Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 50-71

JOURNAL OF INFORMATION SYSTEM AND TECHNOLOGY MANAGEMENT (JISTM)
www.gaexcellence.com/jistm

RAINFALL- DRIVEN SATELLITE-BASED MOBILE EARLY WARNING SYSTEM FOR LANDSLIDE RISK ASSESSMENT IN ULU KLANG, MALAYSIA

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Article Info:

Article history:
Received date: 15.06.2026
Revised date: 16.07.2026
Accepted date: 10.08.2026
Published date: 03.09.2026

Abstract:

Malaysia's equatorial tropical climate is characterised by high rainfall throughout the year, making the country particularly susceptible to rainfall-induced landslides. Landslides can have serious environmental and socioeconomic impacts including loss of lives, damage to infrastructure, damage to properties, and long-term psychological effects on affected communities. Geological factors coupled with intense rainfall have been identified as key factors in slope failures in many high-risk zones . However, existing landslide early warning systems in Malaysia are often limited by limited accessibility, reliance

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 50-71

To cite this document:

Ya'acob, N., Ismail, S. I., Azize, A. M., Ali, D. M., Rasee, M. A., Shukri, M. L. M., & Borhan, M. A. H. M. (2026). Rainfall-Driven Satellite-Based Mobile Early Warning System for Landslide Risk Assessment in Ulu Klang, Malaysia. *Journal of Information System and Technology Management, 11* (44), 50-71.

on ground-based monitoring infrastructure, or the lack of user-friendly mobile platforms that can provide timely risk information to the general public. This study presents a mobile early warning system based on satellite rainfall observations by integrating Global Precipitation Measurement (GPM) rainfall information with a cross-platform mobile application for near real-time landslide risk assessment. The GPM rainfall estimates were pre-processed into JSON format and analyzed using cumulative rainfall thresholds over daily, 3-day and 30-day periods before being visualised through a React Native mobile application. The processed rainfall information was implemented as a cross-platform mobile application accessible on Android and iOS devices. Functional testing showed successful processing of GPM rainfall inputs, implementation of the validated risk assessment model, generation of corresponding landslide warning levels, and visualization of rainfall conditions in an interactive mobile interface. The results demonstrate the potential of combining satellite rainfall observations with mobile technology to promote community-based landslide preparedness and provide a scalable approach to disaster risk reduction in Malaysia.

DOI: 10.35631/JISTM.1144004

Keyword:

JSON data; Global Precipitation Measurement (GPM); Landslide Warning; React Native; Rainfall Threshold

Introduction

Landslides are among the most prevalent natural disasters that may occur in Malaysia. In Malaysia, landslides can be caused by severe rain, erosion, chopping down trees and poor building techniques. For example, natural environment of a place such as slope, soil type, plant cover and water conditions are major elements that determine the frequency of landslides (Ehsan et al., 2021). Such occurrences often have severe consequences, such as damaging essential facilities, destroying communities, killing people and shaking up the economy. Malaysia has a mountainous landscape, and the country experiences heavy rainfall every year and frequent monsoon seasons, which make the country even more vulnerable to landslides caused by rain (Fathani et al., 2016). Landslides generally occur on steep slopes and weak soil structures where the soil becomes unstable due to long or heavy rainfall. The daily variation of rainfall along with consistently high temperatures leads to accelerated weathering and increases slope instability (Muhammad et al.,2016; Dou et al., 2015). States such as Johor, Pahang, Perak and Selangor are among the most frequently affected states.

Remote sensing technologies have become an important tool in monitoring and analyzing landslide-related conditions. Satellite systems such as the Global Precipitation Measurement (GPM) mission provide consistent and spatially distributed precipitation estimates that are

Journal of Information System and Technology Management
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EISSN: 0128-1666
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valuable for rainfall threshold studies (Tajudin et al., 2020). The increasing frequency and severity of landslides in Malaysia, driven by rapid development, urbanisation, land-use change, and climate variability, underscore the need for improved monitoring and predictive methods. The integration of remote sensing data (e.g. GPM rainfall estimations) can assist researchers to determine rainfall thresholds for identifying regions prone to landslides.

The increasing scale of monitoring results in huge amounts of data that can no longer be managed by manual or traditional monitoring systems, thus requiring automated solutions (Bai et al., 2020). Mobile applications have been found to be an efficient platform for disseminating hazard information to the public as they are accessible, easy to use and can display updated datasets. Cross-platform mobile apps can be deployed quickly, and it is easy to add processed rainfall stats in JSON format to analyze and visualize with modern frameworks like React Native and Expo. Although the technology in this project is not real-time, it assists with landslip hazard assessment by providing processed rainfall data such as daily, 3-day and 30-day cumulative rainfall.

The growing adoption of landslide early warning systems worldwide highlights their importance as a cost-effective and sustainable measure compared to traditional physical interventions. These systems allow authorities, communities, and residents in high-risk areas to plan and react promptly to emerging threats, reducing the risk of casualties and damage. Beyond technological aspects, effective early warning systems must also incorporate social and community engagement components to ensure that information is communicated clearly and understood by end users. This project contributes to these efforts by developing a mobile-based platform designed to enhance the awareness and preparedness of residents in landslide-prone areas such as Ulu Klang.

Several major disasters, such as the Batang Kali incident on 18 December 2022, have demonstrated the need for better landslide monitoring in Malaysia. Shah (2022) mentioned that two slope failures occurred within 20-30 minutes releasing around 450,000 m3 of soil debris and affecting 92 victims, resulting in 31 fatalities and numerous injuries. The event was caused by high soil saturation and the accumulation of subsurface water pressure beneath the campsite and has been classified as Malaysia’s second deadliest landslide (Bernama, 2022). The problem is compounded by the fact that rain gauge stations are few in rural areas, making reliable precipitation data unavailable. Patrick et al. (2017) pointed to the importance of satellite-based rainfall products such as TRMM and GPM, which give spatially distributed rainfall estimates, for landslide-prone regions with sparse instrumentation. These conditions reinforce the need for an accessible early warning tool capable of integrating satellite rainfall data and providing clear hazard information to the public.

Note that the proposed system is at present a prototype and is demonstrated using pre-processed satellite rainfall datasets. However, this study aims to develop and validate an operational framework for real-time processing of near real-time satellite rainfall data, automate data workflows, perform threshold-based classification and timely disseminate early warnings through a dedicated mobile application platform.

Literature Review

Factors of Landslides' Occurrence

Landslides are influenced by a combination of natural and anthropogenic factors, with their occurrence being more frequent in areas characterized by steep slopes and loose or poorly compacted soils. Slope stability is highly influenced by the type of soil or rock as this determines the resistance to movement of the soil or rock; for instance, clay soils are less stable than sandy or gravelly soils and are more prone to landslides (Rahman & Mapjabil, 2017). The angle of the slope is also a factor affecting stability, with steeper slopes having more gravitational forces that increase the probability of mass movement. Rainfall is another critical factor, as heavy or prolonged precipitation saturates the soil, reduces shear strength, and increases pore-water pressure, thereby promoting slope failure. Water infiltration along interfaces of sandstone and shale can weaken contact surfaces and trigger landslides (Rosly et al., 2022). Earthquakes also contribute to slope instability, as seismic shaking can generate cracks in the ground, alter the water table, and destabilize slopes, making landslides more likely to occur. Collectively, these factors, geological conditions, rainfall intensity and duration, slope angle, and seismic activity interact to determine both the frequency and severity of landslide events.

Rainfall Threshold of Landslide Occurrence

The concept of a rainfall threshold, which refers to the minimum intensity and duration of rainfall necessary to initiate a slope failure, is fundamental in the examination of rainfall-induced landslides. The threshold is influenced by local factors including soil composition, slope angle, vegetation cover, and the moisture content of the soil before the rainfall event (Gariano & Guzzetti, 2016). Generally, as rainfall intensity increases, the threshold decreases. Even short but heavy rainfall can saturate soil, reduce shear strength, and increase the likelihood of collapse. Clay-rich areas have lower thresholds than sandy areas. Rainfall thresholds are used globally, regionally and locally to consider the different landscapes and landslide types (Gariano & Guzzetti, 2016). Rainfall is the main trigger of landslides and rainfall thresholds are commonly used to predict landslide occurrence in a given region. According to Segoni et al. (2018), a threshold is a quantitative condition, mathematically expressed, that changes the state of a system when exceeded. Ivanov et al. (2020) define thresholds as the minimum hydrological conditions (e.g., rainfall, soil moisture infiltration) required for initiating landslides. Gariano and Guzzetti (2016) pointed out that rainfall thresholds are used at the global, regional and local scales, despite the differences in physiographical settings and landslide types.

The comparison of thresholds and rainfall trajectories through the determination of the rainfall event start is feasible, but human judgement cannot be fully replaced by early warning systems, requiring the expert knowledge during the monitoring and prediction (Segoni et al., 2018). Intensity-Duration (ID) thresholds specify critical rainfall intensity over varying durations that can lead to slope failure, typically modeled by the power function, where is rainfall intensity, is duration, and and are parameters to be determined (De Luca & Versace, 2016). Conventional ID thresholds treat rainfall data uniformly over time and do not account for different temporal patterns, while antecedent long-term rainfall remains a key factor influencing short-term landslide-triggering events.

Global Precipitation Measurement (GPM)

Precipitation is a key factor influencing the global water and energy balance, and it plays a crucial role in hydrological and land surface models (Abraham et al., 2020). Satellite precipitation products have been widely used in research and development for many years, providing near-global data for various applications. Since the launch of the Tropical Rainfall Measuring Mission (TRMM) in 1997, rapid generation of PMW-based precipitation datasets, along with calibrated IR and combined PMW plus IR observations, has significantly contributed to global precipitation studies (Thakur et al., 2017). The Integrated Multi-Satellite Retrievals for GPM (IMERG) is a Level 3 Global Precipitation Measurement (GPM) system that integrates rain gauge and satellite data to provide comprehensive global rainfall information (Hidayat et al., 2019). IMERG produces three main product categories: NRT IMERG Early run, Late run, and PRT IMERG Final run, enabling timely and accurate monitoring of precipitation patterns worldwide.

Early Warning System as a Monitoring Tool for Landslides

Early warning systems (EWS) are significant in landslide-prone areas to reduce the damage and casualties of natural disasters. EWS can offer reliable and cost-effective monitoring through the comparison of the rainfall thresholds with the factor of safety for landslides, particularly in the areas where natural landslides are common (Naidu et al., 2018). According to Dixon et al. (2018), slope-instability EWS are necessary to warn the users, help in the evacuation of vulnerable populations, and enable rapid maintenance of critical infrastructure. EWS may include alarm, warning, and forecasting components. Alarm systems are used to provide immediate alerts when slope movement reaches pre-defined levels. Warning systems are used to alert specialists to implement mitigation measures and identify early signs of progressive degradation (Calvello & Piciullo, 2016). Landslide early warning systems (LEWS) can operate at two scales. Lo-LEWS are typically used to monitor hazards generated by one or more known landslides (Piciullo et al., 2018). While Lo-LEWS are designed for specific landslide sites, Te-LEWS refer to large areas such as regions, lakes or states (Calvello & Piciullo, 2016; Segoni et al., 2018). In addition to early warning, spatial assessment tools such as Landslide Susceptibility Maps can provide planners with predictive knowledge of potential hazard locations.

Landslide Susceptibility Map

A landslide susceptibility map (LSM) is a map that determines an area with a low to high risk level based on the slope, soil type, and the effect of water flow. The LSM is an essential step for controlling and planning the development of natural resources and plays a role in sustainable development in the region (Arabameri et al., 2019). Understanding the factors of landslide occurrence and their zoning will provide planners with essential directions for soil management, natural resource preservation, tourism, electrical transmission planning, and urban and rural development (Ahlmer et al., 2018). Pham et al. (2017) also mentioned that LSM is useful for visualizing and predicting landslides by evaluating the conditions similar to past events and emphasizing the significance of spatial relationships between causative factors. Arabameri et al. (2019) also suggested that the most reliable means for LSM is to generate a landslide inventory map (LIM) from aerial photographs, field surveys or historical landslide records. For example, in Shangzhou District, Shangluo City, Shaanxi Province, China, LSM

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was generated by DS, LR and ANN models based on GIS and the Landslide Susceptibility Index (LSI) was divided into four classes by the natural break method.

In the present study, no Landslide Susceptibility Map was prepared due to non-availability of appropriate satellite imagery and detailed field data. However, the above discussion shows the potential application of LSM for future assessment of landslide risk in the study area.

Methodology

Framework of the Research

Figure 1 shows the framework of this study as a structured workflow to develop the Rainfall–Landslide Early Warning System (RLEWS). Rainfall and hydrological data are first obtained from satellite and sensor sources, which are then analyzed and used to create warnings. Second, the collected data are processed and analyzed in the data processing and analytics layer to identify the factors leading to landslide risk. Third, the RLEWS mobile application is designed to feature the hazard mapping and alert dissemination. Finally, the early warning system is developed and tested for providing the timely risk warning, reliability and efficiency for community preparedness.

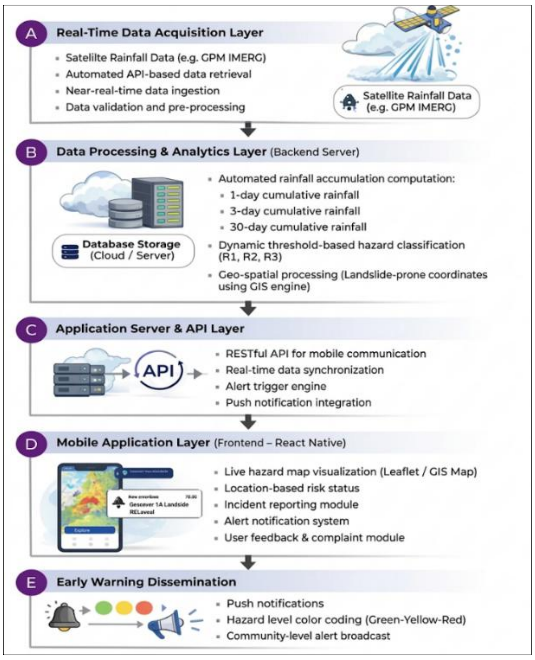

Figure 1: Framework of the Research

Overview of the Study Area

The study area is situated in Ulu Klang, Selangor, approximately 10 km from Kuala Lumpur, as illustrated in Figure 2. The data used in this study were collected on 6 May 2023. Due to rapid urbanization in Kuala Lumpur, the demand for land in Ulu Klang for economic development, particularly housing and real estate projects, has significantly increased. As a result, Ulu Klang has become one of the most landslide-prone regions in Malaysia and has experienced recurring landslide events since the 1990s.

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Figure 2: Location of The Study Area In Ulu Klang, Selangor, Showing the Nearest GPM Grid Point Used for Rainfall Data Extraction

For this study, rainfall data were obtained from the nearest point, Kemensah (Ulu Klang), with coordinates 3.184°N and 101.7675°E. This point corresponds to a gridded location in the GPM dataset, which provides satellite-based precipitation estimates at a spatial resolution of 0.1° × 0.1°.

Data Collection

The daily rainfall data used in this study were obtained from the Global Precipitation Measurement (GPM) satellite at the nearest gridded point representing the Ulu Klang area. The selected grid point provides precipitation data with a spatial resolution of 0.1°×0.1°, which enables consistent and reliable estimation of local rainfall variability. The GPM Integrated Multi-satellite Retrievals for GPM (IMERG) product is available on the Google Earth Engine (GEE) platform, which provides efficient cloud-based processing to extract rainfall spatial and temporal information. The interface and the extraction procedure through GEE are shown in Figure 3.

The rainfall data used in this study was obtained from the GPM satellite product, which was then converted into a structured JSON format for the mobile application. The prototype is currently using pre-processed rainfall datasets to help with the system development, functional testing and demonstration of the warning framework. The system architecture was designed to support future integration with near-real-time satellite rainfall products, although real-time data streaming has not yet been implemented, and enables automated data processing, threshold computation, and dissemination of early warning.

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EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 50-71

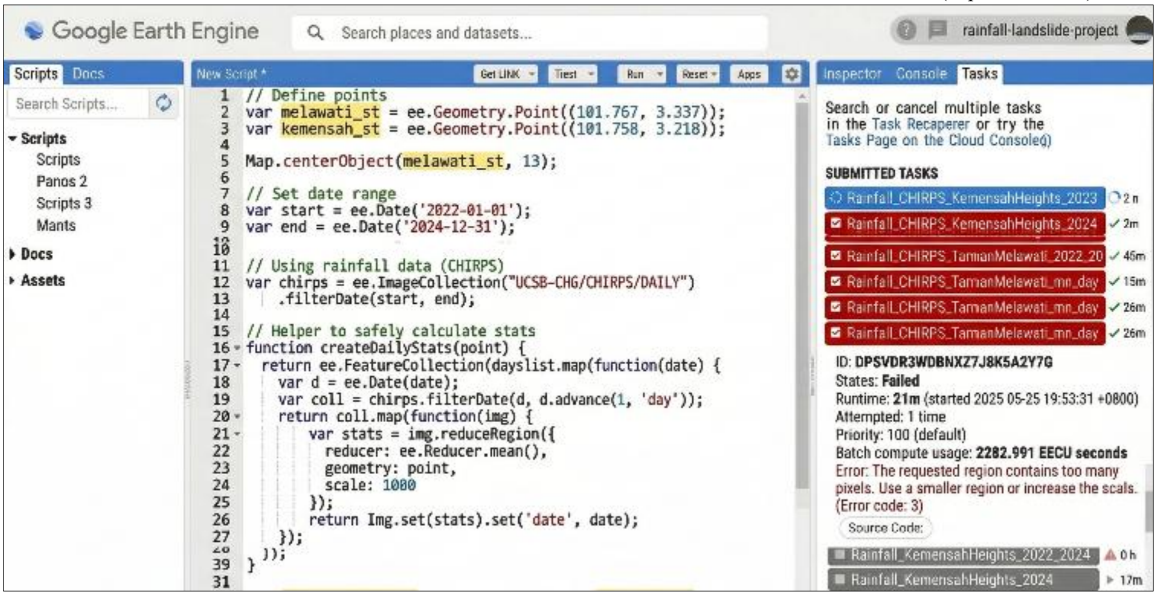

Figure 3: Google Earth Engine (GEE) Interface Used to Access and Extract GPM IMERG Daily Rainfall Data for The Ulu Klang Study Area

Rainfall Threshold Model for Landslide Prediction

In this study, the rainfall threshold was evaluated using GPM satellite precipitation estimates based on 1-day, 3-day, and 30-day cumulative rainfall. A threshold is a quantitative condition expressed as a mathematical relationship that, when crossed, changes the state of a system (Segoni et al., 2018). Thresholds are defined by Ivanov et al. (2020) as the minimum hydrological conditions (e.g. rainfall intensity and soil moisture infiltration) that trigger landslides. Gariano and Guzzetti (2016) highlighted that the rainfall thresholds are commonly used at global, regional and local scale, considering different rainfall features, physiographical conditions and types of landslides.

The rainfall threshold levels in this study were adopted from the previous study (Pham et al., 2017). The threshold for Ulu Klang, Selangor was derived based on 3-day and 30-day cumulative rainfall (E3–E30). The threshold determination justifies the classification of potential landslide warning levels, including minor landslides, major landslides and extreme rainfall events. The existing Landslide Susceptibility Map (LSM) adopted from previous work provides the spatial probability of landslide occurrence and integrated with rainfall thresholds to improve the reliability of early warning (Ivanov et al., 2020). Spatial probability categories were divided into three classes: low, moderate, and high. Table 1 summarises the rainfall threshold levels, the limiting threshold equations, the associated warning levels, and the corresponding landslide predictions.

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EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 50-71

Table 1: Rainfall Thresholds and Warning Classifications for Landslide Prediction in Ulu Klang

Rainfall Threshold Level	Rainfall Threshold Equation	Warning Levels	Landslide Prediction
R1	$E_{3(MAJOR)} = 192.8 - 0.56E_{3(30)} > \text{Rainfall}$	Low	No Landslide
R2	$E_{3(EXTREME)} = 182.48 - 0.27E_{3(30)} > \text{Rainfall} > E_{3(MAJOR)} = 192.8 - 0.56E_{3(30)}$	Moderate	Minor Landslide
R3	$\text{Rainfall} > E_{3(MAJOR)} = 192.8 - 0.56E_{3(30)}$ $\text{Rainfall} > E_{3(EXTREME)} = 182.48 - 0.27E_{3(30)}$	High	Major Landslide

Functioning of the Rainfall-Landslide Early Warning System

Once the rainfall thresholds are identified, the system processes the data to produce warning levels and hazard maps, which form the basis of the Rainfall-Landslide Early Warning System (RLEWS). The 1-day cumulative rainfall data were extracted from the GPM IMERG product satellite at the nearest grid point of Ulu Klang retrieved from Google Earth Engine platform. This rainfall data is analysed by the system to determine warning levels i.e Low, Moderate and High. On the basis of these levels a Rainfall-Landslide Hazard Map (RLHM) is produced to visualise the areas at risk. Users can then view the outputs including the current warning level, the hazard zone map and daily rainfall analyses in graphical form. This workflow allows a continuous surveillance and supports a timely decision-making for landslide risk mitigation. The overall workflow of the system is illustrated in Figure 4, showing the sequence of steps involved in data acquisition and user access.

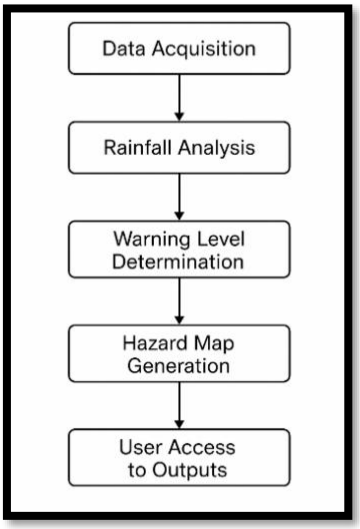

Figure 4: Flowchart Illustrating The Operational Workflow Of The Rainfall-Landslide Early Warning System (RLEWS)

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Design and Development of a Mobile Application-Based System

With the rapid evolution of mobile technologies, it has become possible to develop intelligent, user-centric systems that could provide real-time information and decision support to end users. Therefore, the design and development of a mobile application-based system intends to provide an accessible, scalable and efficient platform for data monitoring, processing and dissemination. In order to improve responsiveness, access to information, and timely decision-making in dynamic environments, the system integrates interactive mobile interfaces and automated data workflows.

The development of the mobile application system is based on React Native (Expo SDK 53), which allows the application to be deployed on Android and iOS devices. Expo Router is used to implement a file-based navigation system, which provides a flexible and scalable routing structure. TypeScript is used as statically typed programming language to enhance application stability and early error detection.

For user interface design, different React Native components like ScrollView, SafeAreaView and TouchableOpacity are used to develop responsive, user-friendly interaction. Line Charts of Rainfall Data iconography is supported via @expo/vector-icons react-native-chart-kit allows for visualisation of rainfall data. For interactive elements like location picking, we used react-native-picker and for date picking, we used @react-native-community/datetimepicker.

At first, react-native-maps was used for mapping and geolocation functionalities with components like UrlTile, Marker and Circle. OpenStreetMap is integrated using react-native-webview for better stability and a more robust interactive mapping experience.

Static data is handled using JSON files. The file data_map.json saves the key coordinates of the locations. The rainfall data is stored into the file data_location_rainfall.json. Dynamic routing and state management facilitate structured data retrieval and parameterized navigation using the useState, useEffect, and useLocalSearchParams hooks. The application is currently running in an offline environment and is using JSON datasets to be stored locally. The prototype does not gather real time data or stream data as it is produced.

The development workflow incorporates Expo Go for rapid testing during the development phase, and EAS Build (Expo Application Services) for automated production builds. APK and AAB outputs are generated to facilitate direct installation or deployment on Android devices. Finally, react-native StyleSheet is employed to ensure responsive and adaptive layouts, complemented by the Animated API for smooth transitions and fade-in effects, enhancing the overall user experience.

Figure 5 illustrates the data transformation process from raw tabular format, such as Microsoft Excel, into structured JSON files used by the mobile application. The original rainfall and location datasets are organized in spreadsheet columns, which are then programmatically converted into JSON objects to enable efficient storage, retrieval, and integration within the React Native framework. This transformation ensures that the app can dynamically access and render rainfall information and location coordinates, facilitating efficient data access and seamless interaction with mapping and visualization components.

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LOCATION	DATE	1 DAY	3 DAYS	30 DAYS
KEMENSAH HEIGHT	2022-01-01	3.334309459	160.0468455	160.0468455
KEMENSAH HEIGHT	2022-01-02	6.260407448	460.5464071	460.5464071
KEMENSAH HEIGHT	2022-01-03	1.840896428	548.9094356	548.9094356
KEMENSAH HEIGHT	2022-01-04	24.58899428	1569.377146	1729.227496
KEMENSAH HEIGHT	2022-01-05	8.669967015	1568.34443	2145.901377
KEMENSAH HEIGHT	2022-01-06	6.061177011	1560.374664	2149.287866
KEMENSAH HEIGHT	2022-01-07	6.620096642	737.6776854	2467.001673
KEMENSAH HEIGHT	2022-01-08	0.010112017	326.4766745	2471.869011
KEMENSAH HEIGHT	2022-01-09	0	322.5801143	2471.869011
KEMENSAH HEIGHT	2022-01-10	0.060909795	46.11494111	2513.176607
KEMENSAH HEIGHT	2022-01-11	0.223799116	52.44843371	2513.910565
KEMENSAH HEIGHT	2022-01-12	0.022992012	52.44337128	2524.511163
KEMENSAH HEIGHT	2022-01-13	0	11.31477969	2524.511183
KEMENSAH HEIGHT	2022-01-14	0.026567113	1.870057969	2525.786603
KEMENSAH HEIGHT	2022-01-15	0	1.279221196	2575.788609
KEMENSAH HEIGHT	2022-01-16	1.041567992	51.77008145	2575.781166
KEMENSAH HEIGHT	2022-01-17	1.427907072	454.5479874	2080.324826
KEMENSAH HEIGHT	2022-01-18	0.363141974	472.735541	2098.715544
KEMENSAH HEIGHT	2022-01-19	11.07567814	997.7688315	3575.567504
KEMENSAH HEIGHT	2022-01-20	0.047871163	995.2332715	3575.557555
KEMENSAH HEIGHT	2022-01-21	4.212226895	780.7674772	379.28097
KEMENSAH HEIGHT	2022-01-22	7.689555399	584.2522587	4157.799945
KEMENSAH HEIGHT	2022-01-23	11.04411745	1236.360000	4173.977966
KEMENSAH HEIGHT	2022-01-24	22.12624479	20N6.705400	5845.998973
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    "30_DAYS": 160.046845469623
  },
  {
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    "30_DAYS": 548.909435564652
  },
```


Figure 5: Transformation Of Raw Tabular Rainfall And Location Data From Excel Into Structured JSON Files For Integration Within The Mobile Application

Result

Rainfall Threshold Model

The three limiting threshold lines obtained from the reported minor landslides, major landslides and extreme non-landslide rainfall occurrences are shown in Figure 6. The results show that the rainfall threshold may be easily categorised into three categories: no landslide (R1), moderate landslide occurrence (R2), and considerable landslide occurrence (R3). Furthermore, the E30 (extreme) threshold line indicates very high-risk situations when torrential rainfall strongly increases the possibility of landslide happening.

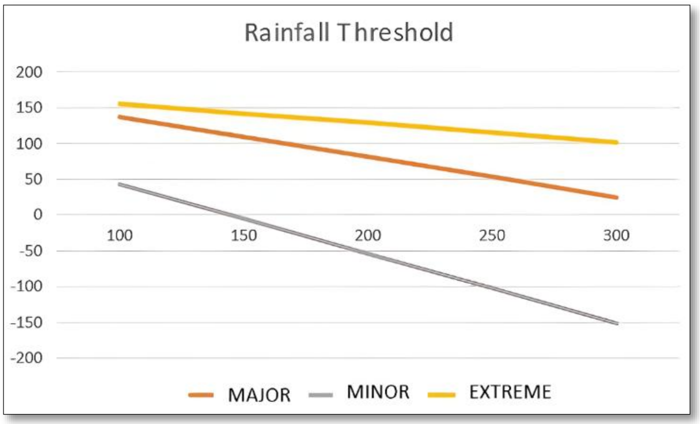

Figure 6: Limiting Rainfall Threshold Lines (R1, R2, And R3) Derived From Minor Landslide, Major Landslide, And Extreme Rainfall Events

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JISTM
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Application Interface and Functionality

The Landslide Early Warning System (LEWS) mobile application is developed to provide timely and actionable information on the landslide hazards in the selected areas around Ulu Klang. The application consists of multiple pages to facilitate user interaction, data input and analysis, enabling users to access real-time rainfall data, assess the hazard levels and review historical information efficiently. Figures 7 to 12 show the interface of each page within the application.

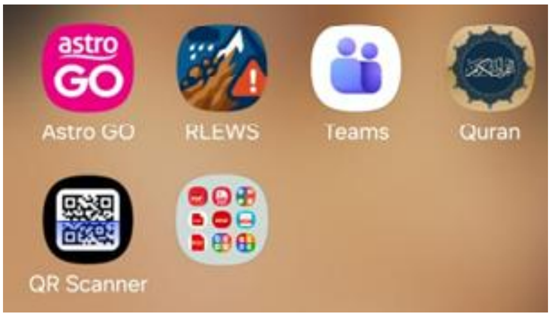

Figure 7: RLEWS Mobile App Development

The entry point of the application is the main page view as shown in Figure 8. The project logo and name are prominently displayed to establish the brand. The home page can be accessed by a single "Explore" button to provide easy navigation. This minimalist approach puts emphasis on clarity and ease of access, thus giving users a professional and inviting interface.

Figure 8: Main Page Of The Mobile Application

The home page view in Figure 9 shows that the user can select location and date via a form. There are two options for location: Kemensah Heights and Taman Melawati. When the user makes their selection and clicks submit, the application will show the location on the map with a pin marker. There is a "Clear Form" button to clear the inputs. There are two navigation buttons: "Complaint & Copyright" (Figure 10) which leads to a page showing the copyright information, the app version and the official portal of Department of Minerals and Geoscience Malaysia and "Info: Location Incidents" (Figure 11) which leads to a page showing articles or news clippings on past landslide events at the selected locations.

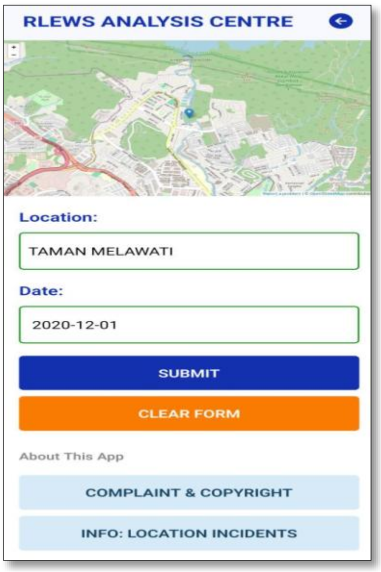

Figure 9: Home Page with Location and Date Input Form

Figure 10: Complaint & Copyright Page

Figure 12 shows the detailed information based on the user selected location and date. The data shown include the name of the location, address, latitude, longitude, and 1-day, 3-day, and 30-day rainfall measurements and the corresponding rainfall status as Low, Moderate, and High. The page also consists of a map showing the selected location with a circular zone and cumulative rainfall charts for 1-day, 3-day, and 30-day durations. The integrated layout provides the user with spatial and temporal insight to make informed decisions for landslide risk management.

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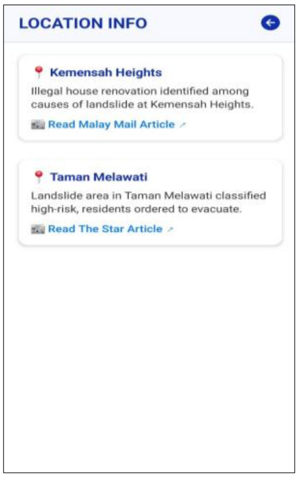

Figure 11: Location Incidents Page

The rainfall data extracted from the GPM IMERG product were analysed using 1-day, 3-day, and 30-day cumulative rainfall indices to evaluate potential landslide triggering conditions in the Ulu Klang area. The threshold classification was applied based on the E3–E30 cumulative rainfall framework, which categorises rainfall conditions into Low (R1), Moderate (R2), and High (R3) warning levels.

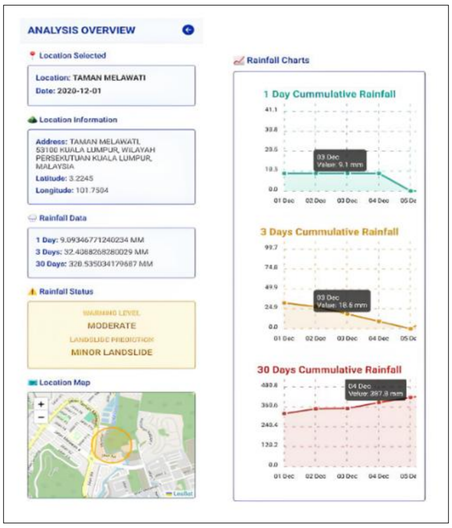

Figure 12: Analysis Page Showing Rainfall Data, Status, Map, And Charts

High Warning Level of Landslide

The analysis of the rainfall threshold was plotted on 1 June 2022 to analyze the potential landslide risk as shown in Figure 13. The warning level was classified as high as the plotted threshold curve was higher than the red threshold line in the E3–E30 graph. The recorded rainfall values were 8.247 mm for the 1-day accumulation, 405.78 mm for the 3-day accumulation and 5827.78 mm for the 30-day accumulation. When plotted against the established rainfall threshold curves, the E3–E30 trajectory exceeded the R3 threshold line which indicated a high landslide warning level. The exceedance suggests that the prolonged antecedent rainfall significantly increased the soil saturation and pore-water pressure which

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elevated the slope instability risk. The result demonstrates the capability of the proposed system to correctly classify critical rainfall conditions associated with potential landslide occurrences. Based on the above indicators, the landslide hazard level for the Kemensah Heights area was classified as high.

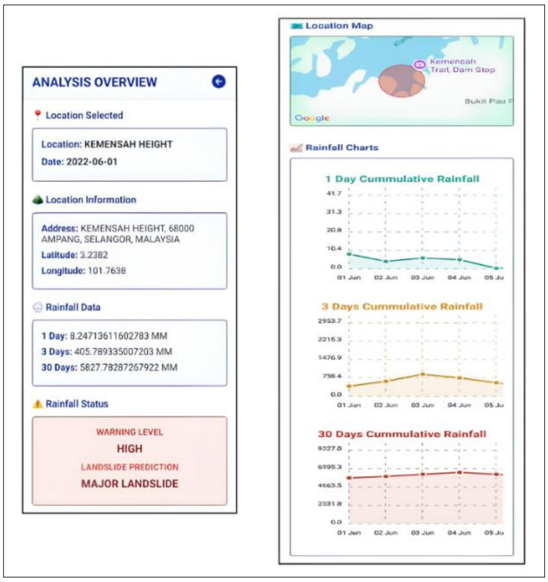

Figure 13: Analysis Page for High Warning Level of Landslide Occurrence

Rainfall Cumulative Pattern

1-Day Cumulative Rainfall

Figure 14 illustrates rainfall behaviour for the 1-day cumulative rainfall pattern for June 2022, where the highest recorded value was 9.8 mm on 1 June 2022, and the lowest was 0.1 mm, indicating relatively low short-term rainfall variability during the observed period, with the minimum value recorded on 5 June 2022.

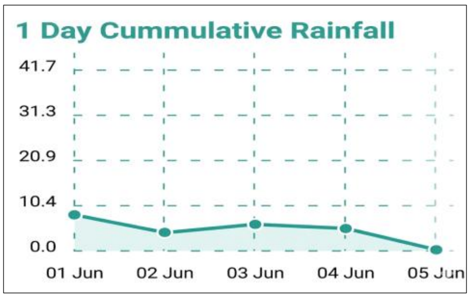

Figure 14: Rainfall Pattern Of 1-Day Cumulative Rainfall of June 2022

Table 2 summarizes the 1-day cumulative rainfall for 1, 3, and 5 June 2022, indicating 9.8 mm as the highest value, 0.1 mm as the lowest, and 5.8 mm as the median, recorded on 3 June 2022. These results reflect the occurrence of the heaviest rainfall on 1 June 2022, followed by a significantly lower rainfall on 5 June 2022.

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Table 2: 1-Day Cumulative Rainfall Pattern In June 2022 For Ulu Klang

Date	1-day cumulative rainfall (mm)
1 June 2022	9.8
3 June 2022	5.8
5 June 2022	0.1

From a hazard perspective, the declining rainfall trend after 1 June suggests a reduced short-term likelihood of rainfall-induced landslide triggering during the later dates of the observation window.

3-Day Cumulative Rainfall

Figure 15 presents the 3-day cumulative rainfall pattern for June 2022, where the highest recorded value was 752.6 mm on 3 June 2022, and the lowest was 50.6 mm on 1 June 2022. Table 3 summarizes the 3-day cumulative rainfall for 1, 3, and 5 June 2022, showing 752.6 mm as the highest value, 50.6 mm as the lowest, and 738.4 mm as the median, recorded on 4 June 2022. These findings indicate that the most intense 3-day rainfall accumulation occurred on 3 June 2022, whereas the lowest cumulative amount was observed on 1 June 2022.

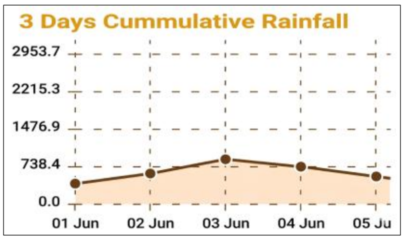

Figure 15: Rainfall Pattern Of 3-Day Cumulative Rainfall Of June 2022

Table 3: 3-Day Cumulative Rainfall Pattern In June 2022 For Ulu Klang

Date	3-day cumulative rainfall (mm)
3 June 2022	752.6
4 June 2022	738.4
1 June 2022	50.6

From a hazard perspective, the pronounced accumulation between 2 and 4 June suggests elevated soil saturation levels, which may significantly increase the probability of rainfall-induced landslides during this period. Compared with the 1-day rainfall pattern, the 3-day cumulative rainfall analysis captures the impact of prolonged rainfall, providing a better basis for landslide early warning.

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30-Day Cumulative Rainfall

Figure 16 presents the 30-day cumulative rainfall pattern for June 2022, showing a peak rainfall accumulation of 6599.3 mm on 4 June 2022 and a minimum value of 5059.5 mm on 1 June 2022.

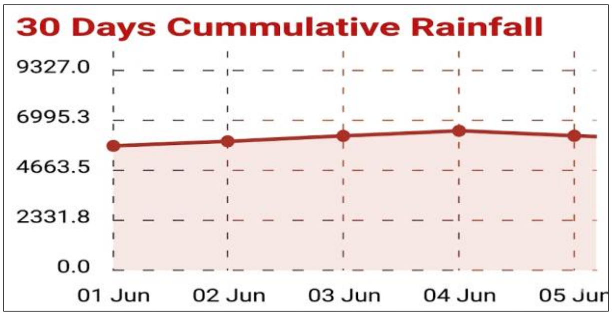

Figure 16: Rainfall Pattern Of 30-Day Cumulative Rainfall Of June 2022

Table 4 summarises the 30-day cumulative rainfall for the selected dates in June 2022. The cumulative rainfall was lowest on 1 June 2022 (5059.5 mm) and increased to its highest value of 6599.3 mm on 4 June 2022. The value recorded on 3 June 2022 was 5599.3 mm, indicating a steady build-up of rainfall during the observation period.

Table 4: 30-Day Cumulative Rainfall Pattern In June 2022 For Ulu Klang

Date	**30-day cumulative rainfall (mm)**
4 June 2022	6599.3
3 June 2022	5599.3
1 June 2022	5059.5

In contrast, the 3-day cumulative rainfall exhibited significantly higher accumulation, reaching a maximum of 752.6 mm, highlighting the dominant influence of multi-day rainfall persistence rather than isolated rainfall intensity in triggering slope instability. Similarly, the 30-day cumulative rainfall reached a peak of 6599.3 mm, reflecting prolonged wet conditions that contribute to elevated antecedent soil moisture levels.

The comparison between short-term and long-term rainfall accumulation suggests that landslide susceptibility in the study area is influenced more by prolonged rainfall than by individual daily rainfall events. This finding is consistent with previous studies, which have shown that antecedent rainfall contributes to soil saturation, reduces soil strength, and increases the likelihood of slope failure in tropical environments.

Threshold Exceedance Frequency and Warning Distribution

The rainfall data were analyzed using three warning levels: Low (below R1), Moderate (between R1 and R2), and High (above R3) in order to evaluate the performance of the threshold-based classification. The majority of the precipitation fell within the Low and Moderate categories. The periods of continuous rainfall were the primary source of high warning levels. When the short-term (E3) and long-term (E30) cumulative rainfall increased simultaneously, the R3 threshold was exceeded, suggesting that the model is more susceptible to long-term rainfall accumulation than to short and isolated rainfall events. The behavior is consistent with the natural landsliding process, in which the slope stability decreases as a result of the increase in soil saturation during continuous rainfall. The landslide risk levels are clearly indicated in the warning outputs, which promotes increased awareness and preparedness. The same analytical approach can be applied to real-time data in future implementations.

System Effectiveness and Operational Reliability

The system processes the satellite rainfall data, organizes it into JSON, and categorizes the levels of warning based on some previously defined rainfall thresholds to ensure a uniform risk assessment. This reduces human error. The testing of ten data sets of simulated rainfall at Kemensah Heights and Taman Melawati proved the reliability and effectiveness of RLEWS data processing methods. The results indicate that RLEWS is capable of determining the corresponding warning levels for each dataset in less than two seconds.

The combination of rainfall analysis and spatial mapping makes it easy to interpret hazard conditions. The mobile application interface was designed to be user-friendly so that non-expert users can quickly access warning levels, maps and cumulative rainfall charts. Initial user testing feedback validated the intuitive interface and timely decision making for landslide risk awareness.

Comparative Evaluation with Sensor Based Mobile Warning Systems

The contribution of the proposed Rainfall-Landslide Early Warning System (RLEWS) is clearly demonstrated by the mobile hazard monitoring application (Lee & Abd Razak, 2024) that was developed previously for evaluation. The system uses ESP32-based hardware and sensors to measure rainfall intensity, water level and flow rate, that provides help in real-time flood monitoring and prediction analysis. The main advantage is the use of on-site measurements which enables fast detection of hydrological changes at certain monitored points with high temporal resolution.

However, sensor-based systems are generally limited to specific monitoring locations, as each unit measures hydrological conditions only within its immediate area, and expanding coverage requires additional hardware, maintenance, and operational costs. In contrast, RLEWS uses satellite-derived rainfall data from the Global Precipitation Measurement (GPM), which provides wide-area precipitation coverage at consistent spatial resolution, enabling regional-scale monitoring without extensive ground equipment. This increases scalability and reduces long-term infrastructure dependency. However, satellite rainfall data may have retrieval uncertainties, while ground sensors provide better point-based accuracy and real-time responsiveness.

Table 5 highlights the main differences between the proposed RLEWS and the previous sensor-based warning system. Sensor-based systems are effective for monitoring conditions at specific sites, whereas RLEWS is better suited for regional-scale landslide risk assessment because it uses satellite rainfall data. Together, these two approaches have the potential to provide a more reliable and comprehensive early warning system.

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Table 5: Performance Comparison: Previous System and Proposed RLEWS

Dimension	**Smart Flood Warning System**	**Proposed RLEWS**
Monitoring Scale	Localized	Regional
Data Acquisition	In-situ sensors (ESP32, rainfall, water level)	Satellite rainfall (GPM IMERG) + real-time sensor integration
Spatial Coverage	Limited to sensor locations	Wide-area (~0.1° grid resolution)
Temporal Resolution	Real-time	Real-time
Infrastructure Requirement	Hardware installation & maintenance	Minimal ground infrastructure
Scalability	Hardware-dependent	Easily scalable via satellite coverage
Operational Cost	High (maintenance, calibration)	Lower long-term cost
Data Uncertainty	Sensor drift, malfunction	Retrieval algorithm uncertainty
Best Application	Site-specific flood detection	Regional rainfall-threshold landslide monitoring
Sustainability	Maintenance-intensive	Infrastructure-light & scalable

Conclusion

It is important to develop a landslide early warning system to mitigate the impact of landslide on lives, infrastructure and environment in Malaysia. The recent advancement in satellite remote sensing, spatial mapping and rainfall analysis has created new opportunities to improve landslip risk assessment and improve disaster management. The proposed Rainfall–Landslide Early Warning System (RLEWS) shows the promise of integrating satellite-derived rainfall data with a mobile application to provide timely hazard information to help communities in Ulu Klang to better understand potential landslip risks and take preventative steps.

Future work will include wider, even international, use of the RLEWS mobile application. A fully developed application could provide real-time updates on hazards, produce accurate maps of landslide-prone areas, and send timely alerts to at-risk users. RLEWS enables communities to respond quickly, improve personal safety, limit damage to property and increase public resilience. The broad use as a monitoring tool shows its capacity to change disaster preparedness and promote sustainable safety for communities.

Several recommendations can be made to further enhance the proposed system. First, the mobile application should be designed to be intuitive, reliable, and compatible across multiple smartphone platforms to ensure broad accessibility. Second, enhanced integration with remote sensing and GIS technologies is essential for generating accurate and up-to-date terrain and hazard information. Third, the early warning system should be linked to a robust communication network to facilitate rapid alert dissemination, particularly to communities in high-risk areas. Finally, continuous performance monitoring and regular system updates are crucial to maintain accuracy and optimize functionality. Implementing these measures will enhance Malaysia's landslide preparedness and response, ultimately improve public safety and protect critical infrastructure.

Acknowledgements:	The authors would also like to thank the Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor for their valuable support. Special appreciation is extended to colleagues and peers who contributed valuable insights and constructive feedback, which greatly enhanced the quality of this paper
Funding Statement:	This research received financial support from Geran Inovasi Sosial (600-RMC/GIS 5/3 (009/2023)).
Conflict of Interest Statement:	The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission to the Journal of Information System and Technology Management (JISTM).
Ethics Statement:	This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
Author Contribution Statement:	All authors contributed significantly to the development of this manuscript. Norsuzila Ya'acob was responsible for the conceptualization, supervision, project administration, and overall guidance of the study. Syila Izawana Ismail contributed to data collection, data analysis, and manuscript preparation. Aziean Mohd Azize contributed to the methodology development, validation, and manuscript review. Darmawaty Mohd Ali contributed to the research design and critical review of the manuscript. Muhammad Aizat Rasee contributed to the development and implementation of the mobile application system. Muhammad Lutfi Muhammad Shukri contributed to software development, system testing, and validation. Muhammad Aiman Hakimi Mohd Borhan contributed to application testing and technical support. All authors reviewed, revised, and approved the final version of the manuscript prior to submission.

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