameter showed a normal distribution (skewness = −0.094, kurtosis = −0.764), indicating the high precision of the designed observation instrument. The precision of photogrammetric observation was also tested by sediment yield and laser scanner data. The relative error between the runoff and sediment collection method and the photogrammetric observation methods was higher before the development of gully erosion than after; it varied from −44.64% to 0.21% in the first rain and from −81.49% to 1.55% in the second rain (Tables 4–5). In this study the soil erosion was calculated from the changes in soil surface derived from the differences in the sequential DEMs. Calculation of soil loss from the 3D data may lead to inaccurate result because soil bulk density changes when rainfall was applied (Gessesse et al., 2010). Therefore, one should not assume volume loss and sediment yield coincide. As shown in Tables 4 and 5 that the discrepancy between soil loss and sediment yield became less with time. Our assumption was that rill erosion becomes significant over time, and that only during the initial phase of the experiment, bulk density changes are important.

Compared to laser scanner, the point cloud map obtained from photogrammetric observation was better at expressing the underlying surface terrain not only because the number of point clouds obtained by photogrammetric observation was higher but also because of the movement perpendicular to the surface in photographic image acquisition. Using 8-fold image overlapping across the observation area, sufficient digital images were obtained of the bottom and bank of the flow channel for the point cloud calculation. In contrast, the laser scanner is
generally fixed at a certain position in front of the measured surface, and due to the linear laser transmission, the beam cannot reach all parts of the channels, resulting in missing data and low resolution. The blank patches in Fig. 9 illustrate the missing data from laser scanning. Because gully erosion is of considerable importance in soil erosion, the technique used must measure gully erosion. Hence, photogrammetric observations are superior to laser scanning because they do not miss important data. However, due to the influence of the water film on soil surface, soil surface is not very contrast rich, which causes problems when identifying common points in overlapping photos. Therefore, errors in the photogrammetric observations were mainly due to image point matching errors, whereas in the laser scanning method, the main sources of error were missing data (Govers et al., 2000).

To measure how close the photogrammetric measured values to the actual value, the reference marker (rectangular and cylinders) were used in this study. A relative accuracy of 1–2% were obtained, which equaled 1:50 (Table 3). In photogrammetry, for experiments in a controlled environment a relative accuracy in the order of 1:10,000 (or better) of the largest object dimension can be expected (Scionii et al., 2014). The main reason for the low relative accuracy in our study may be due to the reference marker we used. The rectangular and cylindrical objects were made from paper, and their shape changed during the measurement, which resulted in an error measurement value. Moreover, the surface of the reference marks is not very contrast rich and that caused problems for identifying common points in point cloud matching. Therefore, well designed reference markers need to be used to test the relative accuracy of the photogrammetry. To make our approach better, we could also improve the image quality by increase the resolution of the camera and improve the accuracy in point cloud registration by improving algorithm.

4.3. The grid resolution of DEM

The number of 3D points derived from images is not an indicator of point density or resolution of the DEM. The resolution cannot be higher than the size of the matching window in object space. In our study, the matching window was 5 × 5 pixels and each pixel represented 0.3 mm (ground sampling distance in Table 2), therefore, each derived 3D point was an average over a 1.5 × 1.5 mm² surface. Anything smaller cannot be captured even if millions of points were matched in this area. Thus, the grid resolution of the derived DEM was 1.5 mm, which was similar to the result conducted by previous photogrammetric methods under no rain conditions (Abd Elbasit et al., 2009; Aguilar et al., 2009; Brasington and Smart, 2003; Peter Heng et al., 2010; Rieke-Zapp and Nearing, 2005).

4.4. Soil erosion and soil loss detection

Soil erosion is a process composed of the erosion–transportation–deposition sub-processes in the underlying surfaces (Morgan, 2005; Shi et al., 1999). Runoff and sediment collection are restricted to evaluating the volume of soil loss instead of the volume of soil erosion, as they are not able to determine the amount of soil replacement during the erosion-transportation-deposition processes. Digital photogrammetry records surface geometry continuously, allowing for the calculation of the soil replacement volume at different times at different positions. Therefore, this method can distinguish the differences between the volume of soil erosion and the volume of soil loss and can also be used to investigate the delivery ratio.

4.5. Suggestions for future studies

Only loess soil was used in the present study, other soil types such as red soil, and black soil with different texture classes and organic matter content could be used in future experiments. More repetitions need to be conducted with different gradients, slope length and rainfall intensity. The illumination system of the lab may influence the light during the imagery, this needs further consideration. In addition, the time required for data acquisition was 2 min, this time was used to bring the camera into position and walk around the soil bin. This constrains the resolution of the photogrammetric observation at the temporal scale, because soil surface may change greatly within 2 min. New image acquisition techniques need to be developed.

5. Conclusions

The purpose of this study was to demonstrate a close-range photogrammetric technique for assessing soil erosion under rainfall conditions. Based on the acquisition of highly overlapped digital images of underlying surfaces during rainfall, digital point cloud matching, DEM generation, the calculation of underlying surface geometry, and a calculation system for the volume of soil erosion, this study established a digital photogrammetric observation technique and method for soil erosion.

We have successfully demonstrated that this technique represents the two dimensions (spatial and temporal) of soil erosion processes during rainfall conditions while achieving both temporal and spatial resolution (in min and mm, respectively). The temporal resolution of the underlying surface point cloud is determined by the time required to acquire images. In a 5 m² area, the observation time interval can be 2 min while maintaining a spatial resolution of 1.5 mm. The digital
photogrammetric observation methods explored in our study provide a reliable way to monitor soil erosion processes under laboratory conditions. These methods can accurately resolve the evolution of the soil erosion on the underlying surface, which is of great importance in understanding soil erosion mechanisms. In addition, digital photogrammetry records surface geometry continuously, allowing for the calculation of the soil replacement volume at different times at different positions. Therefore, this approach can distinguish the differences between the volume of soil erosion and the volume of soil loss.

Digital close-range photogrammetry is a very powerful tool for soil erosion studies. Improving computer hardware and using an improved image-matching approach will make this technique even faster and more efficient in the future. The system was designed to be used in the laboratory but can be applied under continuous rainfall conditions, demonstrating its potential to be used in field experiments under natural rainfall conditions.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.catena.2016.03.036.

References


