



OPEN Random forest-based prediction of shallow slope stability considering spatiotemporal variations in unsaturated soil moisture

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With the increasing incidence of extreme rainfall driven by global climate change, geological hazards like landslides have become more prevalent. This study proposed an efficient framework that combined machine learning and physical models to enhance computational efficiency and reliability for regional slope stability predictions under extreme rainfall. The GEOTop model was employed to simulate volumetric water content (VWC) in unsaturated soil of an area in Singapore under maximum daily and maximum 5-day antecedent rainfall conditions. The result of analyses was then incorporated into Scoops3D for factor of safety (FOS) calculations. The random forest (RF) models were trained using VWC under maximum daily rainfall and applied to predict slope stability under maximum 5-day antecedent rainfall, with outcomes compared to those of Scoops3D. Statistical results and spatial distribution maps both showed that the proposed framework achieved comparable accuracy to Scoops3D at various depths while significantly improving efficiency. The findings also highlighted the critical role of surface soil moisture (at 0.05 m) in slope stability predictions. This framework demonstrates the potential of integrating machine learning and physical models for efficient slope stability prediction, as well as supports the integration of remote sensing or field-measured surface soil moisture data for dynamic predictions in unsaturated soil conditions.

Keywords Unsaturated soil, Slope stability, Machine learning, Soil moisture

In recent times, the intensifying effects of global warming have led to notable climatic shifts, particularly seen in the increased intensity of rainfall across various regions^{1,2}. This surge in precipitation plays a key role in the growing frequency of slope failures^{3–5}, posing significant threats to infrastructure and public safety. Shallow landslide refers to the failure of the upper soil layers, typically within a few metres of the surface. These failures are often triggered by intense or prolonged rainfall, which elevates pore-water pressure, reduces matric suction, and decreases shear strength, which ultimately decreases slope stability. Shallow landslides are characterised by thin failure surfaces and localised movements, primarily involving unsaturated soils. The failure depth is generally less than 2 m, making these slopes highly sensitive to rainfall-induced changes in soil shear strength^{6,7}. Incorporating unsaturated soil mechanics is crucial for accurately analysing slope stability under rainfall conditions^{8–10}.

Rapid and reliable prediction of regional slope stability is essential to identify high-risk areas, facilitating prompt intervention and preventive measures. Methods for slope stability analysis can be broadly categorized into empirical methods, physically-based models, statistical models, and machine-learning models. The physically based techniques for estimating slope stability are generally capable of providing comprehensive and detailed insights and have been widely used by scholars worldwide over the past few decades. Although two-dimensional water balance and slope stability analyses have been extensively studied, they are typically

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applied to individual slopes rather than at a regional scale^{11–15}. As a result, several regional models have been developed, many of which are based on assumptions that either overlook three-dimensional subsurface flow or differ from actual failure surfaces^{16–18}. The commonly used physical models typically incorporate hydrological models and infinite slope, exemplified by the shallow land sliding stability model (SHALSTAB)¹⁹, stability index mapping (SINMAP)²⁰, and transient rainfall infiltration and grid-based slope-stability (TRIGRS)²¹. However, SHALSTAB and SINMAP solely address the impact of lateral flow, neglecting the implications of the water infiltration process, whereas TRIGRS exclusively accounts for the vertical water flow but overlooks the lateral flow. Considering these limitations, Simoni et al.²² proposed the GEOTop-FS, which incorporates the three-dimensional (3D) Richards' equation to take into account both lateral and vertical water flows, as well as the evapotranspiration process, comprehensively assessing the hydrological processes on slope stability. Based on the GEOTop model, Formetta & Capparelli²³ demonstrated the significant effect of hydraulic conductivity anisotropy on slope stability. Cheng & Li²⁴ further applied the GEOTop model at a regional scale, analysing the variations in slope stability along India's National Highway 10 before and after stabilisation.

However, these widely used infinite slope models assume a translational failure surface and overlook the commonly occurring rotational failures. To compensate for this limitation, Scoops3D, a 3D slope stability model proposed by Reid et al.²⁵, accounts for rotational slope failure surface by generating 3D columns within the framework of limit equilibrium analysis. Although studies have proved the efficacy of Scoops3D in slope stability analysis^{26,27}, scholars still sought to explore ensemble methods of Scoops3D, given its lack of rainfall infiltration dynamics. Ip et al.²⁸ incorporated unsaturated soil properties and variations in pore-water pressure by integrating TRIGRS and Scoops3D, demonstrating the effectiveness of this approach in slope stability mapping. Rahardjo et al.²⁹ also deployed a combination of the two models, TRIGRS and Scoops3D, to map the slope susceptibility across different zones in Singapore. Nevertheless, the adoption of the integration of TRIGRS and Scoops3D does not take lateral flow into consideration because of the inherent characteristics of TRIGRS. Researchers have therefore recommended using GEOTop and Scoops3D together to account for rotational slides that consider both lateral and vertical flow in water balance analyses^{30,31}. Rangarajan et al.³¹ verified the results from the GEOTop-Scoops3D analysis using 2D seepage and slope stability analyses in GeoStudio software (SEEP/W and SLOPE/W). The study found that the GEOTop model produced higher pore-water pressures than 2D seepage analysis, leading to a lower factor of safety in the 3D GEOTop-Scoops3D analysis compared to the 2D SEEP/W-SLOPE/W analysis.

Despite the thorough and intricate analyses offered by physically based models, they typically encounter a substantial computing burden and thus compromise on speed, especially in 3D analysis³², presenting a significant limitation in situations that require prompt response. To address this limitation, machine learning has emerged as a promising alternative. Known for its swift processing power, machine learning enables quick predictions, a crucial aspect of early warning systems^{33,34}. Numerous studies have shown that machine learning techniques achieve practically-usable accuracy in slope stability analysis^{35–40}, as well as demonstrating potential in 3D slope stability analysis and understanding the underlying mechanisms with interpretable models^{41–43}. Therefore, the utilization of machine learning approaches not only heightens the accuracy of predictions but also facilitates real-time estimation of the FOS and understanding of the controlling factors, vital for prompt risk management and tailored mitigations.

However, it is crucial to note that the effectiveness of machine learning and deep learning, despite their rapid processing capabilities, can be diminished in scenarios involving extreme weather conditions. This limitation often stems from the lack of sufficient data representing such extreme conditions during the training phase of the model. The rarity of these events means that the models may not have been exposed to enough relevant data to accurately predict outcomes under such circumstances. This shortfall emphasizes the need for a balanced approach that perhaps combines the quick predictive power of machine learning with the depth and comprehensiveness of physically based models. Some scholars have explored the integration of data-driven methodologies with physical models, exemplified by Liu et al.⁴⁴ who introduced a dual-driven approach that integrated Scoops3D and RF, utilising non-landslide points extracted from Scoops3D and a historical landslide inventory for RF model training. Their approach achieved a significant improvement, with an area under the curve (AUC) 20.1% greater than that obtained by the RF model alone. On the other hand, Xue et al.⁴⁵ employed a matrix to integrate the landslide susceptibility mapping results obtained from the RF model with the slope stability outcomes derived from Scoops3D for landslide prediction, with a frequency ratio, when compared to solely using Scoops3D, was 2.24 times higher. However, as far as the authors are aware, there is no research that has integrated data-driven models with physical models in the context of risk management related to extreme weather events for the rapid and accurate prediction of slope stability.

Soil moisture has been proven to be an effective indicator for predicting slope stability, demonstrating impressive performance in various studies^{46–50}. While field instruments provide precise measurements at specific points, their scope is limited. In contrast, remote sensing technologies can assess soil moisture over extensive areas. However, remote sensing methods are limited to analysing only surface soil layers, leading to crucial questions about the importance of soil moisture depth in assessing slope stability. To the best of the authors' knowledge, no studies have focused on the variations in predicting FOS based on moisture contents in surface soil and in other soil layers. This aspect is vital in understanding and effectively predicting slope failures with the future application of remote sensing techniques on a larger regional scale, particularly in the context of the evolving global climate.

To sum up, the existing studies in slope stability prediction may still have limitations in the following aspects: (1) The existing research primarily utilised either physical models or machine learning models for slope stability analysis, with few studies integrating the strengths of both to rapidly predict unseen and infrequent scenarios during extreme rainfall events. (2) There were few studies that have accounted for the influence of soil moisture at different depths, and quantitative research is still required for the rationality of solely using surface soil

moisture (e.g., retrieved from remote sensing). Thus, to bridge these research gaps, this study employed a small region in Singapore as the study area and carried out analyses as follows: (1) The GEOTop model was utilised to determine the pore-water pressure and volumetric water content under scenarios of both maximum daily and maximum 5-day antecedent rainfalls, with the outcomes imported into Scoops3D for FOS calculations. (2) The FOS outcomes under the maximum daily rainfall scenario were employed to train the machine learning model, allowing the efficient estimation of FOS in the maximum 5-day antecedent rainfall scenario and enabling a comparative analysis with prior physically-based modelling outcomes. (3) Soil moisture data incorporated at various depths were used within the machine learning models. The differences in the FOS estimates between the surface-level and multi-depth soil moistures are further discussed.

Physically-based modelling using GEOTop and Scoops3D

A zone in Singapore was selected for the water balance and slope stability analyses performed using the GEOTop^{51,52} and Scoops3D⁵³ software, respectively. The selection of the zone was based on the location of the undisturbed soil sample which was obtained from a slope located along Dalvey Road. The slope is located in Bukit Timah Granite (BTG) formation and is within the BTG42 zonation as per Li et al.⁵⁴ database. In this developed database, Li et al. divided Singapore into 97 zones, with each zone having similar soil properties. Hence, the soil properties obtained from the soil sampling at Dalvey Road were used to represent the soil for the BTG42 zone given that the zone is small and the soil is assumed to be homogenous. Laboratory tests were performed using the soil samples to acquire the soil properties for the numerical analysis which are presented in Table 1. The soil has been classified as clay of high plasticity (CH) under the Unified Soil Classification System and thus has a low saturated permeability of 3.13×10^{-8} m/s. The grain size distribution curve is presented in Fig. 1a. The unsaturated soil properties such as the soil water characteristic curve and permeability function were defined using the van Genuchten (1980)⁵⁵ and modified Mualem equations⁵⁶. The van Genuchten soil water characteristic curve is presented in Fig. 1b. Most of the rainfall-induced slope failures in Singapore occurs within the shallow depths^{57,58}. Thus, the soil between 0 and 10 m depth (i.e. layers 1 to 7) was used to analyse the relationship between soil moisture and factor of safety. The soil thickness for soil layers 1 to 7 modelled in the GEOTop analysis is presented in Fig. 2.

The GEOTop software which is a physically based hydrological model was utilised in this study to perform water balance analysis. This model analyses the subsurface flow in saturated and unsaturated soil using the three-dimensional (3D) Richards’ equation⁵². The water balance equation (Eq. 1) in GEOTop comprises the 3D Richards’ equation q_{sub} ^{59,60} and evapotranspiration term S ⁵¹.

$$\frac{\partial \theta_w(x, t)}{\partial t} + \nabla \bullet q_{sub}(x, t) = -S(x, t)$$
 (1)

where x is the position, t is time, θ_w is the volumetric water content of the soil. The term S represents the evapotranspiration. The term $\nabla \bullet q_{sub}$ refers to the divergence of water per unit volume and is calculated by the Richards’ equation in Eq. 2.

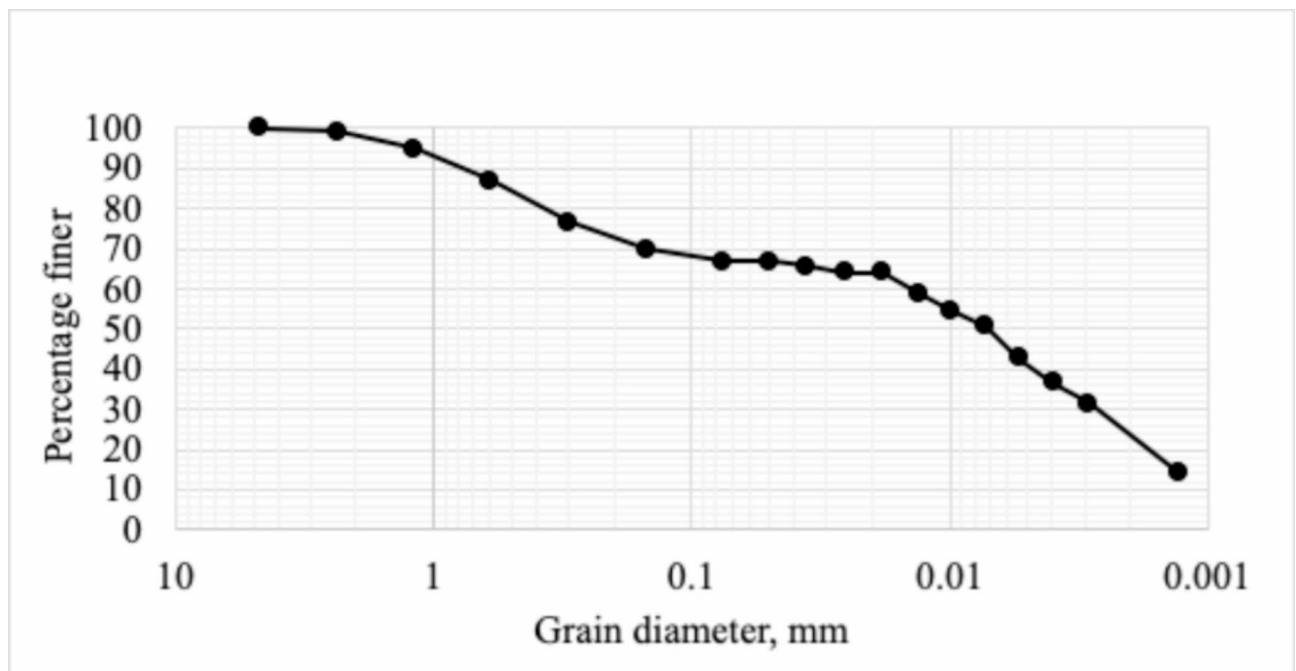
$$q_{sub} = -K \nabla (z + \psi)$$
 (2)

where ∇ is the gradient operator, ψ is the pressure head, z is the elevation head and the term K is the permeability. The required input maps such as the Digital Elevation Model (DEM), slope angle, aspect, and groundwater table (Fig. 3) are used to define the precise topography and groundwater conditions of the zone. The initial pore-water pressure was limited to -100 kPa due to the deep groundwater table depth of 47 m as seen in Fig. 3⁶¹. The resolution of the maps used in the GEOTop analysis is 5 m.

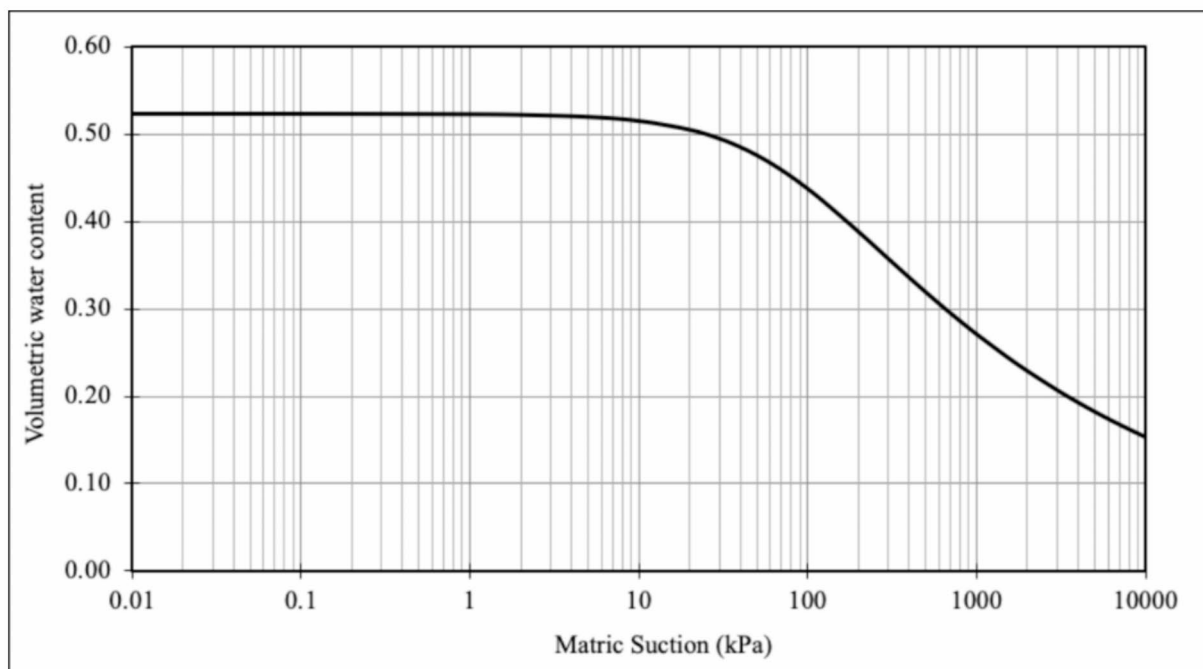
Different soils respond differently to varying rainfall patterns, influencing slope stability in distinct ways. Studies on slope stability in Singapore have shown that regions with low-permeability soils are predominantly affected by antecedent rainfall (e.g., 5-day antecedent rainfall), while areas with high-permeability soils are more influenced by maximum daily rainfall^{62,63}. In the studied zone, characterized by CH soil, the 5-day antecedent rainfall plays a crucial role. Two different extreme rainfall conditions were applied in the water

Soil Properties for Dalvey Road	
Depth of soil sample (m)	3 to 4
Unified soil classification system	CH
Saturated permeability, k_s (m/s)	3.13×10^{-8}
Saturated volumetric water content	0.523
Air-entry value (kPa)	204
van Genuchten (1980) best fitting parameters, α_{vg} (mm ⁻¹)	1.35×10^{-4}
van Genuchten (1980) best fitting parameters, n_{vg}	1.25
Effective cohesion, c' (kPa)	5
Effective friction angle (°)	29
Saturated unit weight (kN/m^3)	16.5

Table 1. Soil properties for Dalvey road.



(a)



(b)

Fig. 1. Soil properties (a) Grain size distribution curve; (b) van Genuchten soil water characteristic curve.

balance analyses; maximum daily and maximum 5-day antecedent rainfall. In the machine learning model, results from physically-based models under the maximum daily rainfall condition were used to train the model and predict slope stability under the maximum 5-day rainfall condition. These predictions were then compared with the physically-based model results under the maximum 5-day rainfall condition to evaluate the model's performance. For the maximum daily rainfall analysis, an extreme rainfall intensity of 22.2 mm/h suggested by Singapore's Public Utilities Board (PUB) Code of Practice on Surface Water Drainage guidelines⁶⁴ was applied continuously for 24 h followed by another 24 h of no rainfall. For the maximum 5-day antecedent

Depth (m)

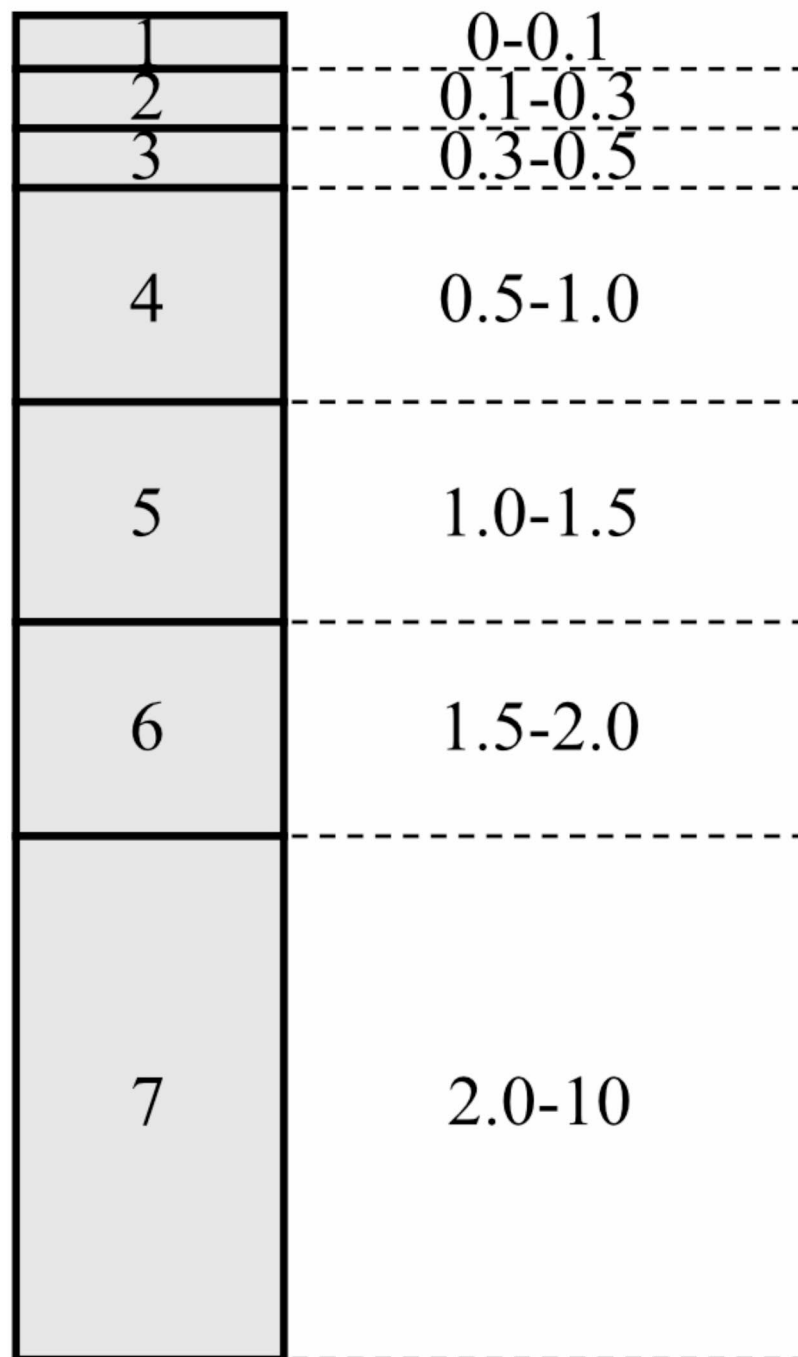


Fig. 2. Soil thickness for soil layers 1 to 7 used in GEOTop analysis.

rainfall analysis, a constant rainfall intensity of 4.94 mm/hour was applied for 5 continuous days followed by an additional 5 days with no rainfall⁶⁵.

The average pore-water pressure results from the water balance analyses are presented in Fig. 4. Pore-water pressure changes were only observed in the first layer (0.05 m depth) in the first hour of rainfall. Subsequently, the pore-water pressure increases from –10 kPa to 0 kPa and –30 kPa to 0 kPa between the 1st hour and 24th hour timesteps for the maximum daily and 5-day antecedent rainfall conditions, respectively. Moreover, the pore-water pressure at the deeper depth of 0.4 m also experienced an increase in pore-water pressure from

Location of Dalvey Road sample

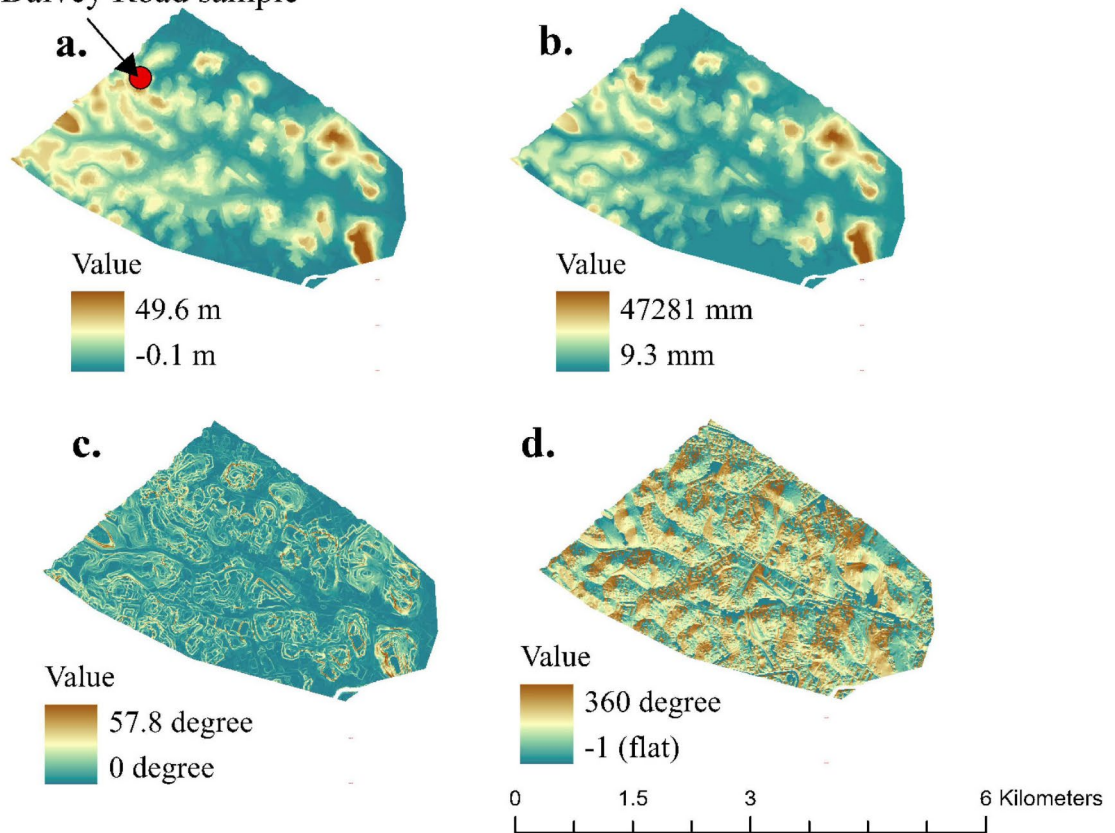


Fig. 3. Inputs maps used in water balance analysis: (a) DEM; (b) Groundwater table; (c) Slope angle; (d) Aspect map for BTG42. (software: ArcGIS Pro; version number: 3.1; URL: <https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview>).

– 62 kPa to approximately – 31 kPa for both rainfall conditions. Therefore, the pore-water pressure changes can be observed to be increasing with depth as the duration of rainfall increases.

The pore-water pressures during the 1st and 24th hour timestep are similar under both maximum daily and 5-day antecedent rainfall conditions. This suggests that despite the higher rainfall intensity in the maximum daily rainfall analysis, the corresponding pore-water pressures are not higher. This is due to the rainfall intensity (22.2 mm/hour = 6.16E–06 m/s and 4.94 mm/hour = 1.37E–06 m/s) exceeding the saturated permeability of the soil (3.13E–08 m/s). Hence, the extended duration of rainfall in the 5-day antecedent rainfall analysis resulted in further penetration of rainfall into deeper soil layers as seen in Fig. 4 where pore-water pressures continued to increase after 24th hour with rainfall infiltration in deeper depths. Nevertheless, likely due to the low permeability of the soil, rainfall infiltrations into depths below 1.5 m remained minimal over the simulation period, resulting in limited variations in pore-water pressure in these deeper layers.

The pore-water pressure and volumetric water content results for the 1st, 24th, and 48th hour timesteps of the maximum daily rainfall analysis and 1st hour, 1, 2.5, 5, 7.5, and 10 days timesteps from the maximum 5-day antecedent rainfall analysis were thereafter imported into the Scoops3D software for the slope stability analysis. The Scoops3D software utilises the 3D limit equilibrium method, Bishop's Simplified Method to calculate the factor of safety (FOS, Eqs. 3 and 4) for each 3D column defined by the resolution of the DEM⁵³. Therefore, to allow for a more precise slope stability analysis, a 1 m resolution DEM was used.

$$FOS = \frac{\sum R_{i,j} [c_{i,j} A_{h,i,j} + (W_{i,j} - u_{i,j} A_{h,i,j}) \tan \phi_{i,j}]}{\sum W_{i,j} [R_{i,j} \sin \alpha_{i,j} + k_{eq} e_{i,j}]} / m_{a,i,j} \quad (3)$$

$$m_{a,i,j} = \cos \epsilon_{i,j} + \frac{\sin \alpha_{i,j} \tan \phi_{i,j}}{FOS} \quad (4)$$

where $R_{i,j}$ is the radial distance from the rotation axis to the centre of the base of each column, $c_{i,j}$ is the cohesion, $A_{h,i,j}$ is the horizontal area of the trial slip surface, $W_{i,j}$ is the weight of the column, $u_{i,j}$ is the pore-water pressure derived from the GEOTop model, $\phi_{i,j}$ is the internal friction angle, $\alpha_{i,j}$ is the apparent dip in the sliding direction, $\epsilon_{i,j}$ is the actual dip of the column, k_{eq} is the horizontal pseudo-acceleration coefficient,

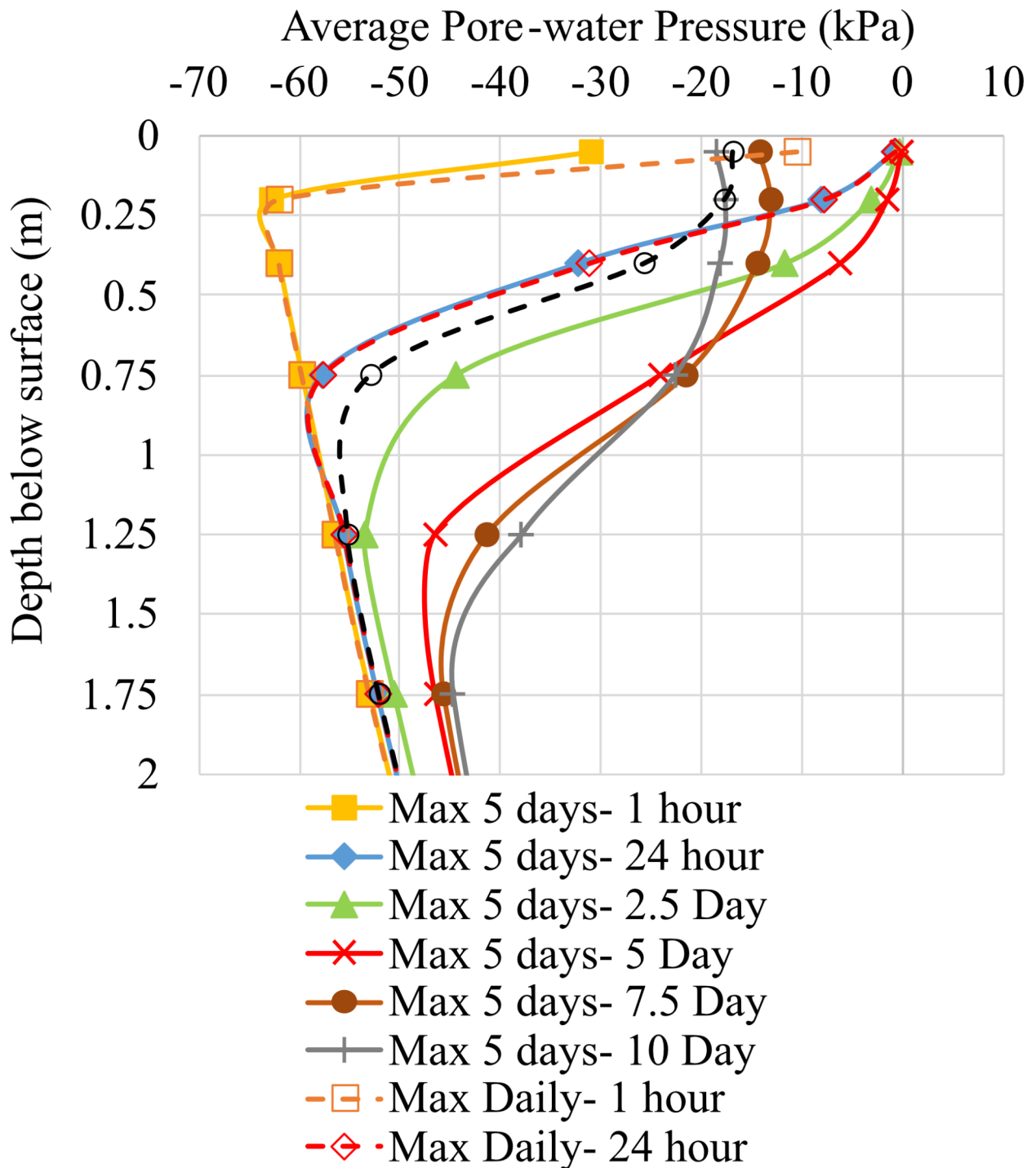


Fig. 4. Average pore-water pressures from water balance analysis.

$e_{i,j}$ is the moment arm for the horizontal driving force. A schematic diagram illustrating the definition of the parameters used in Eqs. 3 and 4 has been provided by Reid et al.⁵³.

Slopes with a FOS less than 1.5 were considered as slopes of concern following the recommendations by the Housing and Development Board of Singapore for slope design⁶⁶. Therefore, the percentage of pixels with FOS less than 1.5 was calculated for both rainfall analyses (Fig. 5). The results show that the FOS continued to decrease after the 24th hour with the end of the maximum 5-day rainfall event having the highest percentage of pixels. These observations agree with the pore-water pressure results in Fig. 4. The higher pore-water pressures at the end of the maximum 5-day rainfall analysis as compared to the end of the 24-hour maximum daily rainfall analysis resulted in more areas having a lower FOS. At the end of the rainfall event, the maximum 5-day

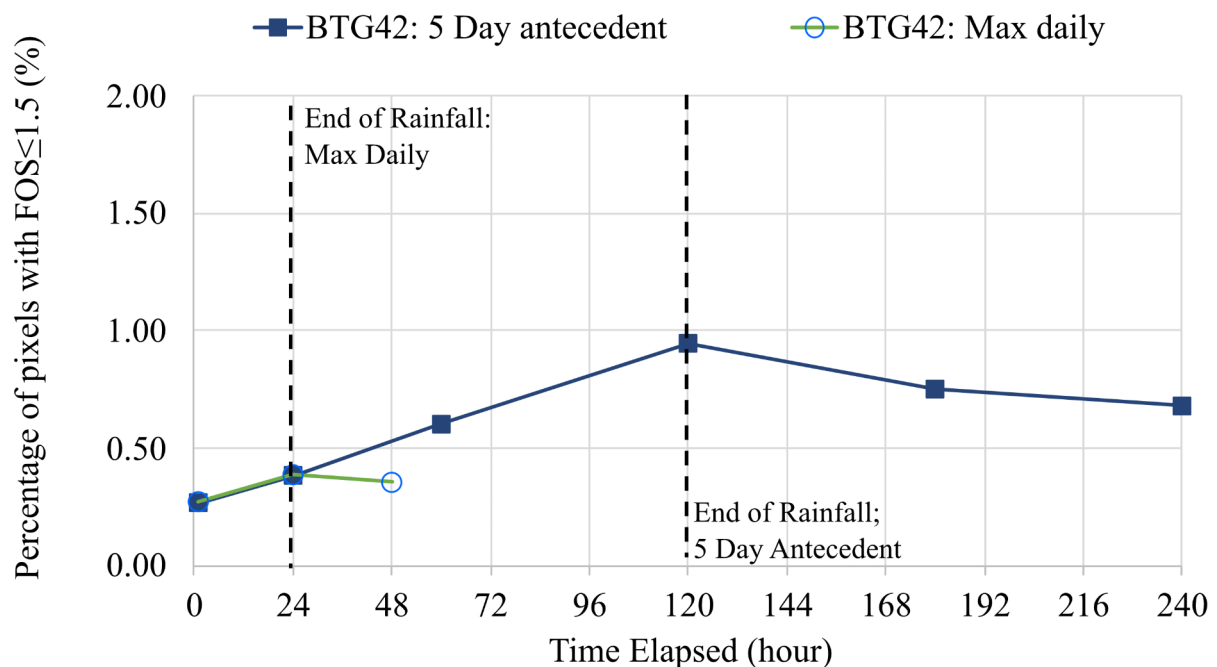


Fig. 5. Percentage of pixels with FOS less than 1.5.

Model	Maximum daily rainfall	Maximum 5-day rainfall
GEOtop	7.32 h	40.32 h
Scoops3D (approximately 14 h per timestep)	For 3 timesteps (i.e. 1st, 24th, and 48th hour), the total duration is 43 h.	For 6 timesteps (i.e. 1st, Day 1, 2.5, 5, 7.5, 10), the total duration is 140 h.

Table 2. The computational time for GEOtop and Scoops3D analyses.

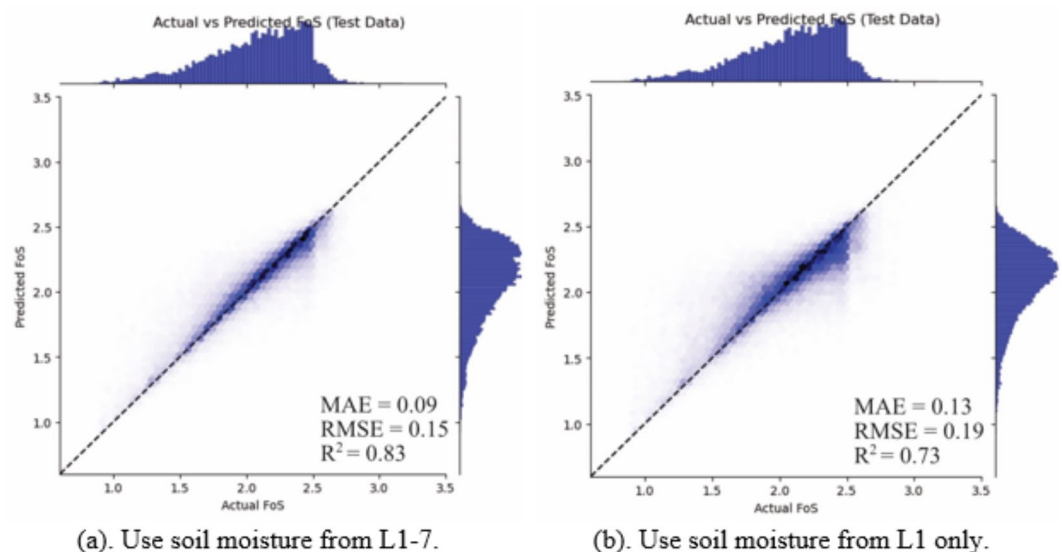
antecedent rainfall analysis had 0.95% of pixels with FOS less than 1.5 while the maximum daily rainfall analysis only had 0.38%. Hence, the slopes in the BTG42 zone are more susceptible to failure under low rainfall intensity but longer duration rainfall events (5-day antecedent rainfall) as compared to rainfall events with higher intensity but shorter duration (maximum daily rainfall). The computational time to run the GEOtop and Scoops3D analyses are presented in Table 2 below.

Machine learning model using random forest regression

The outcomes of the regional FOS assessments, which are derived from physically based models utilising GEOtop for water balance evaluations and Scoops3D for slope stability analyses, serve as a reliable reference point. While computation time for one timestep in regional 3D analyses is time-consuming (Table 2), the results could identify slopes that warrant attention at specific timesteps during critical rainfall scenarios. However, to obtain FOS maps for intervals not covered by these specific timesteps, significant additional computing time is required. Consequently, analysing FOS under typical, rather than critical, rainfall conditions with physically based models demand even more computational effort. Utilising FOS maps generated under critical conditions for real-time monitoring could lead to conservative outcomes. There is a likelihood that some slopes, considered unstable under extreme rainfall conditions, may not present a significant hazard under less severe weather circumstances, particularly when current meteorological conditions are much less intense than the potential extremes that have yet to occur.

Therefore, machine learning methods are proposed as an efficient and effective alternative for real-time monitoring and early warning systems due to their rapid processing and strong nonlinear capabilities. In this study, data from maximum daily rainfall events, encompassing 24-hour rainfall intervals, and 24-hour dry intervals, was employed to train the machine learning model. Subsequently, the model was used to estimate the FOS during the maximum 5-day antecedent rainfall event and to contrast these estimations with outcomes from physically based modelling under identical rainfall conditions. The comparisons were conducted over various timesteps: 1 h, 1 day, 2.5 days, 5 days, 7.5 days, and 10 days, corresponding to times of maximum 5-day preceding

Model	RF(L1)	RF(L1-2)	RF(L1-3)	RF(L1-4)	RF(L1-5)	RF(L1-6)	RF(L1-7)
Depth (m)	0.05	0.2	0.4	0.75	1.25	1.75	6
Number of Input variables	4	5	6	7	8	9	10

Table 3. Evaluated models and their corresponding depths of measurements.**Fig. 6.** RF model performance.

rainfall and 5-day absence of rainfall. Previous studies have demonstrated that the random forest (RF) model can achieve satisfactory results in slope stability prediction^{67–70}. The RF model was developed in this research using input variables that include slope angle, groundwater table (GWT) levels, landcover, as well as VWC results from the GEOTop analyses. To improve the model's accuracy, the original dataset, which had a 5m resolution, was resampled to a more detailed 1m resolution prior to training the RF model. 80% of the data were designated for training the model, while the remaining 20% were reserved for evaluating the performance of the trained model. Additionally, five-fold cross-validation was implemented to fine-tune the model parameters.

Furthermore, it is widely recognised that variations in the soil moisture content layer are crucial for monitoring slope stability^{71,72}. Yet, the significance of this factor in predicting the FOS remains unclear. The use of remotely sensed soil moisture data in slope stability estimation is often viewed with scepticism, primarily because these methods are limited to measuring moisture in the surface layer, without offering insights into the deeper, more substantive soil layers. This raises questions about the reliability of using just the moisture content of the first layer (L1 VWC) for estimating FOS and how it compares to the analyses that incorporate moisture contents from multiple layers. Considering the potential correlation between surface moisture content and the moisture contents of deeper soil layers, it is conceivable that reliable FOS estimates might be derived from the surface VWC alone. Therefore, this study extended its investigation to explore the impact of integrating soil moisture data from different depths, aiming to understand how the inclusion of information from various layers influences FOS. This exploration assessed the effect of using VWC data from all the seven layers, solely from the top layer, or from the selected combinations of layers (Fig. 2), on the accuracy and reliability of FOS estimations. This evaluation involved utilising varying sets of soil moisture inputs when training RF models, which included VWC for all seven layers, as well as subsets ranging from layers 1 to 7, down to layer 1 only. These soil moisture data, along with slope angle, GWT levels, and land cover, served as input variables, with their quantities detailed in Table 3. The study then analysed how these different data configurations influenced the FOS estimations.

Figure 6 presents the comparison between the predicted FOS derived from the RF model and the actual FOS obtained from Scoops3D, under the maximum daily rainfall conditions. The FOS was divided into four categories for slope susceptibility mapping, as recommended by Rahardjo et al.⁷³: very high risk ($FOS \leq 1$), high risk ($1 < FOS \leq 1.25$), moderate risk ($1.25 < FOS \leq 1.5$), and low risk ($FOS > 1.5$). This comparison aims to evaluate the model's performance with the test dataset under scenarios of maximum daily precipitation. Figure 6a features the comparison using VWC data from all seven layers (L1-7) within the RF model, establishing a baseline for comparison. Meanwhile, Fig. 6b highlights the scenario where only the VWC data from the top layer (L1) is used in the RF model, illustrating the predicted FOS under the limited condition of involving only the surface layer's VWC. Additional analyses that involve various combinations of VWC data from differing soil layers within the RF model are elaborated upon in Supplementary Fig. A1. Metrics such as the mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2) were calculated to assess

model performance. Generally, there is a good trend, with the results closely aligning with the 1:1 reference line (black dotted). Notably, the model trained with VWC data from all seven layers exhibited slightly better performance compared to the model with only the first layer's VWC, evidenced by lower MAE, RMSE, and higher R^2 values. Nonetheless, the implications of these findings on downstream outcomes, like FOS maps under alternate scenarios, remain to be explored. As such, scenarios involving the maximum 5-day antecedent rainfall were also examined to discern differences in FOS maps.

Figure 7 displays the estimated FOS maps obtained from the RF model and Scoops3D under conditions of maximum 5-day antecedent rainfall, which is characterized as a period of 5 consecutive days of rainfall followed by 5 days without rainfall, at three representative timesteps: the 1st day, 5th day (marking the end of rainfall), and 10th day. The FOS maps in Fig. 7 from the RF model include results from two configurations: one incorporating VWC from all seven layers and another focusing solely on the top layer's VWC variations. Figure 7 presents the FOS maps for three representative timesteps—1st day, 5th day (end of rainfall), and 10th day (end of no rainfall)—for a specific section of the study area, allowing for better visual comparison. The FOS map for the entire zone is provided in Supplementary Figure A2. FOS maps using all combinations of VWC data from various soil depths at each timestep are shown in Supplementary Figures B1–B6. The FOS distribution patterns from the Scoops3D and RF models are highly similar, with only minor differences. Notably, RF predictions using only the top layer's VWC (RF FOS L1 SM) align more closely with Scoops3D than those incorporating data from all seven layers (RF FOS L1-7 SM).

Alongside visual evaluation, a detailed quantitative analysis was performed to determine the pixel distribution within various FOS categories, excluding the low-risk category pertinent to slope stability (with its percentage being the complement to 100% of the other categories). As illustrated in Fig. 8, this analysis provided a comparison between the results obtained from Scoops3D and those from RF models that accounted for VWC across all seven layers (L1-7), in addition to RF models that exclusively considered VWC from the

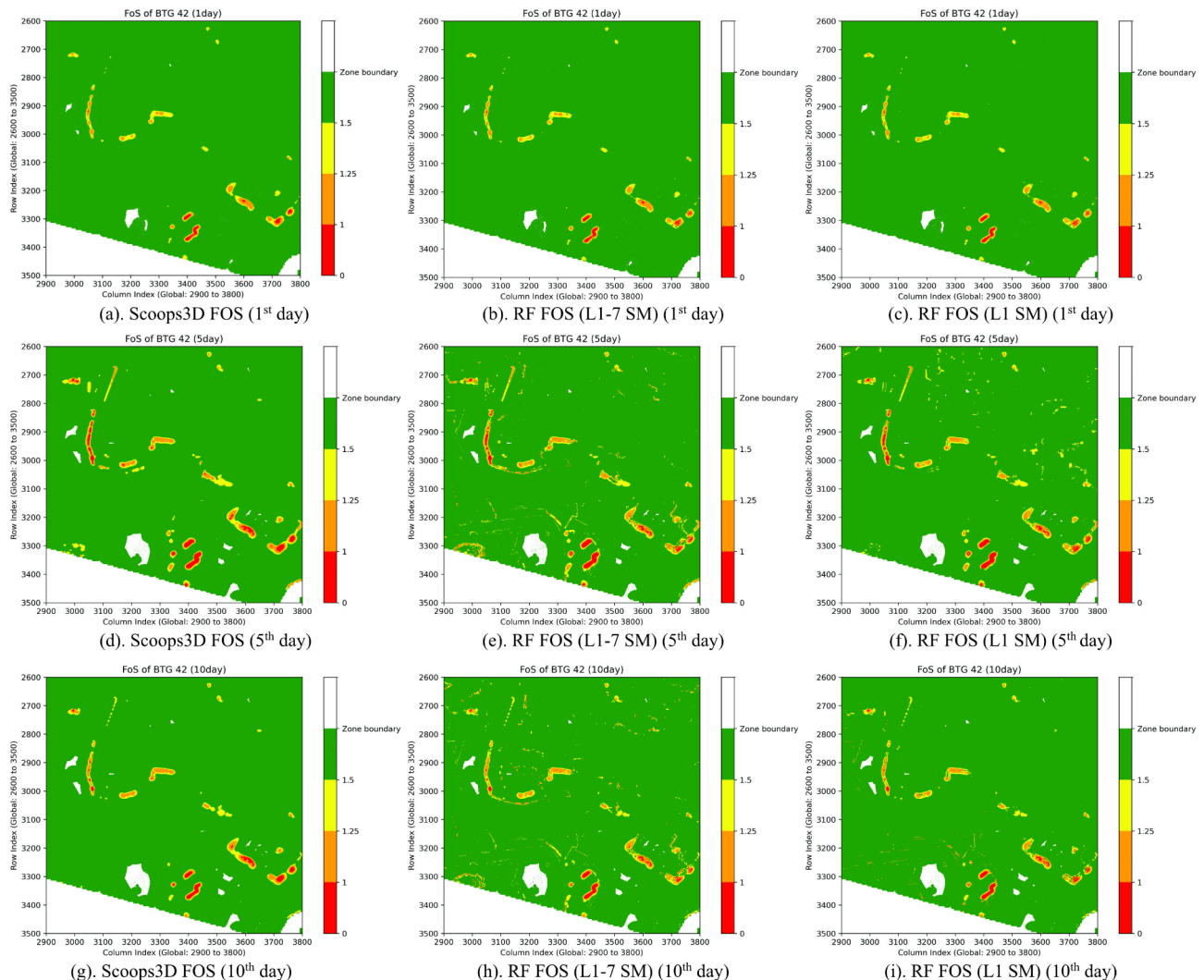


Fig. 7. FOS maps obtained from the RF model and Scoops3D for a specific section of the study area. The full map is provided in Supplementary Figure A2.

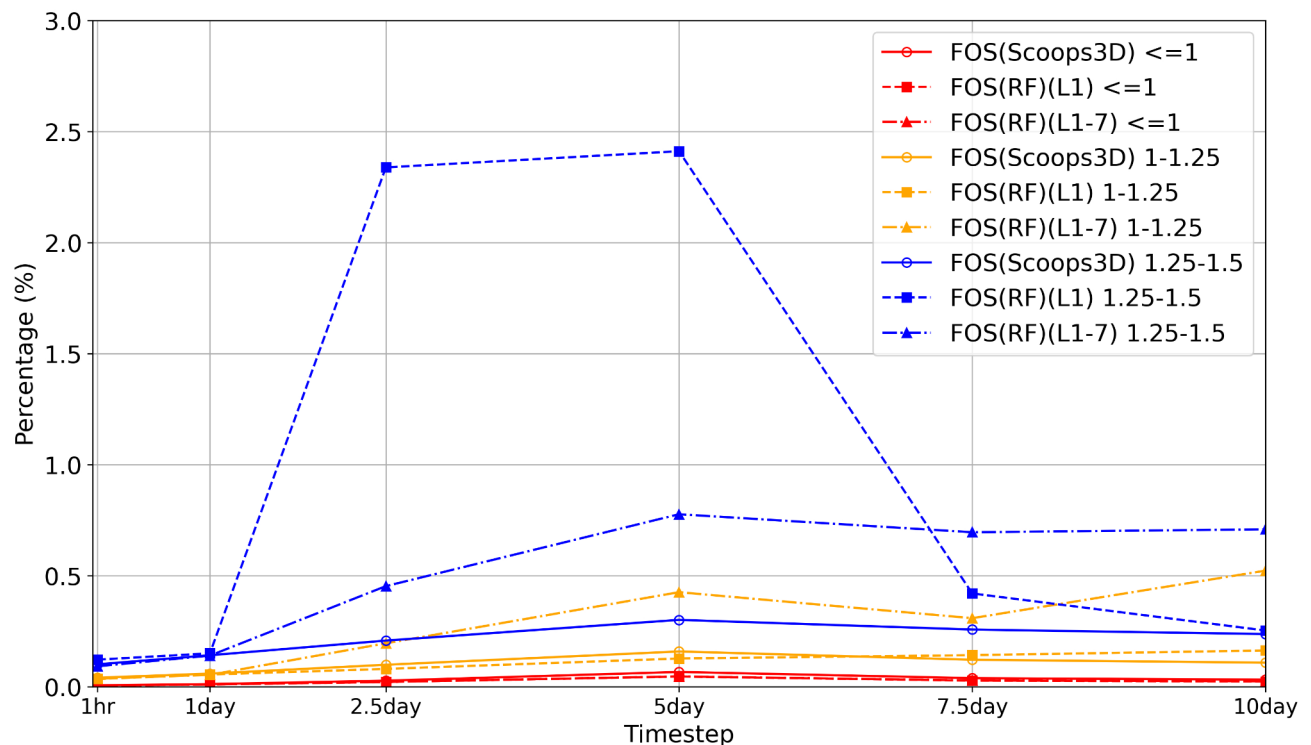


Fig. 8. Comparison of percentage of pixels in each category from Scoops3D and RF results.

surface layer (L1). During the rainfall event, spanning 5 days, a notable decline in FOS was recorded, leading to a marked increase percentage of pixels in all FOS categories (≤ 1.5) by the end of rainfall. Throughout the 10-day analysis, the variance in FOS between Scoops3D and RF models remains minimal for the very high-risk category with $\text{FOS} \leq 1$ (represented by red lines). In the high-risk category ($1 < \text{FOS} \leq 1.25$), highlighted by orange lines, the results from Scoops3D and RF (L1) are closely aligned, whereas RF (L1-7) reveals a substantially larger percentage of pixels within this risk level. At the moderate risk tier ($1.25 < \text{FOS} \leq 1.5$), denoted by blue lines, findings from both RF (L1) and RF (L1-7) show an increased count of pixels in this category compared to Scoops3D, with RF (L1) presenting a further elevated number of pixels. When comparing the outcomes of the three models across various timesteps, a more significant discrepancy is noticed as rainfall progresses, yet the results converge closely after the rainfall stops.

In summary, although the comparisons typically present closely aligned results, RF models are inclined to generate more conservative FOS maps, resulting in lower FOS values compared to those produced by Scoops3D, particularly during ongoing rainfall events. Therefore, the RF model has proven to be an effective and efficient alternative for estimating regional FOS distributions, bypassing the need for more time-intensive physically based models like Scoops3D. This model leveraged the outcomes of physically based modelling under extreme conditions, encompassing a broad range of vertical soil moisture profiles and spatial distributions. It enables the prediction of real-time FOS distributions with the VWC measurements, rendering it an essential asset for early warning systems.

To understand the influence of incorporating soil moisture measurements from various depths, the performance of RF models that considered different numbers of soil layers was evaluated. This involved calculating the MAE and the RMSE in comparison to the Scoops3D results for each model configuration. To demonstrate performance variations of the different model configurations that incorporate moisture contents from different soil depths, MAE and RMSE values, derived from models including VWC from all seven layers, were set as the baseline. Changes in MAE and RMSE, expressed as percentages, were subsequently computed to highlight the impact of integrating varying moisture contents with soil depths into each model configuration. These changes were plotted to visually present how different soil depth integrations affect each model's performance, as depicted in Fig. 9. The analysis indicated that incorporating moisture measurements from deeper soil layers did not consistently improve the model's performance. After rainfall events, the surface soil layer was more significantly influenced by rainfall, resulting in more distinct fluctuations in VWC over time. This variability in surface soil moisture provided the model with distinctive features for identifying changes in slope stability across different time intervals. In contrast, when deeper layers such as layer 4 and layer 5 were included, which exhibited minimal response to rainfall (as shown in Fig. 4), these layers contribute limited variability due to the low permeability of the soil. This lack of variation in deeper layers can reduce the distinctiveness of the VWC signals from the surface layer, which may potentially affect the model's ability to accurately capture and predict the slope stability variations.

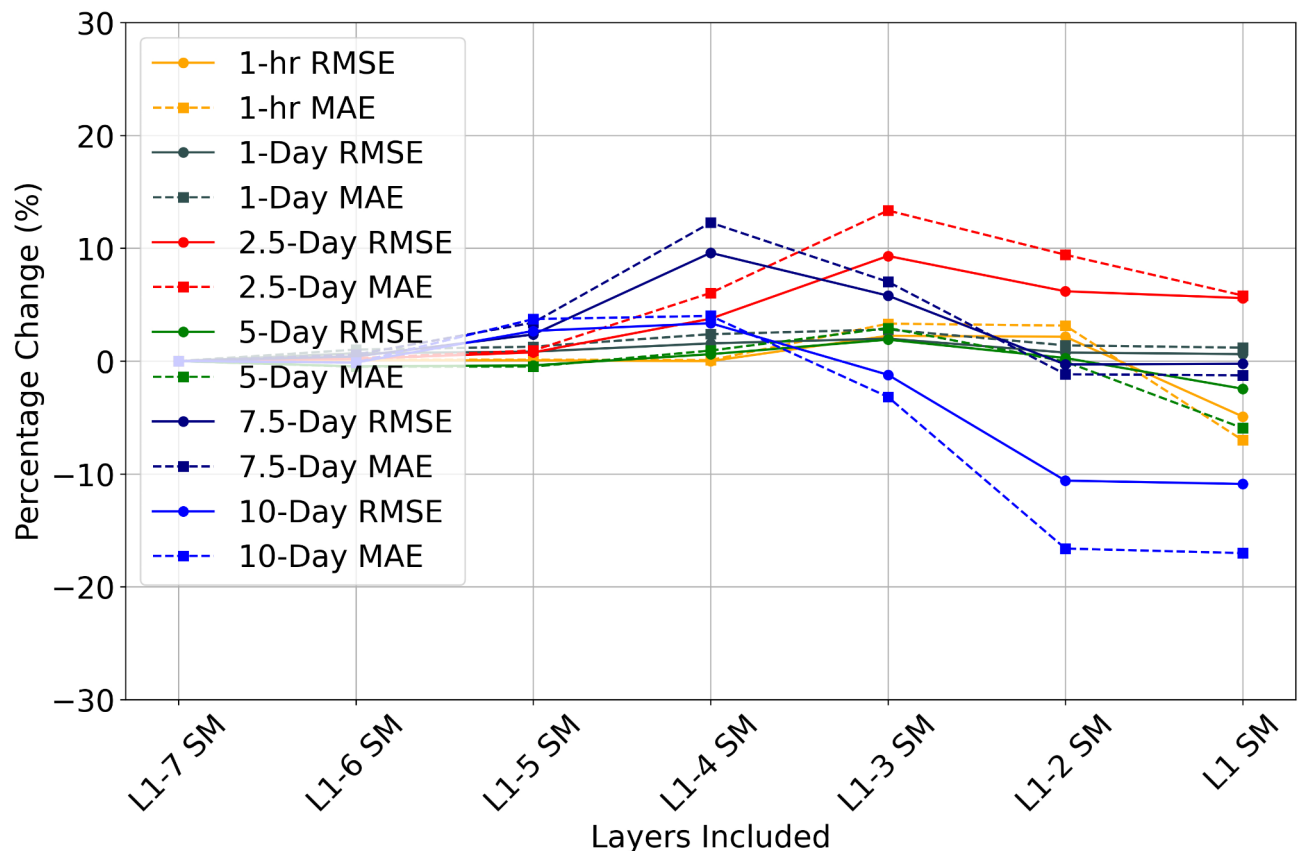


Fig. 9. Percentage changes in RMSE and MAE with the inclusion of soil moisture at varying depths.

Consequently, compared to the RF(L1), models RF(L1-2), RF(L1-3), and RF(L1-4), which included soil moisture from additional layers and greater depths, exhibited lower accuracy, as evidenced by higher RMSE and MAE values throughout the 10-day prediction period. This observation shows that models incorporating only the surface layer's VWC demonstrated strong performance. Furthermore, when compared to models RF(L1-5), RF(L1-6), and RF(L1-7), the RF(L1)'s performance remained comparable, displaying smaller MAE and RMSE at most evaluated timesteps, except for a slight 5% increase in error at the 2.5-day timestep for models using only the surface layer compared to those including all seven layers. For other time intervals, the performance was on par or better, with lower MAE and RMSE, highlighting the efficiency of models that rely exclusively on the surface layer's VWC.

Therefore, the results highlight the critical role of surface layers in FOS estimation and the potential for utilising solely surface moisture. In recent years, numerous missions have been launched to observe surface soil moisture from space, including the Soil Moisture Active Passive (SMAP) and Soil Moisture and Ocean Salinity (SMOS), which are measured in the 0–5 cm layer^{74,75}, and the Global Land Data Assimilation System (GLDAS) which can provide soil moisture in the top 10 cm of the soil column⁷⁶. The success and results of this research could pave the way for the adoption of remote sensing technologies over the traditional field-based moisture sensing methods, significantly enhancing the efficiency of data collection procedures and slope stability mapping over a large area.

However, this study presents a model designed specifically for a single zone in Singapore, where soil properties were assumed to be constant and not considered as variables. The primary aim of this work was to propose a framework (Fig. 10) for training a model that efficiently predicts FOS using surface soil moisture data. Due to the assumption of constant soil properties, the model is currently limited to the illustrated zone. To enhance its applicability and generalisability, future research should focus on expanding the analysis to multiple zones with varying soil properties, such as different soil types and diverse hydraulic and mechanical characteristics. Incorporating these soil properties as input variables would improve the model's ability to predict FOS in regions with high soil property variability, thereby increasing its generalisability across larger areas and to other parts of the world.

Conclusions

This study introduced a methodology utilising a random forest algorithm for efficient regional slope stability prediction in response to precipitation, with a particular focus on the integration of spatiotemporal variability of soil moisture. Through the comparative analysis of the RF model trained with VWC data from various soil

1. Physically-based modelling

- ❑ Conduct regional water balance analyses using GEOtop to obtain volumetric water content (VWC) at different depths under extreme conditions.
- ❑ Perform slope stability analyses using Scoops3D to calculate the Factor of Safety (FOS)



2. Random forest modelling

Develop a random forest model to establish the relationship between:

- ❑ Inputs: VWC at different depths, slope angle, groundwater table (GWT), and land cover.
- ❑ Output: FOS.

It is found that surface VWC at 1st layer (0.05 m) are crucial to predict FOS.



3. Prediction

Use the established random forest model to predict FOS based on monitored surface VWC and other input variables.

Fig. 10. Proposed framework of this study.

depths against the outcomes derived from the GEOtop and Scoops3D models, the feasibility and reliability of the approach were demonstrated.

The verification under the maximum daily rainfall condition indicated favourable results for RF (L1) and RF (L1-7), while the latter showed a slightly superior performance. Additionally, all RF models trained with combinations of VWC data from differing soil layers exhibited MAE lower than 0.15 and RMSE lower than 0.20, suggesting the potential and effectiveness of the proposed method for efficient slope stability prediction under extreme rainfall conditions. For the further comparison under the maximum 5-day antecedent rainfall condition, notable deviations were observed from the RF (L1) on the 5th day, with a greater number of pixels being classified into the moderate risk category, indicating a tendency towards conservative prediction. Nonetheless, RF (L1) demonstrated greater alignment with Scoops3D than RF (L1-7) in the high-risk category, and predictions of both were highly consistent with Scoops3D in the very high-risk tier. Moreover, RF (L1) demonstrated comparable or even superior accuracy in most scenarios compared to RF (L1-7), emphasizing the importance of surface soil moisture (0.05 m) in slope stability prediction. However, the inclusion of deeper

soil moisture data did not consistently improve the performance of the RF models, with a significant accuracy decrease observed in RF (L1-2), RF (L1-3), and RF (L1-4).

In general, this framework is capable of leveraging the strengths of both physically based models and machine-learning approaches for efficient slope stability prediction, offering valuable insights for early warning and mitigation efforts in the context of increasing extreme rainfall events driven by global climate change. While this study highlights the critical role of surface soil moisture in slope stability predictions, these findings are particularly relevant to low-permeability soils. Future study could further investigate whether similar conclusions apply to other soil types. The incorporation of spatiotemporal variations of soil moisture also reinforces the potential of remote sensing-retrieved soil moisture datasets for rapid and dependable slope stability predictions and landslide susceptibility mapping at a larger scale in future studies.

Data availability

The datasets used and/or analysed during the current study will be made available from the corresponding author on reasonable request.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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