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Jotisankasa, A., Mapiam, P. P., Methaprayun, M., Praphatsorn, W., Torsri, K., Supavetch, S., Soralump, S., Linnebach, J., & Bogaard, T. (2026). A satellite soil moisture– and radar rainfall–based methodology for slope-scale seepage–stability modelling of rainfall-induced landslides. *Landslides*, 23(8), 2521-2533. <https://doi.org/10.1007/s10346-026-02732-x>

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Landslides

DOI 10.1007/s10346-026-02732-x

Received: 23 November 2025

Accepted: 4 March 2026

© Springer-Verlag GmbH Germany,
part of Springer Nature 2026Apinit Jotisankasa · Punpim Puttaraksa Mapiam  · Monton Methaprayun ·
Washirawat Praphatsorn · Kritanai Torsri · Soravis Supavetch ·
Suttisak Soralump · Jonathan Linnebach · Thom Bogaard

A satellite soil moisture– and radar rain–fall–based methodology for slope-scale seepage–stability modelling of rainfall-induced landslides

Abstract Satellite-derived surface soil moisture (SSM) data are rarely applied in landslide modelling due to their shallow sensing depth (< 5 cm) and large spatial footprint, limiting their perceived relevance for subsurface hydrological processes. This study presents an integrated approach combining SMAP-Sentinel L2 SSM with high-resolution gridded radar rainfall data for coupled subsurface flow–stability landslide modelling. The 2020 landslide in Khao Yai National Park, Thailand, was used as a case study, supported by two years (2022–2024) of slope monitoring, including soil moisture, rainfall, and tiltmeter-based deformation data. Monthly averaged SSM showed reasonable agreement with in-situ soil moisture ($R^2 = 0.63$) and was applied as an initial boundary condition in flow models to estimate soil moisture variation with depth and time. The SSM-based model produced comparable results to in-situ soil moisture-based model ($R^2 = 0.96$) but generally underpredicted the factor of safety (F_s) by 9% especially during the onset of rain events. Two-dimensional flow and stability analyses revealed that rainfall-induced subsurface flow parallel to the slope reduced F_s to near unity prior to 2020 landslide. A moderate correlation ($R^2 = 0.62$) between soil moisture change and tiltmeter deformation indicated slope contraction during dry periods and downslope movement during wet conditions. These findings support the use of SSM and radar rainfall for improving landslide prediction and early warning systems.

Keywords Satellite soil moisture · Landslide · Subsurface flow · Soil moisture · Slope stability · Radar rainfall

Introduction

Landslides are increasingly more frequent in many regions facing extreme climatic events around the world (e.g. Dalmastri and Uccelli 2024; Shi et al. 2024). The extreme weather patterns exacerbate slope instability due to soil desiccation cracks, degraded vegetation cover during drought and forest fire, and the subsequent heavy rain that triggers landslides and flash floods. Accurate understanding of hydrological processes related to rainfall-induced landslides is crucial for hazard mapping and the development of early warning systems (e.g., Mairaing et al. 2012; Sidle et al. 2019). Traditionally, this requires a coupled analysis of slope stability and variably saturated subsurface flow to represent key hydrological processes—such as infiltration and exfiltration—that govern slope failure (e.g., Jotisankasa et al. 2015; Feng et al. 2023; Luo et al. 2025).

A major challenge in predicting rainfall-induced landslides lies in defining appropriate boundary conditions for seepage analysis. In particular, a number of studies have indicated the importance of surface soil moisture in landslide studies. Marino et al. (2020), modelling the response of slopes to precipitations, highlighted the improvement in landslide forecasting by including near surface and root-zone soil moisture, provided by either field sensors or remote sensing. Ye et al. (2024) quantified the correlation between landslide deformation and soil temperatures and moisture contents, emphasizing the need for comprehensive monitoring and forecasting of these factors. Mirus et al. (2025) discussed key limitations in landslide early warning systems (LWS), noting that hydrologic models often assume diffuse flow and vertical infiltration while neglecting preferential pathways and lateral drainage. They emphasized that the most promising advances in LWS lie in adopting a measure-and-model framework to better capture local controls on subsurface storage dynamics. Roman Quintero et al. (2025) demonstrated that hydrometeorological thresholds—combining rainfall depth with antecedent root-zone soil moisture or aquifer water level—provide more accurate landslide predictions in Campania (Italy) than thresholds based solely on rainfall intensity and duration.

IoT technology has advanced real-time field monitoring of rainfall, soil moisture, and related parameters (e.g., Jotisankasa et al. 2024), but large-scale deployment remains limited by logistical and financial constraints, resulting in scarce regional coverage. Satellite-based surface soil moisture products, available for over a decade (e.g., Entekhabi et al. 2010; Mohanty et al. 2017), offer a potential alternative, though their use in site-specific landslide studies is still limited. For example, Jotisankasa et al. (2023) evaluated SMAP-Sentinel L2 data for soil moisture estimation in Thailand, though focusing primarily on calibration against field measurements. It is also important to distinguish between the direct observations collected by satellite sensors and the derived soil moisture products. Direct observations, such as radar backscatter or passive microwave brightness temperatures, represent measurements of surface physical properties (Entekhabi et al. 2010). However, the translation of these measurements into soil moisture estimates involves retrieval algorithms that rely on assumptions regarding soil texture, vegetation cover, surface roughness, and dielectric properties, making the final soil moisture products inherently model-dependent and subject to uncertainties (Ochsner et al. 2013).

Several studies (e.g., Zhao et al. 2021; Uwihirwe et al. 2022) have examined satellite-derived soil moisture for regional landslide and geohazard assessment, but most remain empirical and focus on antecedent wetness patterns rather than integration into physics-based models. Zhao et al. (2021) found SMAP root-zone soil moisture (L4 product) most suitable for regional-scale hazard assessment in northern Italy. Uwihirwe et al. (2022) showed that cumulative 3-day rainfall was the strongest predictor of landslide initiation when combining satellite near-surface soil moisture with a hydrological model. Although satellite-derived root-zone soil moisture products are available (e.g. ERA5 and ERA5-Land), these estimates are largely model-derived and require site-specific validation for landslide applications, particularly in steep tropical terrain. Consequently, satellite-observed near-surface soil moisture (i.e. SMAP–Sentinel L2), which has been locally validated in Thailand (Jotisankasa et al. 2023), is adopted as the input for calibrated seepage–stability modelling in this study.

Advances in weather radar technology now enable high-resolution rainfall data in both time and space, enhancing the ability to capture localized rainfall patterns that can trigger flash floods and landslides (Mapiam et al. 2009; Cremonini and Tiranti 2018; Tseng et al. 2020). Combining multiple radar stations into

composite products improves rainfall accuracy in mountainous regions and provides a more complete picture of precipitation distribution and movement across large areas (Methaprayun et al. 2025). However, to our best knowledge the use of satellite-derived soil moisture and radar composites in geotechnical landslide analysis has not been explored. This study seeks to fill this gap by explicitly integrating satellite-derived surface soil moisture and radar composites into a variably saturated flow model for landslide prediction. The proposed methodology combines SMAP–Sentinel L2 data and grid-based radar composites with coupled seepage and slope stability models, and is validated against an actual landslide event and observed field behaviour.

Methods and materials

Proposed methodology

As outlined in Fig. 1, the proposed methodology integrates SMAP–Sentinel L2 soil moisture data, radar rainfall, and in-situ observations for slope-scale landslide modelling through the following steps:

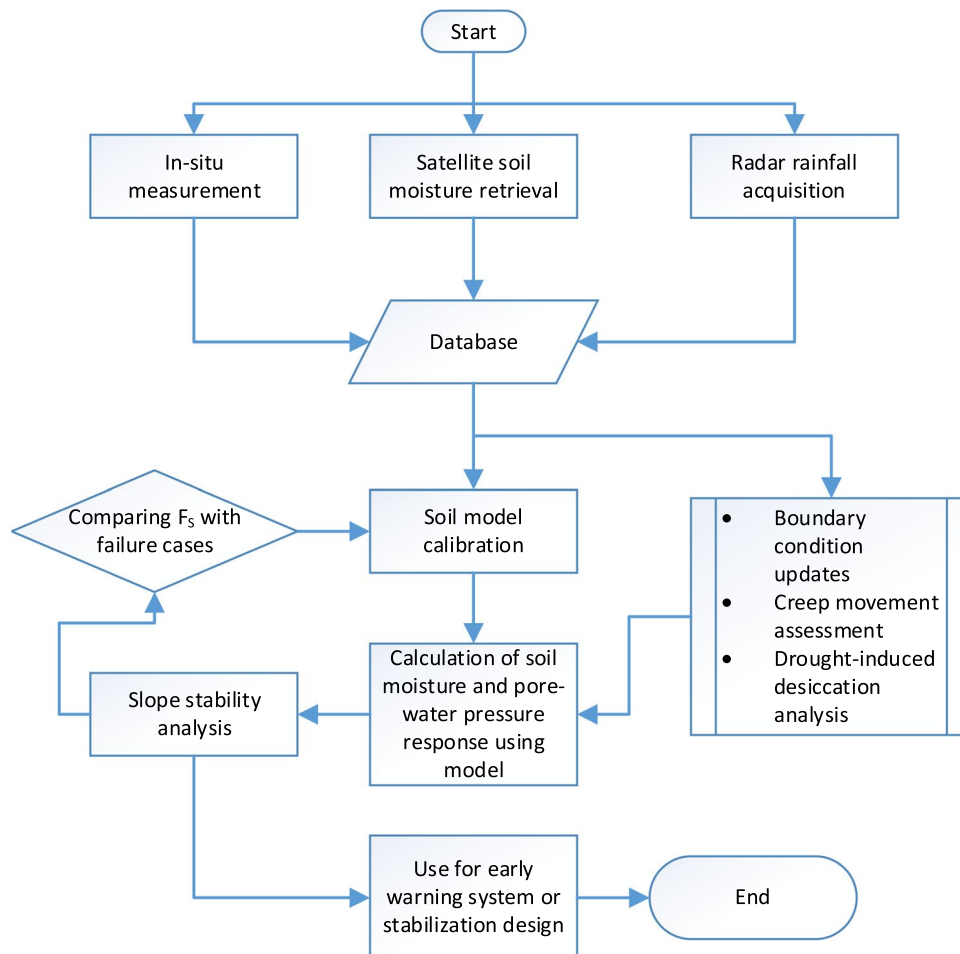


Fig. 1 Proposed methodology for integrating satellite-derived soil moisture data with radar rainfall and in-situ measurements for slope-scale landslide modelling

1. Satellite soil moisture retrieval: Retrieve SMAP-derived surface soil moisture data available every 3 to 7 days, average the values over a one-month period according to the findings by Jotisankasa et al. (2023) to improve accuracy, and apply a correction factor if required.
2. Radar rainfall analysis: Six-minute raw radar reflectivity data from the Sattahip and Phimai radars were composited using the quality index algorithm and converted to 1-min rainfall estimates. Hourly mean field bias (MFB) factors derived from rain gauge observations were applied uniformly as multiplicative corrections to the 1-min radar rainfall within each corresponding hour. The bias-corrected rainfall was then aggregated to 20-min intervals for landslide model configuration.
3. Soil model calibration: Utilize in-situ soil moisture (or pore-water pressure) time series data to calibrate a variably saturated subsurface flow model (1D or 2D) based on the availability of data and site investigation results. This includes determining permeability, soil water retention curves, and bottom boundary conditions.
4. Calculation of soil moisture and pore-water pressure response: The averaged satellite-derived surface soil moisture from the previous month is applied as the initial upper flux boundary condition in the flow model. The initial lower boundary is prescribed as a negative pore-water pressure (suction) value corresponding to the unsaturated permeability that matches the average monthly rainfall from the previous month. For the current month, radar composite rainfall data with a 20-min temporal resolution are applied as the surface flux boundary condition. These inputs are used to simulate the soil moisture

- and pore-water pressure responses to rainfall. Saturated permeability is adjusted to achieve agreement between measured and modelled soil moisture.
5. Slope stability analysis: Calculate the factor of safety by incorporating the obtained pore-water pressure data into an appropriate slope stability model.
6. Boundary condition updates: Update the surface boundary conditions at the beginning of each month to reflect the latest averaged satellite soil moisture data.
7. Parameter adjustments: Factor of safety can be calibrated against in-situ stability observations (e.g., reported failure or tiltmeter-based movement) and shear strength parameters adjusted accordingly. Strength reductions linked to creep can be evaluated where possible

A case study of the 2020 landslide in Khao Yai National Park, Thailand was used to demonstrate this methodology. A series of comparative analyses have been conducted using in-situ measurement of soil moisture and soil-water retention curve combined with a subsurface-flow finite-element model with a) the in-situ antecedent soil moisture condition (Model 1) and b) with the satellite antecedent soil moisture condition (Model 2). Unsaturated-saturated flow was simulated using the finite-element software SEEP/W (Geo-Slope International Ltd., 2012a), which solves the Richards' equation to describe transient water flow through variably saturated soils. Rainfall infiltration was applied as a time-dependent flux boundary condition at the ground surface, limited by soil hydraulic conductivity to allow for runoff when rainfall intensity exceeded infiltration capacity. This formulation is well

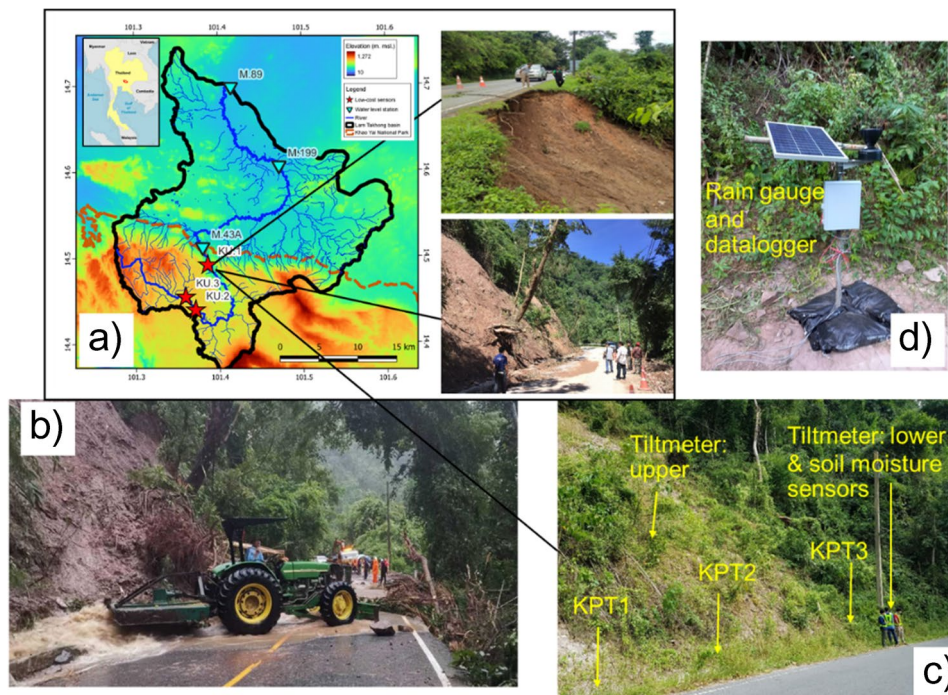


Fig. 2 Study site **a** Khao Yai National Park and landslides in the area; **b** the studied landslide in 2020; **c** the studied slope in 2022 with locations of sensors and in-situ test; **d** datalogger

established for analysing rainfall-induced pore-water pressure in slopes in geotechnical applications.

The computed pore-water pressures from the flow models were used to evaluate the factor of safety (F_s) over time. For the infinite slope stability model considering variably saturated slope, the factor of safety can be described as follows (Fredlund and Rahardjo 1993; Mahannopkul and Jotisankasa 2019):

$$F_s = \frac{c' + (\gamma \cdot z) \cos^2 \beta \tan \phi' - u_w \tan \phi'}{(\gamma \cdot z) \cdot \sin \beta \cdot \cos \beta} \quad (1)$$

where c' is the effective cohesion intercept of soil; γ is soil's total unit weight which varies with degree of saturation; z is the thickness of the failure mass, β is the slope gradient, ϕ' is the effective angle of friction; ϕ^b is the angle of friction with respect to suction (or negative pore-water pressure); and u_w is the pore-water pressure of the soil; $\phi'' = \phi^b$ when $u_w < 0$, and $\phi'' = \phi'$ when $u_w \geq 0$.

The one-dimensional (1D) flow model provides a convenient and computationally efficient approach for coupling with infinite slope stability models, making it particularly suitable for large-scale or GIS-based landslide prediction. However, as the primary objective of this study is to support detailed slope-scale analyses required for geotechnical investigation and slope stabilization design, two-dimensional (2D) flow models combined with limit equilibrium stability analyses (SLOPE/W, Geo-slope International Ltd. 2012b) are adopted, as they better capture complex slope geometry and localized groundwater flow patterns. This paper presents both 1D and 2D modelling approaches to demonstrate their practical applications for different scales and purposes. Both landslide-triggering and post-landslide rainfall events were analysed to examine the temporal variation of factor of safety (F_s).

Study area

The study area is located within Khao Yai National Park (Fig. 2). The area experiences a climate influenced by monsoonal patterns and its topography shaped by a complex mountain range formed from volcanic and sedimentary rocks. On 10th–11th October 2020, a major landslide event occurred along Highway No. 2090 in northern part of the Park, involving multiple types of mass movement, including shallow debris flows, planar rockslides, rockfalls, and rotational failures. This event represents the most severe landslide documented in terms of magnitude and spatial extent since the park's establishment in 1962. Over 70% of failures were shallow soil slides (0.5–1 m thick) from weathered volcanic rocks on steep slopes (30°–40°), with landslide paths ranging from 15 to 50 m. Rain gauge data recorded 133 mm of rainfall over four days, triggering the October 2020 landslides. The failures occurred between 10th and 11th October, following a peak daily rainfall of 81 mm on 8th October. Compared to historical rainfall-induced landslides in Thailand (Mairaing et al. 2012), this rainfall amount was not exceptionally high. A reliable landslide early warning system, incorporating both rainfall and geotechnical data, is recommended to reduce risks within the park.

The selected instrumented slope (Fig. 2c) is located at KM + 27 along Highway No. 2090 (Latitude: 14.485072°, Longitude: 101.387713°), chosen due to its relatively simple landslide mechanism, primarily a translational slide, making it representative of the typical mass movement patterns observed in the area. A 3D model of the slope was developed using UAV photogrammetry mapping, and used to generate the slope cross-section. The slope angle at the study site measures 38 degrees, and the length of the landslide mass is approximately 50 m. An immediate post-landslide survey

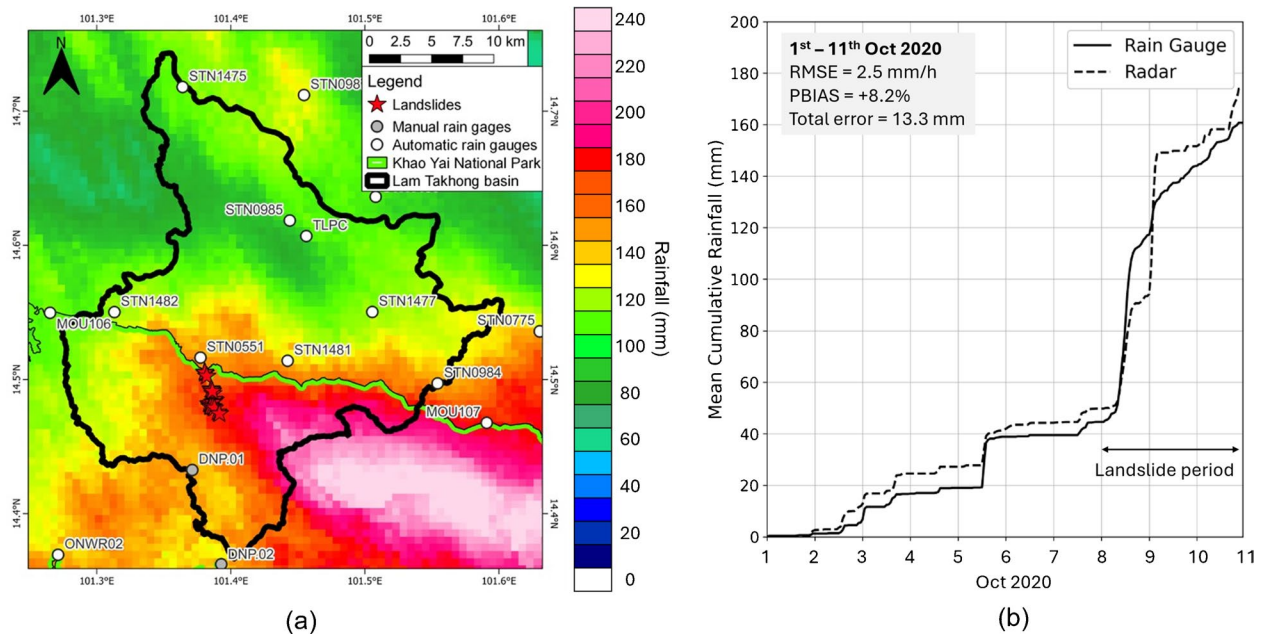


Fig. 3 **a** Radar rainfall accumulation during the landslide event from 8th – 11th October 2020 and rain gauge locations; **b** mass curves of mean cumulative rainfall from radar estimates and observations at four rain gauges near the landslide location (STN1482, STN0551, STN1481, DNP.01) during the landslide period

estimated the failure depth of around 0.8 to 1 m, with a width of 30 m and a total landslide volume of approximately 1,500 cubic meters. The condition of the slope in 2022 showed sparse vegetation mainly being pioneer species of grasses and shrubs, which have started to recolonize the disturbed area.

The site investigation included the lightweight dynamic cone penetration tests (EGAT 1980), conducted at the slope toe above the road surface. The tests revealed an upper loose to medium-dense soil layer with thickness varying from 1.2 to 2 m across the slope. The soil is classified as silty sand (SM) with 18.5% gravel, 64.4% sand, 14.5% silt, and 2.6% clay; and the specific gravity, G_s , of 2.61 and the void ratio of 0.93. Below this layer lies the dense soil layer approximating to the depth of shallow slide. The cross section, particle size distribution curve and strength parameters used in subsequent unsaturated flow and slope stability model are shown in Supplementary material. The soil–water retention curve (SWRC) was determined on the undisturbed sample following the method by Jotisankasa et al. (2009) and Barus et al. (2019), as shown in Supplementary material. The bimodal nature

of the tested SWRC is observed, indicating two distinct pore structures: larger macropores and smaller micropores, a feature commonly found in soils from landslide-prone areas (e.g., Jotisankasa et al. 2009; Rajamanthri et al. 2021).

Field instrumentation

An IoT-based slope monitoring system was deployed at the study site in December 2021, as described by Methaprayun et al. (2023). The system includes a tipping bucket rain gauge and three soil moisture sensors installed at depths of 0.05, 0.30, and 0.50 m near the slope toe (see Fig. 2). In February 2023, two additional tiltmeters were positioned approximately 1.5 m above the slope toe to monitor surface soil movement. These tiltmeters, described in Jotisankasa et al. (2024), each consist of an accelerometer (sensitivity: 140 mV/degree) mounted on a rod driven 0.5 m into the ground. The soil moisture sensors were calibrated in the laboratory using in-situ soil at varying moisture contents, re-compacted to replicate field density.

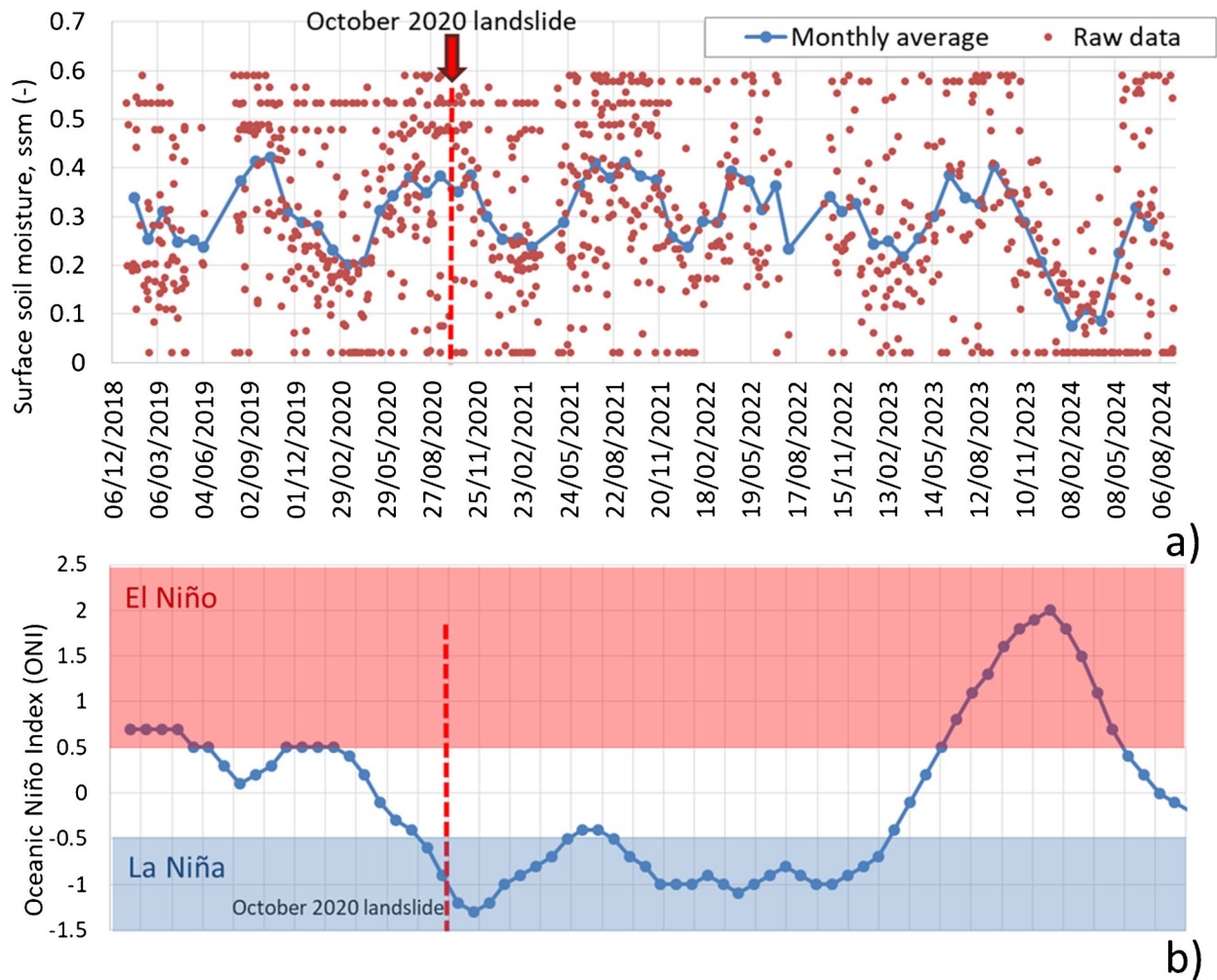


Fig. 4 a Variations of surface soil moisture from SMAP-sentinel L2 from raw data and average monthly values; b Oceanic Niño Index (ONI)

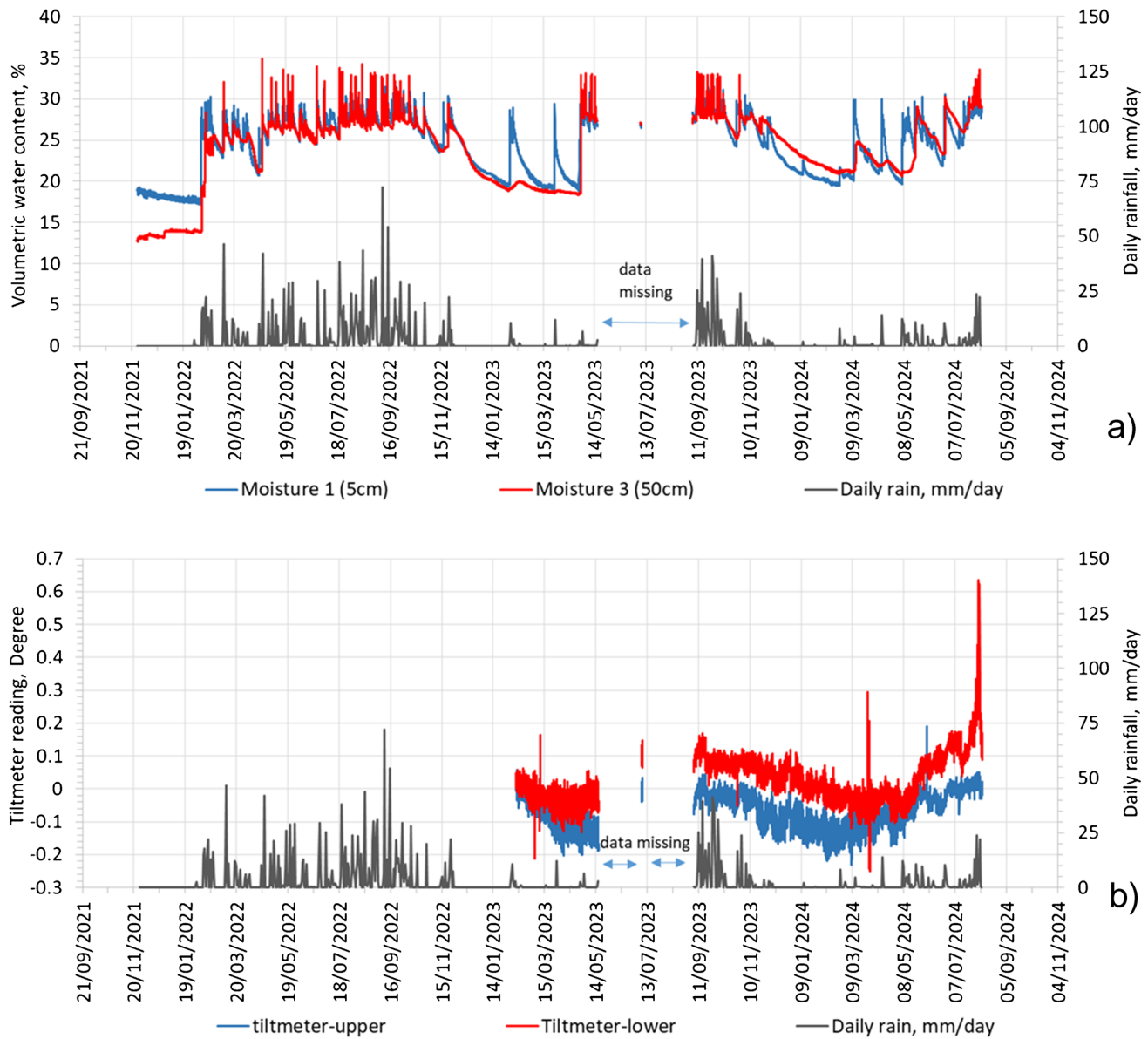


Fig. 5 a Time series of daily rainfall and volumetric soil water content from 2022 to 2024. (b) Slope surface movement derived from in-situ tiltmeter measurements, available from February 2023 onward

High-resolution radar composite rainfall assessment

The nearest rain gauges during the 2020 landslide event were located approximately 5 km downstream from the reference slope (Fig. 3a). As rainfall shows strong spatial and temporal variability in mountainous regions, and downstream gauge measurements cannot adequately represent rainfall conditions at the slope scale, radar-based rainfall data were adopted as a more appropriate and efficient solution. Weather radars provide overlapping coverage, allowing composite techniques to improve rainfall accuracy (Holleman 2007; Antonini et al. 2017). The quality index (QI) method accounts for radar beam blockage, beam height, and distance from the radar to refine rainfall estimation was applied in this study (Saltikoff et al. 2019; Méri et al. 2021; Osródka and Szturc 2022;

Methaprayun et al. 2025). Residual bias in radar-derived rainfall was further corrected using mean field bias (MFB), defined as the ratio of mean radar estimates to rain gauge measurements (Shi et al. 2018; Mapiam et al. 2022, 2023). Hourly MFB factors were applied as multiplicative adjustments to all composite radar pixels to improve the accuracy of hourly rainfall estimates. Additional details are provided in the Supplementary Material.

SMAP-sentinel L2 remote sensing soil moisture

This research employs the soil moisture dataset from the SMAP radiometer and Copernicus Sentinel-1 (L2_SM_SP), specifically identified as the SPL2SMAP_S SMAP/Sentinel-1 L2 Radiometer/Radar 30-Second Scene 3-km EASE-Grid Soil Moisture, Version 3

(Das et al. 2019, 2020). As a Level-2 soil moisture product, it estimates surface soil conditions by integrating observations from SMAP's radiometer during both its 6:00 a.m. descending and 6:00 p.m. ascending orbits, along with radar data from Sentinel-1A and -1B. The soil moisture readings are derived using L-band brightness temperatures from SMAP and C-band backscatter measurements from Sentinel-1.

Measurement results

Radar composite rainfall

During the landslide event from 8th – 11th October 2020, accumulated rainfall over the landslide area reached about 130 mm in 96 h, with peak intensities of 20 mm/h (Fig. 3a). A comparison of mass curves between radar rainfall and rain gauge measurements from four nearby gauges (Fig. 3a and b) was conducted to assess radar accuracy. The radar effectively captured rainfall patterns with a slight 12% overestimation, an RMSE of 1.9 mm/h, and a total error of 7 mm. The maximum discrepancy occurred at 23:00 on 8th October 2020, when the difference in cumulative rainfall reached approximately 24 mm. Previous studies have reported radar–gauge rainfall differences of 20–50 mm/h during heavy rainfall events (Schleiss et al. 2020; De Biase et al. 2025; Qiu et al. 2026), attributable to uncertainties in radar-based estimation as well as limitations of rain gauge measurements in mountainous regions. This indicates that the observed discrepancy falls within a plausible range. The bias-corrected radar rainfall was subsequently used for landslide modelling.

SMAP-sentinel L2 remote sensing soil moisture

Figure 4a and b illustrate the variation in surface soil moisture (SSM) derived from SMAP-Sentinel L2 data over a six-year period from 2019 to 2024. The raw satellite-derived soil moisture data exhibit significant scatter, limiting their direct application. Therefore, a one-month averaging approach was applied to better reveal

seasonal trends in SSM (Jotisankasa et al. 2023). The October 2020 landslide event is indicated in Fig. 4a. No significant increase in SSM was observed during this event in either the raw or monthly averaged data, indicating that the satellite-based SSM did not capture the moisture conditions associated with slope failure. Field evidence and numerical analyses reported by Nguyen et al. (2020) show that landslides in the Khao Yai area are commonly triggered by localized groundwater rise controlled by site-specific geology and channelized topography, rather than by near-surface soil moisture changes detectable by satellite-based SSM products. Satellite-based SSM, representing only the top few centimeters of soil across a broader spatial resolution (approximately 1 km²), may not accurately reflect moisture dynamics at the finer scale (one to ten meters) observed within the landslide mass.

Figure 4 shows that soil surface moisture (SSM) reached its lowest recorded level during the dry season in February 2024, marking the minimum value observed over the entire six-year measurement period. This decrease in SSM appears to correlate with the Oceanic Niño Index (ONI), as illustrated in Fig. 4b. The highest ONI values, indicating an El Niño warm period, were observed at the end of 2023 and the dry season of 2024, likely contributing to the exceptionally low soil moisture. Notably, the landslide event in 2020 aligns with the lowest ONI values (La Niña), which are associated with increased rainfall intensity.

In-situ measurement and correlation with satellite soil moisture

Figure 5 illustrates the variations in in-situ volumetric soil water content, daily rainfall, and soil surface movement (measured as tilt angle) over a three-year period from 2022 to 2024. Throughout the measurement period, with a frequency of two minutes, the recorded volumetric soil water content ranged from a maximum of 0.329 to a minimum of 0.185. Notably, the peak in-situ volumetric water content ($\theta_{s,insitu} = 0.329$) is lower than the maximum value (0.503) obtained from the soil–water retention curve (SWRC) test on an undisturbed sample, reflecting the difference in porosity of the two cases. In addition, the surface soil layer exhibits a more rapid increase in soil moisture during rainfall events and a faster depletion during dry periods due to evapotranspiration, whereas deeper soil moisture responds more slowly and is less affected by short-term atmospheric forcing.

To address the temporal variability of soil moisture across different scales, a normalization scheme was applied to align SMAP satellite soil moisture data with in-situ measurements using monthly averages. The normalized volumetric water content, $S_e = \frac{(\theta - \theta_r)}{(\theta_s - \theta_r)}$, was calculated, where θ_s is the saturated volumetric water content, θ_r is the residual volumetric water content. The details about the determination of θ_s and θ_r are explained in Supplementary material. Figure 6 displays the correlation between the normalized water content values obtained from the satellite and in-situ measurements, showing a reasonably strong correlation ($R^2 = 0.63$).

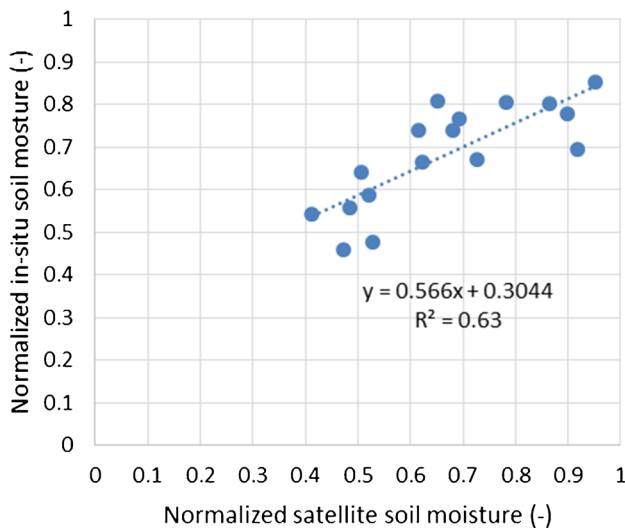


Fig. 6 Correlations between normalized satellite and in-situ soil moisture contents (only using data from December 2021 until October 2023)

Correlation between tilt rate and soil moisture

In-situ tiltmeter readings were used to calculate the rate of movement on a monthly basis and were correlated with the changes in in-situ soil moisture, as shown in Fig. 7. The slope surface movement at the toe, measured as tilt (in degrees) and shown in Fig. 7b, was then used to determine the rate of movement (Tilt degree/day) through linear regression over a one-month interval. For periods with missing data (June 2023), linear interpolation was applied to estimate the tilt rate.

As shown in Fig. 7, the rate of change in soil moisture, calculated using linear regression in the same manner as the tilt rate, reasonably correlates with the tilt rate. A reduction in soil moisture (and thus an increase in soil suction) during the dry season leads to slope shrinkage or uphill tilting (negative tilt rate). In contrast, an increase in soil moisture causes downhill slope movement (positive

tilt rate) or creep. The R-squared value between the two rates ranged from 0.226 (when all data were included) to 0.618 (when only data from October 2023 onwards were used in the regression).

Modelling and results

Seepage–stability modelling was carried out with respect to cumulative rainfall by explicitly examining three representative rainfall events: February 2022, September 2022, and the October 2020 landslide events. The February 2022 event represents rainfall infiltration under dry antecedent conditions, while the September 2022 event typifies rainfall during the wet season with elevated antecedent moisture. The October 2020 event corresponds to the documented slope failure period. These events were selected to capture contrasting antecedent moisture states and rainfall characteristics relevant to slope response.

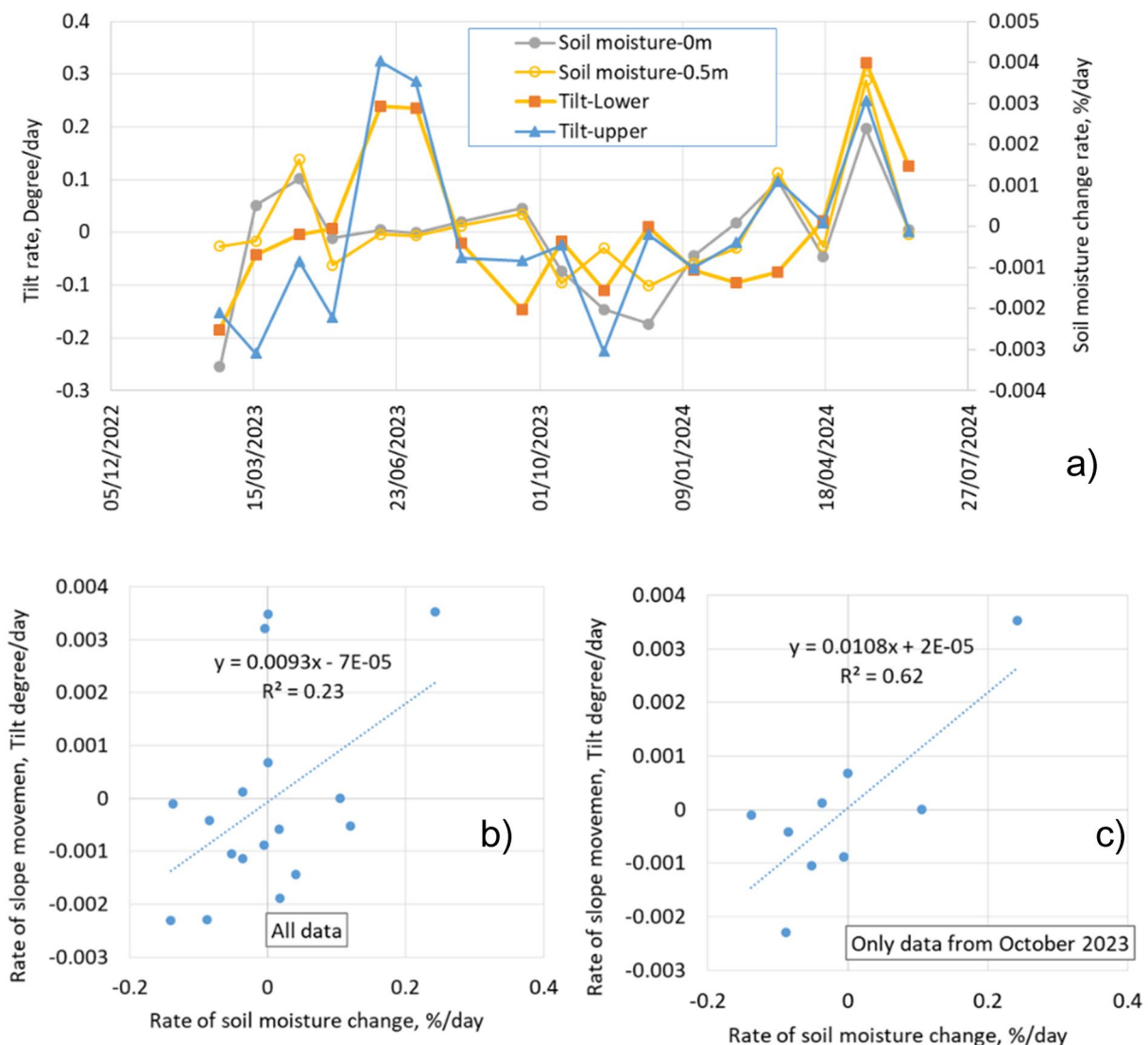


Fig. 7 a Slope movement measured as tilt rate and soil moisture change rate (monthly basis) with time; b correlation between rate of change in tilt and soil moisture (1 month interval) using all data and c using only data from October 2023 onwards

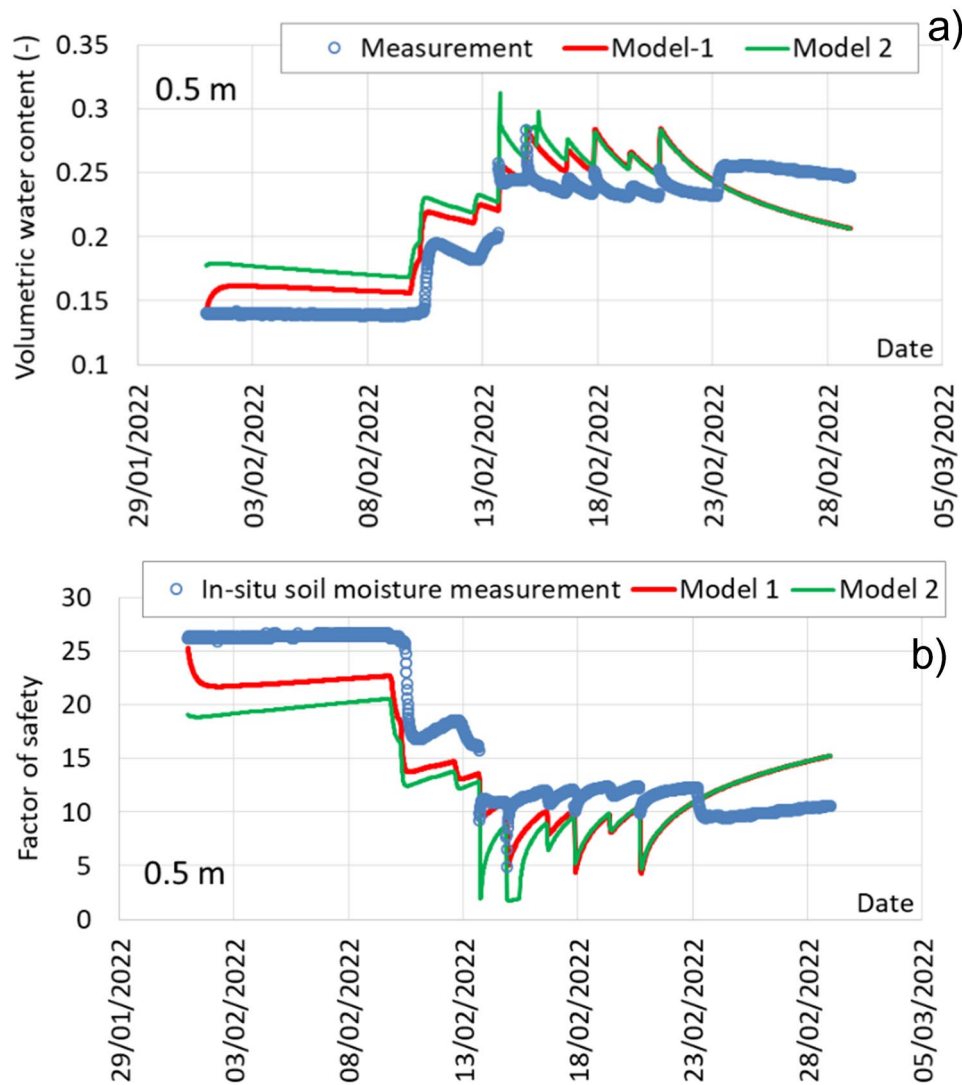


Fig. 8 Temporal variation of **a** volumetric soil water content and **b** factor of safety in February 2022 based on in-situ soil moisture measurement, Model 1 (in-situ soil moisture as initial condition) and Model 2 (satellite soil moisture as initial condition)

One-layer soil column model calibration

One-layer vertical flow soil column (0.5 m thick) model was first assumed to determine the saturated permeability of the upper soil layer. A series of analysis using the finite element method were performed, using measured rainfall flux (recorded at 20-min intervals) and soil moisture data to calibrate the model by adjusting the saturated permeability, k_s . Details about the model calibration are given in Supplementary material.

Transient flow modeling of the February 2022 infiltration was first conducted using two approaches (Model 1 and Model 2). Model 1 used the measured in-situ soil moistures as initial condition while Model 2 used satellite-derived soil moisture. The upper boundary was set to the monitored rainfall intensity, while the base boundary was defined as a unit gradient, representing a freely draining base. By varying the saturated permeability, k_s , between 2×10^{-8} m/s and 2×10^{-3} m/s, the modeled time series of volumetric water content

at three depths was compared with field measurement. The best-fitting k_s value was found to be 2×10^{-4} m/s, yielding a minimum RMSE of 0.021 [m^3/m^3]. The pore-water pressure values derived from Models 1 and 2 were then used to calculate factor of safety in infinite slope stability analysis. As shown in Fig. 8b, both models yielded lower factors of safety compared to those based on direct in-situ measurements of soil moisture. Model 2, which relied on satellite soil moisture, produced slightly lower factors of safety than Model 1 due to the higher pore-water pressure estimates especially at the onset of rain events.

Two-layer soil column model calibration

To further validate the model with data from the rainy season, the September 2022 dataset was used. As deeper infiltration was expected during the rainy season, the two-layer model having a total soil depth of 1 m was assumed, comprising an upper and a

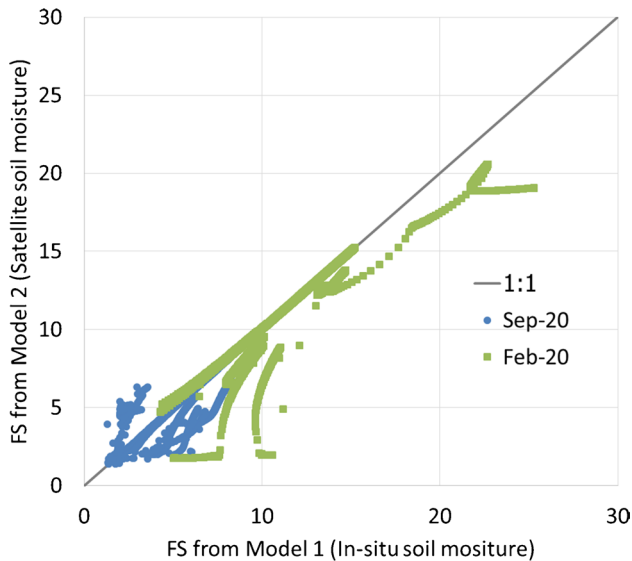


Fig. 9 Comparison of factor of safety (F_s) calculated using ISM approach (Model 1) and SSM approach (Model 2) from 2020 dataset

lower layer, each 0.5 m thick. The details of the model and calibration process are explained in Supplementary material. The F_s predictions obtained from Models 1 and 2 were compared ($R^2 = 0.96$), as illustrated in Fig. 9. For the February 2020 dataset, representing the dry season, the SSM-based approach (Model 2) produced factors of safety approximately 9% lower than those from the ISM-based model (Model 1), primarily due to higher estimated pore-water pressures, resulting in a generally conservative prediction. Similarly, for the September 2020 dataset representing the rainy season, Model 2 underpredicted F_s by an average of 8%. However, there were also periods where Model 2 slightly overpredicted F_s compared to Model 1.

2020 Landslide model

The daily rainfall data from the landslide event in October 2020 was used to model temporal variations in soil moisture and pore-water pressure using both 1-dimensional and 2-dimensional flow models, which were subsequently incorporated into the slope stability analysis. Initial conditions for soil moisture and pore-water pressure in the flow analysis were prescribed using calibrated satellite-derived surface soil moisture data from September 2020. This approach aimed to reproduce the conditions leading to the landslide initiation reported between 10th and 11th October 2020.

As illustrated in Fig. 10, the 1D-flow infinite slope model indicates that between 1st and 11th October 2020—the day the landslide was reported—there were several episodes of pore-water pressure pulses that reduced F_s to below 1.1. Notably, the calculated pore-water pressure peaked at -0.88 kPa at a depth of 1 m on 9th October 2020 at 02:00 h, corresponding to an F_s of 1.09. These recurring pulses of increased pore-water pressure (or reduced matric suction) likely contributed to progressive slope weakening, ultimately triggering the landslide. As the lower boundary of this simplified model was defined as free-draining, pore-water pressure dissipated relatively quickly during rainfall-free periods due to drainage. This behaviour is representative of the middle portion of the slope, where the soil profile is relatively thick, and the wetting front can be redistributed rapidly, preventing the development of significant positive pore-water pressure. In such areas, repeated pore-water pressure pulses and the associated reductions in F_s appear to be the dominant slope destabilisation mechanism. However, at the slope toe, where groundwater tends to accumulate, a two-dimensional seepage model is more appropriate to capture lateral flow and pressure build-up.

Figure 10 shows the 2D-flow limit equilibrium modelling results yield the lowest F_s values of 0.968 and 1.009 for two periods: 3rd October 2020 at 16:21 and 9th October 2020 at 02:11, respectively. The computed seepage flow was parallel to the slope surface, and the critical slip surface extended to approximately 1 m depth (shown in Supplementary material). These findings suggest that the landslide mechanism involved a series of progressive slope destabilisations

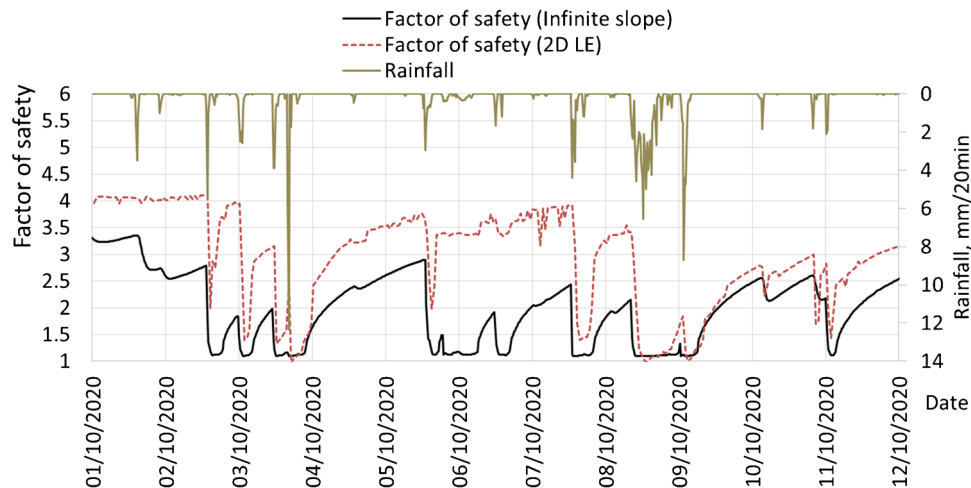


Fig. 10 Calculated factor of safety during 2020 landslide from 1D-flow-infinite slope model and 2D-flow limit equilibrium model

induced by water saturation, increased pore-water pressure, and seepage flow, which collectively reduced the FS to near unity. Under such conditions, irreversible slope movements likely accumulated, contributing to strength degradation and ultimately leading to the total slope collapse reported on 10th and 11th October.

Discussion

The main limitation of satellite-based surface soil moisture (SSM) lies in its reliance on monthly averaging to achieve acceptable accuracy. While this temporal resolution cannot capture individual landslide events, it provides a useful estimate of antecedent conditions for coupled stability–flow analysis. In this study, SSM-based antecedent conditions (Model 2) generally produced higher subsurface moisture and pore-water pressure, leading to lower factors of safety compared with models initialized with in-situ measurements (Model 1). While conservative, this approach does not require on-site instrumentation, making it suitable for remote and data-scarce regions, particularly in developing countries. The integration of satellite-based SSM, radar-derived rainfall, and slope-scale seepage–stability modelling provides a transferable framework for analysing rainfall-induced landslides in areas with limited monitoring infrastructure and supports global efforts in landslide susceptibility assessment, early warning, and slope stabilization design.

Tiltmeter measurements revealed that long-term seasonal changes in soil moisture and pore-water pressure can drive creeping slope movements, which can contribute to progressive shear strength reduction and eventual failure (Leroueil 2001; Carey and Petley 2014; Soralump et al. 2021; Pepe et al. 2024). The observed correlation between tilt rate and soil moisture change ($R^2 = 0.62$) highlights the potential of satellite soil moisture for predicting long-term slope deformation based on annual amplitude of soil moisture change. A mechanical framework, such as that reported by Shrestha et al. (2019), could be applied to link desiccation crack development with soil moisture depletion rates. These findings encourage further research into the use of remote-sensing soil moisture for prediction of such long-term hydro-mechanical interactions.

Conclusions

The study proposed the methodology for using the satellite-derived SSM, in combination with bias-adjusted composite radar rainfall data, in-situ soil moisture measurement and a well-calibrated seepage-stability model, as an effective early warning tool for rainfall-induced landslide prediction. A landslide case study from Khao Yai National Park in Thailand, which occurred in 2020, and long-term in-situ measurement were examined. The following conclusions can be drawn.

- A reasonable correlation ($R^2 = 0.63$) was found between normalized satellite-derived surface soil moisture (SSM) and in-situ soil moisture (ISM) when using monthly average values. This monthly SSM data were applied as initial boundary conditions for flow modelling, allowing prediction of soil moisture variations with depth (up to 0.5 m) in response to rainfall.
- There was a good agreement between the SSM- and ISM-based approaches ($R^2 = 0.96$) in simulating soil moisture and

factor of safety within the soil profile. However, the SSM-based model generally conservatively underpredicted F_s by approximately 8–9%.

- Two-dimensional seepage modelling and limit equilibrium analysis revealed that rainfall-induced rises in pore-water pressure significantly reduced the factor of safety (F_s), reaching unity several times within the week preceding the 2020 landslide.
- A reasonable relationship ($R^2 = 0.62$) was observed between the rate of change in soil moisture and slope tilt rate, where decreasing soil moisture during the dry season led to uphill tilting (slope shrinkage) while increasing soil moisture during rainfall events resulted in downhill movement (slope creep).

Acknowledgements

The authors express their sincere gratitude for the financial supports provided by the Faculty of Engineering, Kasetsart University; the Hydro-Informatics Institute; Agricultural Research and Development Agency (Public Organization) and the Thailand Science Research and Innovation (TSRI) under Fundamental Fund No. 204604 (S2S Thailand Project); and the Kasetsart University Research and Development Institute (KURDI) under Project No. FF(KU-SRIU)4.67. The authors also gratefully acknowledge Khao Yai National Park for granting access to the study site. We wish to thank the Department of Royal Rainmaking and Agricultural Aviation (DRRAA) for providing the radar reflectivity data, and the Hydro-Informatics Institute (HII) and the Department of Water Resources (DWR) for providing rain gauge data used in this study. Special thanks are extended to the students and staff of the Geotechnical Division, Departments of Civil Engineering and Water Resources Engineering, Kasetsart University, for their assistance. The support provided by Green Ground Solutions Co., Ltd. during site visits is also greatly appreciated.

Author contributions

Jotisankasa: Conceptualization, Methodology, Formal analysis and investigation, Supervision, Writing (original draft preparation and review).

Mapiam: Conceptualization, Methodology, Supervision, Writing (original draft preparation and review), Funding acquisition.

Methaprayun: Formal analysis and investigation, Writing (original draft preparation).

Praphatsorn: Formal analysis and investigation.

Torsri: Resources, Writing (review), Funding acquisition.

Supavetch: Formal analysis and investigation.

Soralump: Resources, Writing (review).

Linnebach: Formal analysis and investigation, Writing (review).

Bogaard: Conceptualization, Methodology, Supervision, Writing (review).

Data Availability

Data for the formal analysis are presented in the article. Raw data are available upon request from the corresponding author.

Declarations

Competing interests The authors declare no competing interests.

Declaration of generative AI and AI-assisted technologies in the writing process During the preparation of this work the authors used ChatGPT, a language model developed by OpenAI in order to refine the original draft of this paper. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

- Antonini A, Melani S, Corongiu M, Romanelli S, Mazza A, Ortolani A, Gozzini B (2017) On the implementation of a regional X-band weather radar network. *Atmosphere* 8:25. <https://doi.org/10.3390/atmos8020025>
- Barus RMN, Jotisankasa A, Chaiprakaikeow S, Sawangsuriya A (2019) Laboratory and field evaluation of modulus-suction-moisture relationship for a silty sand subgrade. *Transp Geotech* 19:126–134. <https://doi.org/10.1016/j.trgeo.2019.03.005>
- Carey JM, Petley DN (2014) Progressive shear-surface development in cohesive materials: implications for landslide behaviour. *Eng Geol* 177:54–65. <https://doi.org/10.1016/j.enggeo.2014.05.009>
- Cremonini R, Tiranti D (2018) The weather radar observations applied to shallow landslides prediction: a case study from North-Western Italy. *Front Earth Sci* 6:134. <https://doi.org/10.3389/feart.2018.00134>
- Dalmastri C, Uccelli R (2024) Mortality from extreme meteorological and hydrogeological events in Italy: a rising health threat connected to climate change. *Safety in Extreme Environments* 6(3):173–181. <https://doi.org/10.1007/s42797-024-00100-3>
- Das N, Entekhabi D, Dunbar S, Chaubell J, Colliander A, Yueh S, Jagdhuber T, Chen F, Crow WT, O'Neill PE, Walker J, Berg A, Bosch D, Caldwell T, Cosh M, Collins CH, Lopez-Baeza E, Thibeault M (2019) The SMAP and Copernicus Sentinel 1A/B microwave active-passive high-resolution surface soil moisture product. *Remote Sens Environ* 233:111380. <https://doi.org/10.1016/j.rse.2019.111380>
- Das N, Entekhabi D, Dunbar RS, Kim S, Yueh S, Colliander A, O'Neill PE, Jackson T, Jagdhuber T, Chen F, Crow WT, Walker J, Berg A, Bosch D, Caldwell T, Cosh M (2020) SMAP/Sentinel-1 L2 Radiometer/Radar 30-second scene 3 km EASE-grid soil moisture, version 3. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed. <https://doi.org/10.5067/ASB0EQO2LYJV>
- De Biase M, Lupiano V, Chiaravallotti F, Iovine G, Muto M, Terranova O, Tripodi V, Pisano L (2025) Integrated rainfall estimation using rain gauges and weather radar: implications for rainfall-induced landslides. *Remote Sens* 17(21):3629. <https://doi.org/10.3390/rs17213629>
- EGAT (1980) Soil exploration by Kunzelstab penetration test. Electricity Generating Authority of Thailand (in Thai)
- Entekhabi D, Njoku EG, O'Neill PE, Kellogg KH, Crow WT, Edelstein WN, Entin JK, Goodman SD, Jackson TJ, Johnson J et al (2010) The soil moisture active passive (SMAP) mission. *Proc IEEE* 98:704–716. <https://doi.org/10.1109/JPROC.2010.2043918>
- Feng S, Huang RH, Zhan LT, Liu HW (2023) Semi-analytical solution of pore-water pressure in unsaturated ground and infinite slope considering highly nonlinear soil hydraulic properties. *Comput Geotech* 164:105795. <https://doi.org/10.1016/j.compgeo.2023.105795>
- Fredlund DG, Rahardjo H (1993) Soil mechanics for unsaturated soils. Wiley, New York, p 517
- Fornasiero A, Bech J, Alberoni PP (2006) Enhanced radar precipitation estimates using a combined clutter and beam blockage correction technique. *Nat Hazards Earth Syst Sci* 6:697–710. <https://doi.org/10.5194/nhess-6-697-2006>
- Geo-slope International Ltd. (2012a). Seepage modeling with SEEP/W, an engineering methodology.
- Geo-slope International Ltd. (2012b). Stability modelling with SLOPE/W, an engineering methodology.
- Holleman I (2007) Bias adjustment and long-term verification of radar-based precipitation estimates. *Meteorol Appl* 14:195–203. <https://doi.org/10.1002/met.22>
- Jotisankasa A, Vathananukij H, Coop M (2009) Soil-water retention curves of some silty soils and their relations to fabrics. *Proceeding of the 4th Asia Pacific Conference on Unsaturated Soils*, 23–25 November 2009, Newcastle, Australia.
- Jotisankasa A, Mahannopkul K, Sawangsuriya A (2015) Slope stability and pore-water pressure regime in response to rainfall: a case study of granitic fill slope in northern Thailand. *Geotechnical Engineering Journal of the SEAGS & AGSSEA* 46(1):45–54
- Jotisankasa A, Torsri K, Supavetch S, Sirirodwattanakool K, Thonglert N, Sawangwattanaphaibun R, Faikrua A, Peangta P, Akaraneer J (2023) Investigating correlations and the validation of SMAP-Sentinel L2 and in situ soil moisture in Thailand. *Sensors* 23:8828. <https://doi.org/10.3390/s23218828>
- Jotisankasa A, Praphatsorn W, Siriyakorn V, Sanposh P, Janthong I, Tipsuwan Y, Sawangsuriya A, Jitareekul P (2024) Development of IoT slope monitoring system and its applications for Kratu-Patong Road landslide in Phuket, Thailand. *Geotech Eng J Southeast Asian Geotech Soc AGSSEA* 55(1):74–83. <https://doi.org/10.14456/seagj.2024.8>
- Jurczyk A, Szturc J, Ośródko K (2020) Quality-based compositing of weather radar derived precipitation. *Meteorol Appl* 27:e1812. <https://doi.org/10.1002/met.1812>
- Leroueil S (2001) Natural slopes and cuts: movement and failure mechanisms. *Geotechnique* 51(3):197–243. <https://doi.org/10.1680/geot.2001.51.3.197>
- Luo Y, Zhang J, Tang C-S, Jiang G, Bogaard T (2025) Impact of dynamic desiccation cracks on hydrological processes and stability in expansive clay slopes: a coupled dual-permeability modeling approach. *Eng Geol* 357:108377. <https://doi.org/10.1016/j.enggeo.2025.108377>
- Mahannopkul K, Jotisankasa A (2019) Influences of root concentration and suction on *Chrysopogon zizanioides* reinforcement of soil. *Soils Found* 59(2):500–516. <https://doi.org/10.1016/j.sandf.2018.12.014>
- Mairaing W, Jotisankasa A, Soralump S (2012) Some applications of unsaturated soil mechanics in Thailand: an appropriate technology approach. *Geotech Eng J Southeast Asian Geotech Soc AGSSEA* 43(1):1–11. <https://doi.org/10.14456/seagj.2012.29>
- Mapiam PP, Sharma A, Chumchean S, and Sriwongsitanon N (2009) Run-off estimation using radar and rain gage data. The 18th World IMACS Congress and MODSIM09 International Congress on Modelling and Simulation. Cairns Australia, July 2009, 13–17.
- Mapiam PP, Methaprayun M, Bogaard T, Schoups G, Ten Veldhuis MC (2022) Citizen rain gauges improve hourly radar rainfall bias correction using a two-step Kalman filter. *Hydrol Earth Syst Sci* 26(3):775–794. <https://doi.org/10.5194/hess-26-775-2022>
- Mapiam PP, Sakulnarak S, Methaprayun M, Makmee C, Marjang N (2023) Downscaling the Z–R relationship and bias correction solution for flash flood assessment in a data-scarce basin, Thailand. *Water Sci Technol* 87(5):1259–1272. <https://doi.org/10.2166/wst.2023.056>
- Marino P, Peres DJ, Cancelliere A, Greco R, Bogaard TA (2020) Soil moisture information can improve shallow landslide forecasting using the hydrometeorological threshold approach. *Landslides* 17(9):2041–2054. <https://doi.org/10.1007/s10346-020-01420-8>
- Méri L, Gaál L, Bartok J, Gažák M, Gera M, Jurašek M, Kelemen M (2021) Improved radar composites and enhanced value of meteorological radar data using different quality indices. *Sustainability* 13(9):5285. <https://doi.org/10.3390/su13095285>
- Methaprayun M, Jotisankasa A, Khunwisetkul R, Bogaard T, Mapiam PP (2023) Low-cost sensor observations for flash flood and landslide early warning systems in the mountainous area. Poster presented at European Geosciences Union (EGU) General Assembly 2023,

- Vienna, Austria, 23–28 Apr 2023. <https://doi.org/10.5194/egusphere-egu23-4872>
- Methaprayun M, Bogaard T, Mapiam PP (2025) Enhancing the accuracy of weather radar heavy rainfall estimates in mountainous regions using combined radar quality indices. *J Hydrol* 662:133907. <https://doi.org/10.1016/j.jhydrol.2025.133907>
- Mirus BB, Bogaard T, Greco R, Stähli M (2025) Invited perspectives: integrating hydrologic information into the next generation of landslide early warning systems. *Nat Hazards Earth Syst Sci* 25(1):169–182. <https://doi.org/10.5194/nhess-25-169-2025>
- Mohanty BP, Cosh M, Lakshmi V, Montzka C (2017) Soil moisture remote sensing state-of-the-science. *Vadose Zone J* 16:1–9. <https://doi.org/10.2136/vzj2016.10.0105>
- Nguyen TS, Likitlersuang S, Jotisankasa A (2020) Stability analysis of vegetated residual soil slope under rainfall conditions. *Environ Geotech* 7(5):338–349. <https://doi.org/10.1680/jenge.17.00025>
- Ochsner TE, Cosh MH, Cuenca RH et al (2013) State of the art in large-scale soil moisture monitoring. *Soil Sci Soc Am J* 77(6):1888–1919. <https://doi.org/10.2136/sssaj2013.03.0093>
- Ośródká K, Szturc J (2022) Improvement in algorithms for quality control of weather radar data (RADVOL-QC system). *Atmos Meas Tech* 15(2):261–277. <https://doi.org/10.5194/amt-15-261-2022>
- Pepe G, Musante B, Rizzi G, Viola G, Vigo A, Ghirotto A, Armadillo E, Cevasco A (2024) A study on the factors controlling the kinematics of a reactivated and slow-moving landslide in the Eastern Liguria region (NW Italy) through the integration of automatic geotechnical sensors. *Appl Sci* 14(16):6880. <https://doi.org/10.3390/app14166880>
- Qiu X, Green AC, Blenkinsop S, Fowler HJ (2026) Developing a radar-rain gauge hourly blended precipitation dataset for Great Britain using the Gauss blending method. *J Hydrol*. <https://doi.org/10.1016/j.jhydrol.2026.134954>
- Rajamanthri K, Jotisankasa A, Aramrak S (2021) Effects of *Chrysopogon zizanioides* root biomass and plant age on hydro-mechanical behavior of root-permeated soils. *Int J Geosynth Ground Eng* 7(36):1–13. <https://doi.org/10.1007/s40891-021-00271-0>
- Roman Quintero DC, Marino P, Abdullah A, Santonastaso GF, Greco R (2025) Large-scale assessment of rainfall-induced landslide hazard based on hydrometeorological information: application to Partenio Massif (Italy). *Nat Hazards Earth Syst Sci* 25(8):2679–2698. <https://doi.org/10.5194/nhess-25-2679-2025>
- Saltikoff E, Haase G, Delobbe L, Gaussiat N, Martet M, Idziorek D, Leijnse H, Novák P, Lukach M, Stephan K (2019) OPERA the radar project. *Atmosphere* 10(6):320. <https://doi.org/10.3390/atmos10060320>
- Schleiss M, Olsson J, Berg P, Niemi T, Kokkonen T, Thorndahl S, Nielsen R, Ellerbæk Nielsen J, Bozhinova D, Pulkkinen S (2020) The accuracy of weather radar in heavy rain: a comparative study for Denmark, the Netherlands, Finland and Sweden. *Hydrol Earth Syst Sci* 24:3157–3188. <https://doi.org/10.5194/hess-24-3157-2020>
- Shi X, Liu Y, Chen J, Chen H, Wang Y, Lu Z, Wang R-Q, Fung JCH, Ng CWW (2024) Escalating tropical cyclone precipitation extremes and landslide hazards in South China under global warming. *NPJ Clim Atmos Sci* 7(1):107. <https://doi.org/10.1038/s41612-024-00654-w>
- Shi Z, Wei F, Chandrasekar V (2018) Radar-based quantitative precipitation estimation for the identification of debris flow occurrence over earthquake-affected regions in Sichuan, China. *Nat Hazards Earth Syst Sci* 18:765–780. <https://doi.org/10.5194/nhess-18-765-2018>
- Shrestha A, Jotisankasa A, Chaiprakaikeow S, Pramusandi S, Soralump S, Nishimura S (2019) Determining shrinkage cracks based on the small-strain shear modulus–suction relationship. *Geosciences* 9(9):362. <https://doi.org/10.3390/geosciences9090362>
- Sidle RC, Greco R, Bogaard T (2019) Overview of landslide hydrology. *Water* 11(1):148. <https://doi.org/10.3390/w11010148>
- Soralump S, Shrestha A, Thowiwat W, Sukjaroen R, Chaithong T, Yangsanphu S, Koirala A, Jotisankasa J (2021) Assessment of landslide behaviour in colluvium deposit at Doi Chang, Thailand. *Sci Rep* 11:22960. <https://doi.org/10.1038/s41598-021-02363-3>
- Tseng CW, Song CE, Wang SF, Chen YC, Tu JY, Yang CJ, Chuang CW (2020) Application of high-resolution radar rain data to the predictive analysis of landslide susceptibility under climate change in the Laonong watershed, Taiwan. *Remote Sens* 12(23):3855. <https://doi.org/10.3390/rs12233855>
- Uwihirwe J, Riveros A, Wanjala H, Schellekens J, Sperna Weiland F, Hrachowitz M, Bogaard TA (2022) Potential of satellite-derived hydro-meteorological information for landslide initiation thresholds in Rwanda. *Nat Hazards Earth Syst Sci* 22(11):3641–3661. <https://doi.org/10.5194/nhess-22-3641-2022>
- Ye X, Zhu H-H, Wu B, Tian F, Zhang W, Hu X, Schenato L, Pasuto A, Catani F (2024) Near-surface soil hydrothermal response feedbacks landslide activity and mechanism. *Eng Geol* 341:107690. <https://doi.org/10.1016/j.enggeo.2024.107690>
- Zhao B, Dai Q, Zhuo L, Zhu S, Shen Q, Han D (2021) Assessing the potential of different satellite soil moisture products in landslide hazard assessment. *Remote Sens Environ* 264:112583. <https://doi.org/10.1016/j.rse.2021.112583>
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- Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s10346-026-02732-x>.
- Apinit Jotisankasa · Washirawat Praphatsorn · Soravis Supavetch · Suttisak Soralump**
Department of Civil Engineering, Kasetsart University, Bangkok, Thailand
- Punpim Puttaraksa Mapiam (✉) · Monton Methaprayun · Thom Bogaard**
Department of Water Resources Engineering, Kasetsart University, Bangkok, Thailand
Email: punpim.m@ku.th
- Kritanai Torsri**
Hydro-Informatics Innovation Division, Ministry of Higher Education, Science, Research and Innovation, Hydro-Informatics Institute, Bangkok, Thailand
- Jonathan Linnebach · Present Address: Thom Bogaard**
Department of Water Management, Delft University of Technology, Delft, The Netherlands