Catena 150 (2017) 32–38

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

Using real time particle tracking to understand soil particle movements during rainfall events

Robert A. Hardy, Michael R. James, Jacqueline M. Pates, John N. Quinton *

Lancaster Environment Center, Lancaster University, Lancaster LA1 4YQ, UK

ARTICLE INFO

Article history:
Received 2 June 2016
Received in revised form 2 November 2016
Accepted 3 November 2016
Available online 10 November 2016

Keywords:
Particle tracing
Soil erosion
Fluorescent imaging
Fluorescence
Tracer

ABSTRACT

Very little is known about how individual soil particles move over a soil surface as a result of rainfall. Specifically there is virtually no information about the pathway a particle takes, the speed at which it travels and when it is in motion. Here we present a novel technique that can give insight into the movement of individual soil particles. By combining novel fluorescent videography techniques with custom image processing and a fluorescent soil tracer we have been able to trace the motion of soil particles under simulated rainfall in a laboratory soil flume. The system is able track multiple sub-millimeter particles simultaneously, establishing their position 50 times a second with sub-millimeter precision. An analysis toolkit has been developed enabling graphical and numerical analysis of the data obtained. For example, we are able to visualise and quantify parameters such as distance and direction of travel. Based on our observations we have created a conceptual model (Stop, hop, roll) which attempts to present a unified model for the movement of soil particles across a soil surface. It is hoped that this technology will open up new opportunities to create, parameterise and evaluate soil models as the motion of individual soil particles can now be easily monitored.

© 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

1. Introduction

“Transfer soil material into a plastic tray for air drying”. This statement was taken from page one of *Procedures for Soil Analysis* (ISRIC) and succinctly illustrates how traditional soil science is conducted. In short, one goes into the field, collects a sample and then brings it back to the laboratory for analysis, which inherently limits the amount of information that can be collected about a given location. Firstly, sampling involves perturbation to the system being studied, and the more a system is studied the more perturbation occurs, leading to a delicate balancing act between the number of samples to be collected (and therefore the amount of data available) and need to limit the unwanted perturbation to the system. Secondly, soil is known to be a highly heterogeneous, both temporally and spatially, as are the erosion processes that redistribute soil particles and deliver them to surface waters (Armstrong et al., 2011).

To address the constraints introduced by sampling, and the costs associated with sample processing and analysis, there has been a growth in proximal soil sensing (PSS) to collect in field measurements of soil properties. These methods include the development of near-infrared spectroscopy for carbon measurements (Dhawale et al., 2015) and the use of hand-held X-ray fluorescence for metal determinations (Vanhoof et al., 2004). Such measurement techniques are generally much faster and cheaper than traditional methods, as there is no need to collect samples and data are generally acquired in digital form. As a result, more data can be collected with the same amount of resources. PSS methods are also often complementary to more traditional techniques and can be used, among other things, to inform targeted sampling. Here, we focus on a new PSS method, which can help inform our understanding of soil erosion.

To date, work on soil erosion processes has included seminal studies of splash erosion (Bollinne, 1978; Hudson, 1965), concentrated flow erosion (Knapen et al., 2007) and the interaction of splash erosion processes with shallow overland flow (Kinnell, 1988). These studies have led scientists to develop process-based modelling approaches to the prediction of soil erosion, such as WEPP (Nearing et al., 1990), EUROSEM (Heng et al., 2011; Morgan et al., 1998) and MAHLERAN (Wainwright et al., 2008a; Wainwright et al., 2008b; Wainwright et al., 2008c).

Most soil erosion process studies have focused on bulk soil properties, deriving empirical relationships between soil properties and the erosive agent. For example, Bollinne (1978) related the kinetic energy of the rainfall to the mass of material ejected from a splash cup, and the relationships developed by Govers and Rauws (1986) to explain sediment concentration in overland flow related flow shear velocity to sediment concentrations. While these approaches have led to advances in our understanding of water-based erosion processes, our ability to progress beyond studies of bulk soil properties has been hampered by the availability of suitable methods.

Recent advances in image analysis have allowed scientists to examine the physics of erosion processes in more detail. Model systems,

* Corresponding author.
E-mail address: j.quinton@lancaster.ac.uk (J.N. Quinton).

http://dx.doi.org/10.1016/j.catena.2016.11.005
0341-8162/© 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

based on the measurement of single raindrop impacts on a bed of sand-sized particles, have allowed some insights to be gained into the likely effects of a raindrop impact. Much work has focused on developing a detailed understanding of the formation of splash craters and associated physics (Delon et al., 2011; Katsuragi, 2011; Nefzaoui and Skurtys, 2012). More recently Long et al. (2014) investigated the ejection of particles from a single raindrop impact, showing that the vast majority of ejected particles have low velocity and a high ejection angle, resulting in a small displacement, while <3% ejected particles have a low angle and high velocity resulting in larger travel distances (Long et al., 2014). Although not intended to mimic natural systems and working with single drops at small (<1000 mm^2) scales, this work suggests that soil particles are likely to be displaced via a series of small movements with intermittent larger movements.

Particle movement processes are beginning to appear in soil erosion models. Tucker and Bradley (2010) have proposed a particle-based model, which has been incorporated into MAHLERAN (Cooper et al., 2012; Tucker and Bradley, 2010). This approach uses a 'marker in a cell' approach, which moves a marker (particle) through a series of cells. The cells contain hydrological information and the particles are passed through the cells. The model was tested using soil movement data from a single plot scale (13.75 × 6.5 m) ^{137}Cs tracer experiment. The empirical endpoints of the experiment were compared to the simulations of particle movements in the model. However, no temporally-resolved data is available about the movements of individual particles throughout the experiment to allow validation of the model's movement of the particles. Instead validation can only be carried out based on the net movement of particles throughout the whole experiment.

Given the paucity of data on particle dynamics in response to erosion processes and the need to provide validation data for a new generation of particle-tracking soil erosion models, we set out to develop a simple and cost effective methodology that allows the motion of individual particles to be ascertained at high temporal and spatial scales. We demonstrate an experimental system that allows individual grains of a ~250 μm diameter fluorescent tracer to be tracked through time and space during a simulated rainfall event. A data set based on this work is presented and the potential for further work highlighted.

2. Materials and methods

2.1. Experimental setup

2.1.1. Soil box setup

Following the methodology adopted by Armstrong et al. (2012), a soil box (0.2 × 0.3 × 0.15 m) was filled with 40 mm of gravel, followed by a fabric membrane, 30 mm of sand, and 40 mm of soil. The soil was sandy loam soil of the Oak 2 association from Calthwaite, Cumbria, U.K., a Eutric Cambisol (WRB classification), (54.7544° N, 2.8281° W) and had been screened to 4 mm, prior to being packed carefully into the box in 1 cm layers with a bulk density of 0.9 g cm^{-1}. A coated natural particle tracer (Partrac Ltd. www.partrac.com) with a nominal diameter of 220 μm (250 μm after coating), consisting of a sand core and a green fluorescent coating, was applied to the surface of the upper area of the soil box. Note that other particle sizes are available and mixtures of particle sizes are possible. To produce a more natural pitted soil surface and to allow the particle tracer to become more integrated with the soil, the box was placed in water to a depth of 1 cm above the soil-sand interface for 24 h following tracer application, the box was then exposed to simulated rainfall (40 mm h^{-1}) for 45 min, and finally drained for 1 h before starting the experiment. The soil box was set on a slope of 5°.

For the experiment, the box was initially covered to prevent rain from impacting on the soil. It was videoed for 78 s before the cover was removed, and videoing continued for a further 4 min while the soil was exposed to rainfall (40 mm h^{-1}).

2.1.2. Lighting set-up

Illumination to excite the fluorescent coating was provided by 20 high-power 450 nm (blue) LEDs in two arrays. The LED arrays were located ~2 m from the soil box and positioned just behind and either side of the camera to reduce shadowing on the soil surface. The laboratory was blacked out, so there was no natural light present. Background lighting (for safety) was provided by another 450 nm LED array in the middle of the laboratory, pointing at the ceiling. To prevent fluctuation in lighting intensity, the LEDs were driven from a constant current and voltage source (12 V, 0.7 A), with excess heat removed through aluminium heat sinks and forced air cooling.

2.1.3. Video setup

Full HD video, 1920 × 1080 pixels at 50 frames per second, was captured using a Panasonic HC-X920 digital video camera in telemacro mode, at the maximum image brightness setting. The camera was located 2 m from the soil box and imaged an area of 96 × 54 mm downslope of the tracer application area, giving a nominal pixel footprint on the soil surface of 50 × 50 μm. Due to the non-orthogonal nature of the camera in relation to the soil box the size of the pixel footprint will vary in the x direction. In the current work, this error is expected to be small due to the relatively small distances over which the particles are being tracked. However if the particles were to be tracked over larger areas then it may be important to consider the systematic error in pixel area in future. The camera was fitted with a 490 nm longpass filter (Thorlabs), which prevented almost all of the light emitted from the LEDs from entering the camera, while allowing the particle fluorescence to be captured. The camera, lighting and soil box were positioned as show in Fig. S1.

2.2. Initial data processing

Data processing was conducted on a Dell Precision T3500 running Ubuntu 14.04 LTS. All frames were extracted from the video using ffmpeg 2.2.4 (Fig. 1a) and saved at their native resolution in a JPEG format to keep file sizes small. Code to pre-process the images was written using Spyder (Scientific PYthon Development EnviRonment) running Python 2.7.10. This code removed the red and blue channels (as they contain no useful information) and then minimised noise by setting all pixels with an intensity value less than a threshold, to zero. The threshold value was selected to most effectively reduce the noise without adversely affecting particle detection, through trial and improvement over a subset of the images. The threshold value, 110 in the example described here, was then applied to the image set (Fig. 1b). Each pre-processed frame was then searched for particles (Fig. 1c) using the Python library trackpy (https://github.com/soft-matter/trackpy). Trackpy recognises a particle by identifying a small image region having a 2-D Gaussian-like distribution of pixel brightness, and determines sub-pixel coordinates of the brightness centroid, as well as other parameters.

2.3. Pathway location

A linking algorithm was used to match particles detected in different frames into pathways representing the movement of individual particles (Fig. 2a). Each identified particle in a frame was linked to an identified particle in the subsequent frame, if it was located within a defined spatial range (75 pixels in this case) of the original particle location, with no prediction made of the particle movement direction. If there was no particle within the area, the algorithm searched forward through subsequent frames until one was found. If a maximum number of frames (50 in this case) was exceeded, then a pathway was ended. The resulting particle pathway (Fig. 2a) was given a unique number (Pathway Number), which was stored along with other parameters. Sometimes a clearer impression of a pathway can be gained by visualising the discrete particle locations as a continuous line (Fig. 2b);

Download English Version:

https://daneshyari.com/en/article/6407629

Download Persian Version:

https://daneshyari.com/article/6407629

Daneshyari.com