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Soil surface change data of high spatio-temporal resolution from the plot to the catchment scale

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S1 Data description

This dataset was generated to improve the calibration and validation of process-based soil erosion models by applying high-resolution, multi-scale and time-lapse photogrammetric observations. Although soil erosion models are vital for understanding and predicting surface processes, they face challenges due to limited spatio-temporal data resolution, assumptions of parameter stationarity and model equifinality. To address these limitations, a unique, nested, cross-scale dataset was collected using Structure from Motion (SfM) photogrammetry at plot, hillslope and catchment scales. The primary objective of the data collection was to capture changes to the soil surface during erosional processes at varying temporal resolutions and spatial extents in order to support model evaluation and development.

The dataset comprises three main components:

1) Plot-scale time-lapse data: High-frequency SfM data (Digital Elevation Model (DEM) generation at 10–60 second intervals) were captured during artificial rainfall simulations. These datasets enable the detailed monitoring of micro-topographic surface changes, including rill initiation, soil settling and compaction processes.
2) Field-scale data: Daily to sub-daily SfM observations (with DEM intervals as fine as 0.2 mm of rainfall) were recorded under natural rainfall conditions over a nearly four-year monitoring period. This data is also supplemented by UAV (uncrewed aerial vehicle) data. This data represents longer-term erosional dynamics and surface evolution under natural climatic conditions.
3) Catchment scale UAV data: Aerial imagery was captured via UAV platforms and processed into digital elevation models and orthophotos using SfM methods. These data extend the spatial scale of analysis and enable the linkage between plot-level processes and larger-scale sediment transport patterns.

All data were acquired using calibrated digital cameras and processed through standardised SfM workflows, employing open-source and commercial photogrammetric software. Ground control points and quality assurance procedures were used to ensure geometric consistency and repeatability across datasets. Additional validation was performed using reference targets and control DEMs from laser scanning in selected experiments.

The dataset is organised into individual folders corresponding to different spatial scales and time periods. Each folder contains raw imagery, processed DEMs, orthophotos, metadata and processing logs. The dataset is made available in an open-access, structured zip archive format. Full details of the data processing steps can be found in Grothum et al. (2025) and Eltner et al. (2025). A 'List of Files' document is also provided to help you navigate the folder structure.

This comprehensive, high-resolution dataset supports retrospective and real-time analysis of erosion processes, and can be used to validate existing and emerging soil erosion models. It has already been used in studies evaluating models, with a focus on distinguishing between erosional and soil compaction processes (Epple et al., 2025; Epple et al., submitted). The data are intended for reuse by the soil erosion and geomorphology research communities, and can be incorporated into future model development, data assimilation techniques and remote sensing applications.

S1.1 Sampling method

Soil samples were collected in the immediate vicinity of the photogrammetric monitoring plots in order to characterise the initial properties of the soil and evaluate any changes that occurred during the rainfall simulation experiments. Sampling was conducted at three distinct time points: before the first run, during the experimental break and after the second run had concluded. Undisturbed topsoil cores were taken at each stage using steel cylinders with a volume of 100 cm^3, resulting in a total of twelve cores: six before the experiment, three during the break and three after the final run.

No International Geo Sample Numbers (IGSNs) were assigned to the samples in this study. However, information on the samples can be found in the 'read.me' file in the 'protocol_fieldwork' folder. The information is sorted by date in this folder and summarised in CSV files.

S1.2 Analytical procedure

Laboratory: Freiberg (2020-05-05 until 2020-05-22), laboratory of the chair of Physical Geography at the Friedrich-Schiller-University Jena, Germany (all later laboratory analyses)

The bulk density and volumetric soil moisture content of each core sample were determined by weighing it in the laboratory before and after oven-drying at 105 °C. Due to space constraints in the experimental setup, sampling was concentrated in the central region of the plot.

Further samples collected next to the plot were analysed for particle size distribution using the ultrasonic dispersion and sedimentation method according to the Köhn sieve-pipette technique, and total organic carbon (TOC) content was measured using an elemental analyser coupled with isotope ratio mass spectrometry (EA-IRMS). In addition to soil sampling, field observations were conducted to record surface conditions. These included visual estimates of surface vegetation and stone cover expressed as a percentage and manual slope measurements using a clinometer.

S1.3 Data processing

The analytical data underlying this dataset were derived from terrestrial and UAV-based photogrammetric image sequences, which were processed through a standardised, quality-controlled workflow. The goal was to generate spatially and temporally precise 3D surface models suitable for soil erosion process monitoring and model evaluation. The methods, transformations and analytical steps applied during data processing are outlined below:

Camera calibration and synchronization

Prior to image acquisition, all cameras employed for terrestrial applications at plot and slope scales underwent pre-calibration using a temporary calibration field (Grothum et al., 2025). The coordinates of the markers on the calibration field were measured with millimetre precision using a folding rule, ensuring accurate modelling of the internal camera geometry and, in particular, the ray path from object points to the image sensor.

Camera triggering during data collection was synchronised via a wired connection to ensure simultaneous image capture. However, for longer-term field-scale data collection over four years, clock drifts and occasional trigger failures necessitated the development of an automatic image time-matching algorithm (Grothum et al., 2025).

Georeferencing and ground control

To georeference the models in a real-world coordinate system, ground control points (GCPs) were deployed across the plot, slope and micro-catchment setups. Their 3D coordinates were measured with millimetre-level accuracy using a Leica TCRM 1102 total station. During rainfall simulation experiments, the GCPs were also measured using a folding rule. GCP identification in images was automated using:

- Template matching with normalised cross-correlation for plot-scale data
- Deep learning-based bounding box detection was used for field-scale data (Blanch et al., 2025).
- Ellipse-fitting was used to refine GCPs at the slope to sub-pixel accuracy (Grothum et al., 2025).

Photogrammetric reconstruction and adjustment

Images were processed in *Agisoft Metashape v1.8.3* using a bundle adjustment that estimated:

- External camera parameters (positions and orientations);
- Internal camera parameters (focal length and principal point only), based on pre-calibrated values (the distortion parameters were taken from the temporary calibration and set as fixed).

Tie points identified through image matching were analysed for positional precision (James et al., 2017) and the minimum number of tie points. If the accuracy or quantity thresholds were not met, the input parameters (i.e., tie point accuracy and the minimum number of image matches) were iteratively adjusted.

A multi-view stereo (MVS) algorithm was then applied to reconstruct dense point clouds from the adjusted image sets. These dense point clouds were cleaned through filtering procedures to remove outliers and non-soil elements, such as vegetation (Grothum et al., 2023).

Change detection and uncertainty estimation

Uncertainty in 3D measurements was explicitly accounted for by interpolating the precision of tie points to the dense point cloud. This enabled the derivation of spatially variable levels of detection (LOD), which are essential for meaningful change detection. Surface change was quantified by comparing each time series point cloud with the initial point cloud using the M3C2 (multiscale model to model cloud comparison) method (Lague et al., 2013). This allowed robust, statistically constrained detection of topographic change at high spatial and temporal resolutions.

Comprehensive descriptions of the data processing methods, parameter selection and filtering steps can be found in the works of Epple et al. (2025a) and Grothum et al. (2025).

S2 File description

S2.1 File inventory

The dataset is organized hierarchically by spatial scale into three main folders:

- I_catchment
- II_slope
- III_plot

Each of these scale-specific folders is subdivided into:

- 0_raw: containing raw input data as acquired in the field

- 1_processed: containing outputs from data processing workflows (e.g., dense point clouds, change detection)

Catchment scale (folder: I_catchment)

- I_catchment_0_raw contains:
    - UAV_images: UAV imagery sorted by flight date folder (yyyy-mm-dd)
    - GCPs: Ground control point data
- I_catchment_1_processed contains:
    - UAV_dense: Dense point clouds from UAV imagery in .ply and .e57 formats

Slope scale (folder: II_slope)

- Subdivided by slope position: lower_slope, middle_slope, upper_slope,
    - SLR subdivided by months (yyyy-mm) and further by camera number
    - Dense point, ptPrecision subdivided by months (named yyyy-mm)
    - Fieldwork subdivided by days (yyyy-mm-dd)
- M3C2 organised according to the reference date (no more subdivision)
- UAV-images subdivided by date (yyyy-mm-dd)
- II_slope_0_raw contains:
    - GCPs: Coordinates and positions of ground control points
    - Protocol_fieldwork: Field metadata (e.g., bulk density, soil moisture, soil cover, rainfall intensity, organic carbon, grain size distribution, discharge timeline)
    - SLR: Raw image data by slope position and camera ID
    - UAV_images: UAV imagery sorted by flight date
    - Weather: Time series from the on-site weather station (2020-09-04 to 2022-10-05)
- II_slope_1_processed contains:
    - Camera_calibration
    - SfM_timelapse: Dense point clouds and precision maps (filtered/unfiltered), M3C2 (named by reference date and time yyyy-mm-ddThh-mm-ss and compare dataset yyyy-mm-ddThh-mm-ss); sorted by slope position and date, including also summary log- and ptPrecision-file

Plot scale (folder: III_plot)

- Subdivided by date of rainfall simulation
- III_plot_0_raw contains:
    - GCPs: Coordinates and positions of ground control points
    - Protocol_fieldwork: Field metadata (e.g., bulk density, soil moisture, soil cover, rainfall intensity, organic carbon, grain size distribution, tillage, crop type and stage, discharge and sediment time series [min])
    - SLR: Raw camera data from DSLR cameras
- III_plot_1_processed contains:
    - Camera_calibration: Internal camera parameters and calibration information (format TBD; typically JSON/XML or CSV)
    - SfM_timelapse: Dense point clouds and precision maps (filtered/unfiltered), sorted by experiment date; includes .txt files for M3C2 change detection outputs (referenced to first time step), including also each a summary log- and ptPrecision-file

Each major folder includes a read.me file to guide users through the data content and structure.

S2.2 File naming convention

Naming by date is always structured yyyy-mm-dd, by date and time in some occasions a time information is also added, these are organized yyyy-mm-ddThh-mm-ss (proc = processed).

Table S1: File naming convention of the data set.

scale	data type	naming	
catchment>raw	raw flight images	numbered consecutively	.jpg
	GCP information	'coordinates_catchment', 'positionsGCPs'	.txt, .png
catchment > proc	dense point cloud	by date	.e57
slope>raw	GCP information	by date	.txt, .png
	laboratory/field information	information included	.csv
	raw camera data	numbered consecutively	.jpg
	raw flight images	numbered consecutively	.jpg
	weather	observation period	.csv
slope>proc	calibration information	by number of camera	.xml
	dense point cloud	by date + time	.ply
	log files	numbered and date + time	.txt
	point precision	numbered and date + time	.txt
	M3C2	date + time compared to reference day + time	.txt
	dense point clouds (UAV)	by date	.ply
	RMSE information	numbered consecutively	.txt
plot>raw	GCP information	by date	.txt, .jpg
	laboratory/field information	information included	.csv
	raw camera data	numbered consecutively	.jpg
plot>proc	calibration information	by name of camera	.xml
	dense point clouds	numbered consecutively	.ply
	RMSE information	numbered consecutively	.txt
	M3C2	named by min. to reference min.	.txt
	point precision	numbered consecutively	.txt

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