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Article

Development of a Landslide Early Warning System in Indonesia

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Abstract: Landslides are one of the most disastrous natural hazards in Indonesia, in terms of number of fatalities and economic losses. Therefore, Balai Litbang Sabo (BLS) has developed a Landslide Early Warning System (LEWS) for Indonesia, based on a Delft–FEWS (Flood Early Warning System) platform. This system utilizes daily precipitation data, a rainfall threshold method, and a Transient Rainfall Infiltration and Grid-based Regional Slope-stability model (TRIGRS) to predict landslide occurrences. For precipitation data, we use a combination of 1-day and 3-day cumulative observed and forecasted precipitation data, obtained from the Tropical Rainfall Measuring Mission (TRMM) and the Indonesian Meteorological Climatological and Geophysical Agency (BMKG). The TRIGRS model is used to simulate the slope stability in regions that are predicted to have a high probability of landslide occurrence. Our results show that the landslides, which occurred in Pacitan (28 November 2017) and Brebes regions (22 February 2018), could be detected by the LEWS from one to three days in advance. The TRIGRS model supports the warning signals issued by the LEWS, with a simulated factor of safety values lower than 1 in these locations. The ability of the Indonesian LEWS to detect landslide occurrences in Pacitan and Brebes indicates that the LEWS shows good potential to detect landslide occurrences a few days in advance. However, this system is still undergoing further developments for better landslide prediction.

Keywords: landslides; early warning system; precipitation forecasts; rainfall threshold; slope stability model

1. Introduction

Landslides are one of the most disastrous natural hazards affecting a small spatial extent over regions, as compared to other hazards, such as earthquakes, floods, droughts, and hurricanes. Landslides are mainly caused by a complex interaction of multiple factors, including dynamic triggers (e.g., heavy precipitation and earthquake), ground condition variables (e.g., slopes, geological condition, and soil types), and anthropogenic disturbances (e.g., de-vegetated slopes and road cuts) [1–5]. In terms of the number of fatalities and economic losses, landslides have significant and comparable impacts to other natural hazards, such as floods, droughts, and earthquakes. The economic losses due to landslides in several countries, such as United States, Japan, Europe (especially in regions surrounding Alpine areas), and India, are quite similar in magnitude ($1–5 billion per year) [6–8]. Ref. [9] reported that around 2620 fatal landslides with a total 32,322 fatalities were recorded worldwide, between 2004 and 2010. Based on the number of landslide occurrences, Asia, Southeast Asia, and North America are listed as the regions with the largest proportions of reported landslide and consequent fatalities [9–11].

The number of losses and damages caused by landslides worldwide will increase in the future due to the increase of extreme events (e.g., heavy precipitation) associated with climate change [12]. To reduce the losses and damages due to landslides triggered by heavy precipitation, the development of weather-related landslide early warning systems is of the utmost importance for disaster preparedness and hazard management in landslide-prone regions. These systems, however, should be able to give a warning signal from hours to days ahead for short time-scale hazards such as landslides [13,14]. As current numerical weather predictions (NWP) are accurate enough to predict cyclonic air masses producing storm rainfalls on a short time-scale [15,16], these predictions present new opportunities to be used in Landslide Early Warning Systems (LEWSs). For this reason, LEWSs, in particular for rainfall-induced landslides, have been well-developed in several countries, such as in Italy [17–19], Norway [20], the U.S. [21], Brazil [22], and Japan [14].

Like many other countries in the world, landslides are also one of the most disastrous natural hazards in Indonesia, in terms of economic loses and fatalities. Together with China, Indonesia is ranked in the top three countries with the highest percentage of landslide fatalities [10]. In the most populated island, Java, for example, more than 1000 landslide disasters have been reported from 1981 to 2007, with the number of people affected by landslides exceeding thousands [23,24]. In the same period, Ref. [25] reported that the frequency of landslide occurrences in Java reached 49 events per year on average. The high number of casualties caused by landslides in Indonesia is due to many people living in landslide-prone areas [23]. Moreover, the climatic (frequent and high intensity of rainfall), geographic (mountainous regions), and geological conditions of Indonesia (on the junction of three tectonic plates) make it susceptible to landslides [26,27].

In Indonesia, a LEWS for Java Island has been initiated by [13,28]. Later, Ref. [29] developed a standard for LEWSs, providing guidance in conducting landslide detection, prediction, interpretation, and response. The LEWS developed by [28] has now been implemented in some landslide-prone areas in Sumatera, Java, Kalimantan, Sulawesi, and the Papua Islands [29]. This system was developed based on a rainfall-induced landslide, extensometer, and community-based approach. This system, however, only gives a warning signal if the cumulative precipitation exceeds 100 mm and if the extensometer is pulled out up to 4 cm [28]. This indicates that the Indonesian LEWS can only provide a warning signal a few minutes or hours before a landslide occurs. A short lead-time, from when a warning signal is issued to when the landslide incident occurs, limits the landslide preparedness and response actions by both the local community and authorities. Therefore, the Experimental Station for Sabo (known as Balai Litbang Sabo, BLS), Research Center for Water Resources, has developed a new LEWS across Indonesia, from the east to the west, which can provide a warning signal four days in advance. This system has been built by utilizing the daily-observed precipitation, daily precipitation forecasts up to four days ahead, a rainfall threshold method, a map of landslide-prone areas, and a slope stability model. The rainfall threshold for landslide occurrences and the map of landslide-prone areas are saved in the Delft–FEWS (Flood Early Warning System) platform [30,31], while the observed and forecasted precipitation data are downloaded by Delft–FEWS twice a week (every Tuesday and Friday).

In this paper, we present a newly developed Indonesian LEWS, which is operational under BLS, and its capability to detect landslides a few days in advance. The detailed information on the system is presented in Section 2. The outcomes of the LEWS and two examples of LEWS prediction results based on landslide events in Pacitan and Brebes are presented in Section 3. We discuss the limitations of the LEWS system and outlooks for further development in Section 3. Section 4 concludes the findings.

2. Data and Methods

The study area covers the Indonesia region from 11° S to 6° N and from 95° to 141° E. Indonesia is an archipelago country, consisting of more than 17,000 islands, which is located between the Pacific and Indian Oceans and between the Asian and Australian continents. For this reason, the climate in Indonesia is strongly influenced by the Asian-Australian monsoon and the El Niño-southern oscillation (ENSO) [32]. Precipitation over Indonesia exhibits large variability, due to the complex island topography and ocean-atmosphere fluxes. During the rainy season (from October to March), Indonesia receives abundant precipitation, ranging from 1000 mm in the south-eastern part of Indonesia to more than 5000 mm in the south-western part of the country [33]. The central part of the large islands, such as Sumatera, Java, Sulawesi, and Papua Islands, have mountain ranges with more than 79 active volcanoes [34]. On average, many regions in Indonesia are located in the mountainous (27%) and hilly areas (20%), with slopes of >30% and 15–30%, respectively. The remaining regions (53%) are located in the undulating and flat-sloping areas, with a slope between 0–15%.

The data required for developing the Indonesian LEWS consist of observed precipitation data, daily precipitation forecasts, a map of landslide-prone areas, a rainfall threshold, and soil properties data for slope stability analysis using a Transient Rainfall Infiltration and Grid-based Regional Slope-stability model (TRIGRS, [35]). The data and method are described as follows (see Figure 1 for the flowchart).

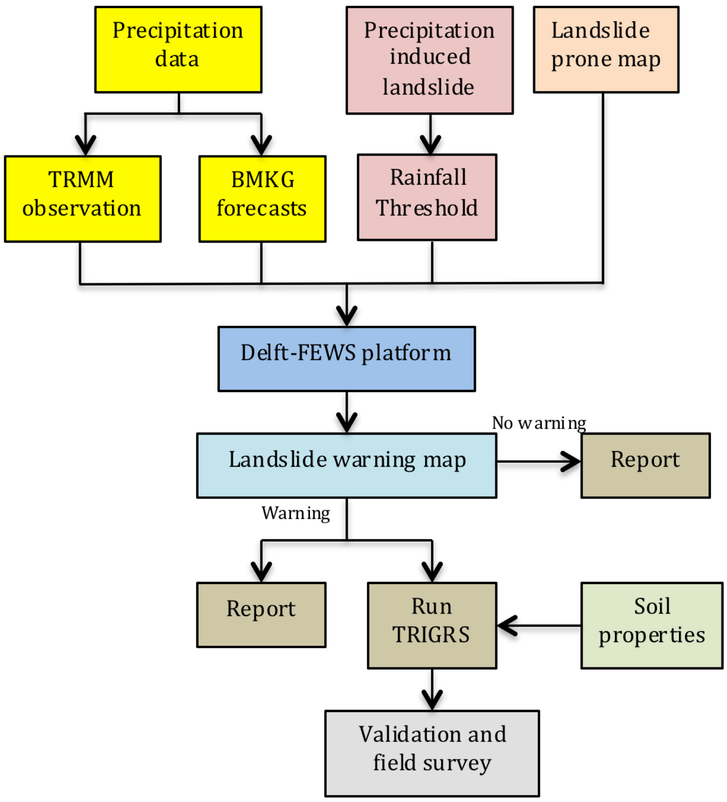


Figure 1. Flowchart data and method for developing the Indonesian Landslide Early Warning System (LEWS).

2.1. Data

2.1.1. Observed and Forecasted Precipitation Data

The observed precipitation data were obtained from the Tropical Rainfall Measuring Mission (TRMM) satellite, run by the Japan Aerospace Exploration Agency (JAXA). TRMM is a joint mission between the National Aeronautics and Space Administration (NASA, the U.S.A.) and JAXA (Japan), which was designed to monitor and study tropical and subtropical precipitation (within 35° N–35° S and with 0.25° spatial resolution and in 3-hourly temporal resolution), which has a strong influence on climate and environmental change. The TRMM instruments consist of a Precipitation Radar (PR), a TRMM Microwave Imager (TMI), a Visible and Infrared Radiometer (VIRS), a Clouds and the Earths Radiant Energy System (CERES), and a Lightning Imaging Sensor (LSI) [36–38]. Bias correction of TRMM data with in situ observations is performed using an algorithm encapsulated in Delft–FEWS following the method described in [39]. From 5 April 2015, the TRMM mission stopped its operations and data collection after the spacecraft spent its fuel reserves. However, the observed precipitation data for LEWS are obtained from the multi-satellite 3B42RT/TMPA product, which was still providing data until 31 December 2019 (https://trmm.gsfc.nasa.gov, accessed on December 2018). For continuity of the LEWS, BLS has planned to switch TRMM satellite data with another better satellite product.

For precipitation forecasts, the data are obtained from a mutual collaboration agreement between the Research Centre for Water Resources (Pusat Litbang Sumber Daya Air) and the Meteorological Climatological and Geophysical Agency (BMKG). Daily precipitation forecast data with a lead-time of 10 days are available two times a week (every Tuesday and Friday). However, we only use forecasted precipitation data with a lead-time of four days. For example, on Tuesday, we issue the warnings for Wednesday, Thursday, Friday, and Saturday; and, on Friday, we issue the warnings for Saturday, Sunday, Monday, and Tuesday. The downscaling of the precipitation forecasts data are performed by BMKG to match with the TRMM spatial resolution.

2.1.2. Rainfall Threshold Data

The TRMM precipitation data were used to determine the rainfall threshold for landslide occurrences. Landslide data were collected from the website of the Indonesian National Board for Disaster Management (BNPB). Based on this information, identification of the rainfall threshold for landslide occurrence was carried out by using the 1-day and 3-day cumulative precipitation data [40–44]. The 3-day cumulative precipitation data were used to consider the importance of the antecedent precipitation events influencing soil moisture conditions before a landslide occurs. As the measurement of soil moisture is not widely available across Indonesia, we used 3-day cumulative precipitation data to establish the rainfall threshold. For 3-day cumulative precipitation with a lead-time of 1 day, we combined the 1-day precipitation forecast with 2-day observations; for a lead-time of two days, we combine 2-day precipitation forecasts with 1-day observations, and so on for lead-times of three or four days. The landslide data were collected from various landslide events throughout Indonesia, although landslides mostly occur in Java [10,24]. During the development phase of LEWS, BLS only managed to collect 83 landslide events, as shown in Figure 2.

The rainfall threshold line was defined from a median of 1-day and 3-day precipitation data (Figure 2). This line acts as a separator for the precipitation conditions that triggered (above the line) and did not trigger (below the line) landslides [45,46]. We decided to choose the median values, in order to reduce the false alarms and minor landslide occurrences. In the first phase of the LEWS development, we focused on the major and fatal landslide occurrences in Java, which were usually preceded by heavy precipitation. Java is the most populated Island in Indonesia, with around 80% of people living in Java, and many major landslides have occurred in Java. We discuss the use of the median threshold value and future threshold development in the discussion section.

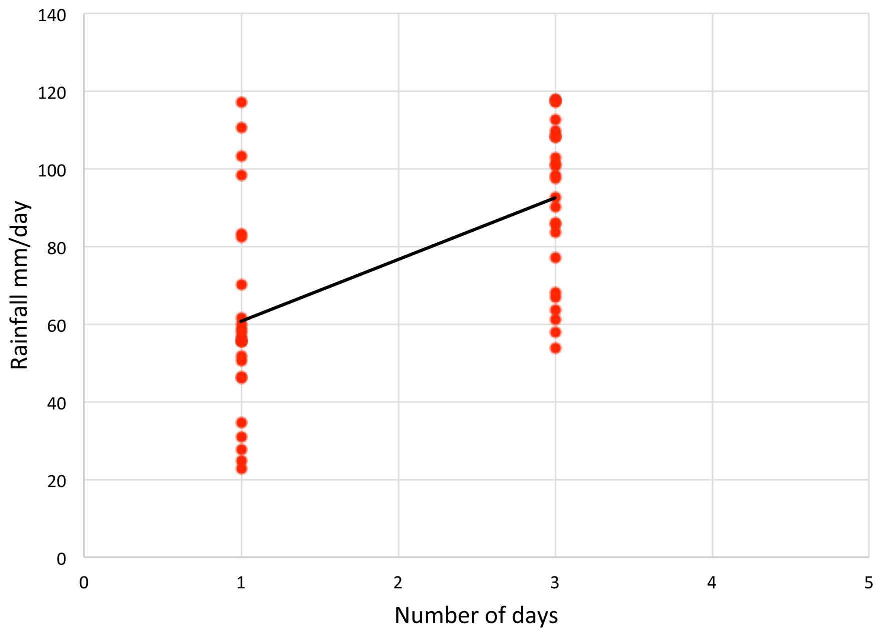


Figure 2. 1-day and 3-day cumulative precipitation data, which triggered landslides at 83 locations in Indonesia.

2.1.3. Map of Landslide-Prone Areas

A map of landslide-prone areas (Figure 3) was obtained from the Geological Agency, located in Bandung. The map of landslide-prone areas has a resolution of 1:250,000 and consists of four hazard zones, represented with colors. A green color indicates zones that have a very low probability of landslide occurrence (0 ≤ slope < 5%), a blue color indicates low probability of landslide occurrence (5 ≤ slope < 10%), an orange color indicates moderately high probability of landslide occurrence (10 ≤ slope < 25%), and a red color indicates very high probability of landslide occurrence (slope ≥ 25%). The landslide analysis was carried out only for the orange and red zones because there was no landslide reported in other zones (green and blue zones, [24,29]).

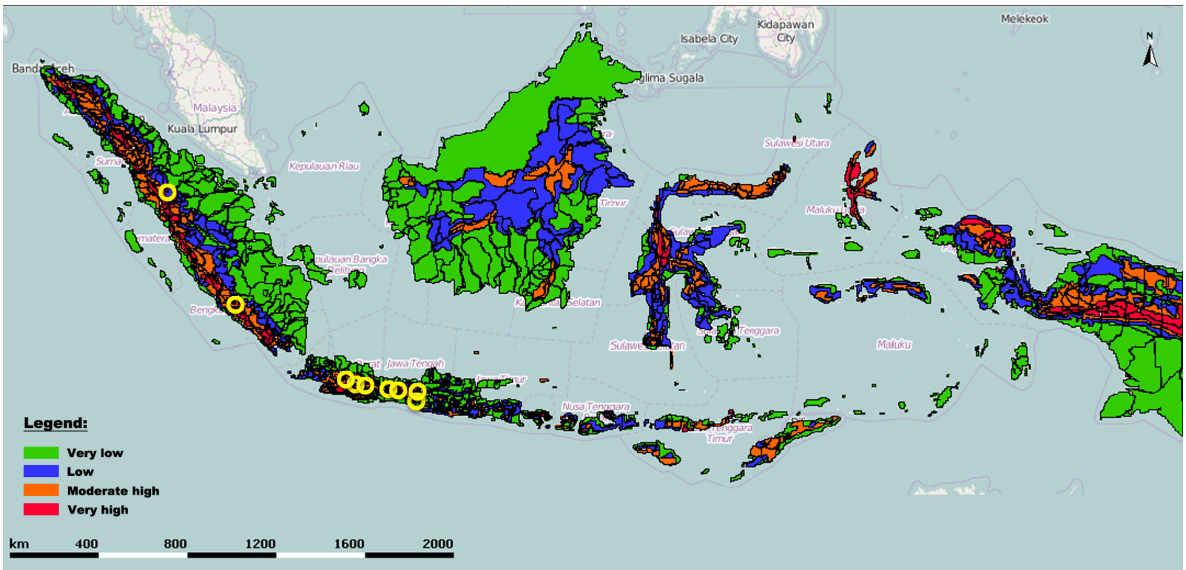


Figure 3. Map of landslide-prone areas across Indonesia. Yellow circles indicate the locations where the soil samples were taken.

2.1.4. Data to Run the TRIGRS Model

TRIGRS is a program coded in Fortran, based on an infinite-slope model and designed to predict the potential shallow landslide events through calculating a factor of safety (FS) [35,47–49]. In the TRIGRS program, the precipitation will partly become surface runoff, and the rest will infiltrate into the soil. Thus, the infiltrated precipitation will affect slope stability in a certain region where the precipitation falls. In general, the data used for running TRIGRS are soil properties, precipitation data, and morphological conditions [35,50]. Soil properties data consist of soil parameters, such as cohesion (c'), the friction angle (ϕ'), soil weight (γ_s), saturated hydraulic conductivity (ks), soil depth (Z), and initial groundwater table (deptw). Those geotechnical data are used to calculate soil diffusivity (D_0), volumetric water content (θ), and the soil water characteristic curve (SWCC). The soil property data are derived from the empirical approach and also from the analysis of soil samples, which were tested in the laboratory. For the moment, the soil samples were taken from nine landslide locations in Indonesia: Kulon Progo, Purwokerjo, Banjarnegara, Magelang, Garut, Tasikmalaya, Cianjur, Pangkalan west Sumatera, and Bengkulu (see Figure 3, yellow circles). Furthermore, soil property data are used as input variables in the TRIGRS model to simulate the slope stability. Geospatial data sets, such as the Digital Elevation Model (DEM) and terrain slope map, were obtained from the Indonesian Geospatial Information Agency. The initial resolution of the DEM is 8 m. However, due to the limitation of resolution that can be used in the TRIGRS model, the resolution was resampled to 20 m when DEM was transformed to a slope map (slope.asc), flow direction map (flowdirection.asc), permeable depth soil (zmax.asc), groundwater table map (depthwt.asc), zonation map (zones.asc), and precipitation map (ri.asc).

2.2. Methods

All data and map are stored and processed by the Delft–FEWS platform. Delft–FEWS can be used to manage the forecasting process and save time-series data [30,31]. This platform can be simply coupled with distributed hydrological models using PCRASTER, satellite data, and the Atmospheric Ocean Global Climate Model (AOGCM), such that the data management and forecasting can be easily and quickly executed [30]. The Delft–FEWS system is automatically programmed to download the newest TRMM precipitation data and precipitation forecasts from BMKG, every Tuesday and Friday. These data are, then, processed using a data processing software, GrADS, embedded in Delft–FEWS. Basically, this system was developed for flood forecasting in Indonesia by a joint consortium between Deltares-Netherlands, BMKG, and the Research Center for Water Resources.

The warning signals are issued in the landslide-prone areas by utilizing the precipitation threshold method (Figure 2) encapsulated in the Delft–FEWS program, with the following criteria:

1. If the 1-day precipitation and 3-day cumulative precipitation are greater than the rainfall threshold line (>61 mm and >91 mm, respectively), then the Delft–FEWS will produce a red exclamation mark (both conditions met);
2. if the 1-day precipitation or 3-day cumulative precipitation is greater than the rainfall threshold line, then the Delft–FEWS will produce a yellow exclamation mark (one condition meet); and
3. if the 1-day precipitation and 3-day cumulative precipitation do not exceed the rainfall threshold line, then the Delft–FEWS will produce a green round mark (both conditions are not met).

A report is then made, based on the outcome of the LEWS warning signals. It should be noted that Delft–FEWS only provides landslide warning results in areas that have moderately high and very high hazard zones (orange and red colors, respectively; Figure 3). If precipitation occurring in the red zone (very high hazard) or orange zone (moderately high) exceeds the 1-day and 3-day rainfall thresholds, then the Delft–FEWS will give a red exclamation mark. However, if the precipitation occurred on the green zone (least) or blue (less) exceeds the 1-day and 3-day rainfall thresholds, then the Delft–FEWS will not issue any warning signal. The report will be made even if there is no warning. The outcomes of the Delft–FEWS model are daily maps, starting from when the new data are available (Tuesday and Friday) up to four days ahead, containing exclamation marks (if any), and green round marks for no landslide warning on the landslide hazard areas. A table summarizing the warnings is also presented under the maps. The landslide warning report is issued in HTML format for easy publishing on the BLS website.

Simulation of slope stability at every landslide-prone location could not be performed, due to the limitations of the number of soil datasets that have been collected. Thus, the slope stability simulation using TRIGRS is only conducted at several landslide-prone locations where soil samples were taken (Section 2.1.4) and only for areas that are identified by red exclamation marks. The TRIGRS model analyzes the topographic data using a TopoIndex program [35] to generate the surface flow direction. Other important data, such as precipitation, geotechnical, and geological data, are considered as input parameters for dividing the area into landslide zones. The interaction between the soil and rock layer is not discussed in this research because the slip-plane layer is usually located along the contact between the soil and bedrock [51]. The 6-day rainfall data before the landslide occurred, obtained from TRMM data, is used as a spin-up procedure for the TRIGRS model to reach the equilibrium soil condition. The outcome of the simulation is a map, which indicates safety factor values in certain areas. We determine the factor of safety (FS) value of 1 to be a slope stability threshold [35,52]. An FS value below 1 suggests that the area is prone to landslide occurrence, and vice versa for FS above 1.

3. Results and Discussion

3.1. Landslide Early Warning with Delft–FEWS

Example of precipitation data observed by TRMM and forecasted by BMKG on 1 October 2019 covering Indonesia region is shown in Figure 4. The results clearly indicate that TRMM produces relatively higher precipitation data, compared to BMKG forecasts. The precipitation intensities of TRMM and BMKG data over Papua Island are 20–50 mm/day and 0–20 mm/day, respectively. There are some precipitation events, which were not predicted by the BMKG forecasts, e.g., over Papua and Maluku Islands (black circles in Figure 4). The difference between the observed and forecasted data shows the deficiency of forecasts to accurately simulate the precipitation amount that leads to an inaccuracy of landslide prediction.

After the observed and forecasted precipitation data were processed, the 1-day and 3-day cumulative precipitation data were overlapped on the map of landslide-prone areas. The warnings are given for moderately high hazard zone (orange) and very high hazard zone (red) areas (Figure 3), which had high precipitation forecasts (above the threshold, see Section 2.2). The warnings for the next four days were, then, displayed online on the BLS website (http://202.173.16.248/status_longsor.html, see Figure 5). Figure 5 shows some locations that have moderately high potential landslide hazards (yellow exclamation mark). Landslide warnings that were issued on 22 March 2019 (with a lead-time of one day) were located at several locations (Sumatera, Java and Papua Islands). The forecast issued for 23 March 2019 (with a lead-time of two days) showed some locations that were predicted with landslide warnings, such as in Java, Papua, and also in Kalimantan. The warning signals in Sumatera disappeared with the second lead-time.

In addition to the map showing the warning locations, the BLS website also provides a summary of the detailed locations that have moderately high and very high landslide hazard levels (Figure 6). The information is provided as a table, containing potential hazard levels with a lead-time of four days (today, tomorrow, the day after tomorrow, and two days after tomorrow), and forecasted precipitation information for 1-day and 3-day cumulative precipitation, for each river basin across Indonesia. As BLS is an institution under the Research Centre of Water Resources, the outcomes of the work should, thus, support the Directorate General of Water Resources, Ministry of Public Works and Housing. This is the main reason why the warning is given for each river basin, and not for Regency, City, or Province. One should keep in mind that the LEWS resolution is quite coarse ($0.25° \times 0.25°$), and thus one grid cell may cover several small river basins. It can be seen that the number of landslide warning signals depicted on the map (yellow marks, Figure 5) are less than the number of landslide hazard areas represented in Figure 6. Hence, we recommend users to consult the table (Figure 6) displayed on the BLS website for detailed information.

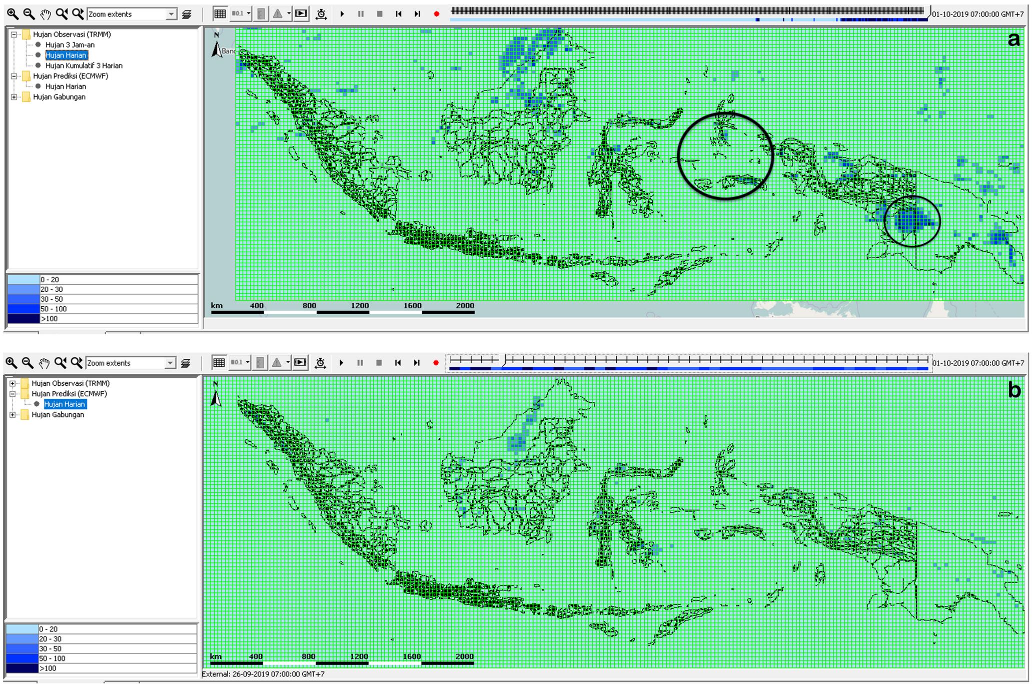


Figure 4. Examples of spatial precipitation data on 1 October 2019: (**a**) precipitation observed by the Tropical Rainfall Measuring Mission (TRMM) satellite; and (**b**) precipitation forecasted by the Meteorological, Climatological, and Geophysical Agency (BMKG) with a lead-time of 1 day. Black circles indicate Maluku Islands (left) and Papua Island (right).

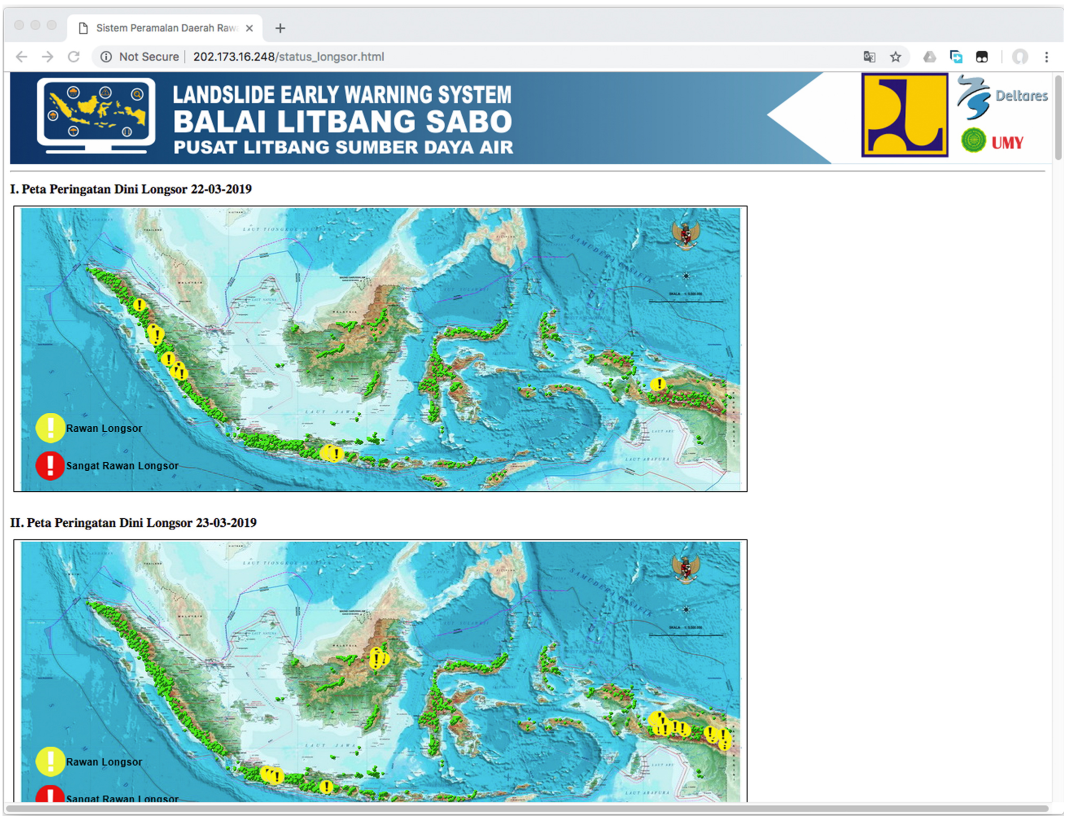
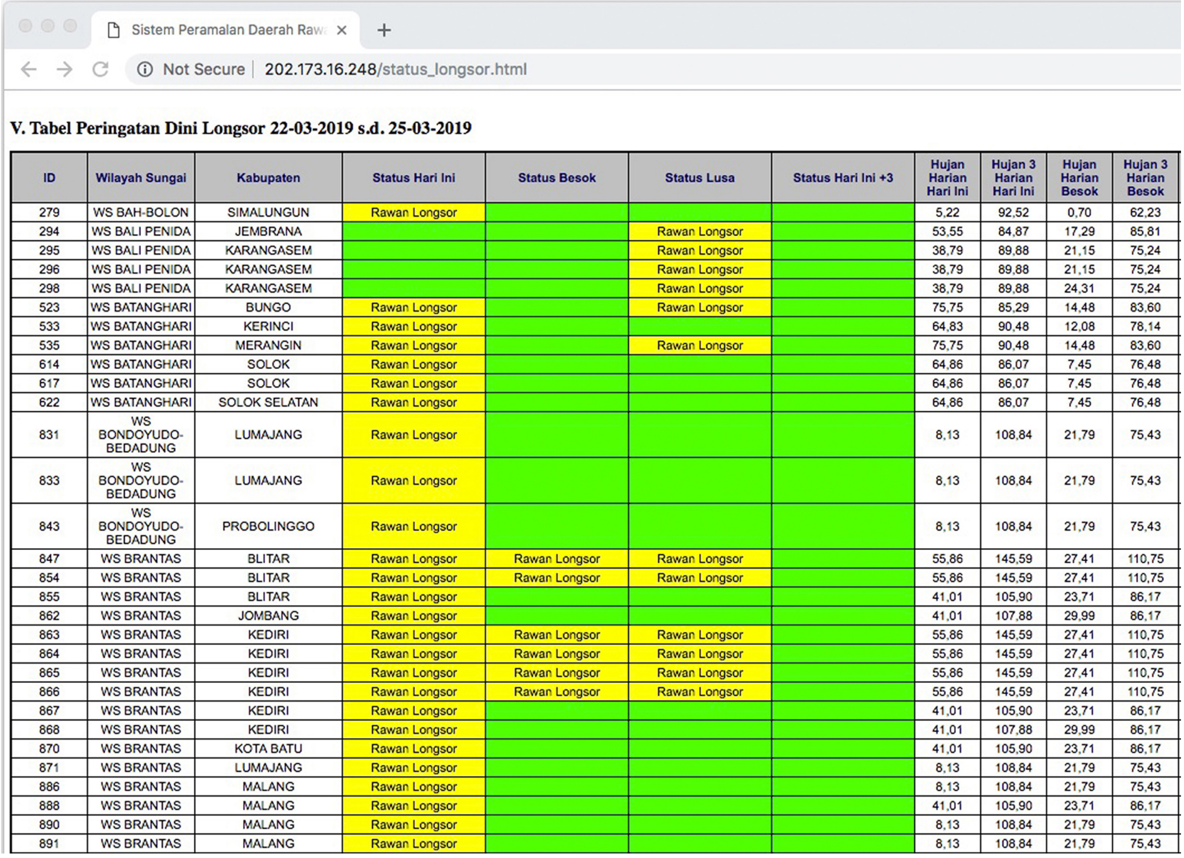


Figure 5. An example of LEWS results displayed on the Balai Litbang Sabo (BLS) website.



V. Tabel Peringatan Dini Longsor 22-03-2019 s.d. 25-03-2019

ID	Wilayah Sungai	Kabupaten	Status Hari Ini	Status Besok	Status Lusa	Status Hari Ini +3	Hujan Harian Hari Ini	Hujan 3 Harian Hari Ini	Hujan Harian Besok	Hujan 3 Harian Besok
279	WS BAH-BOLON	SIMALUNGUN	Rawan Longsor				5,22	92,52	0,70	62,23
294	WS BALI PENIDA	JEMBRANA			Rawan Longsor		53,55	84,87	17,29	85,81
295	WS BALI PENIDA	KARANGASEM			Rawan Longsor		38,79	89,88	21,15	75,24
296	WS BALI PENIDA	KARANGASEM			Rawan Longsor		38,79	89,88	21,15	75,24
298	WS BALI PENIDA	KARANGASEM			Rawan Longsor		38,79	89,88	24,31	75,24
523	WS BATANGHARI	BUNGO	Rawan Longsor		Rawan Longsor		75,75	85,29	14,48	83,60
533	WS BATANGHARI	KERINCI	Rawan Longsor				64,83	90,48	12,08	78,14
535	WS BATANGHARI	MERANGIN	Rawan Longsor		Rawan Longsor		75,75	90,48	14,48	83,60
614	WS BATANGHARI	SOLOK	Rawan Longsor				64,86	86,07	7,45	76,48
617	WS BATANGHARI	SOLOK	Rawan Longsor				64,86	86,07	7,45	76,48
622	WS BATANGHARI	SOLOK SELATAN	Rawan Longsor				64,86	86,07	7,45	76,48
831	WS BONDOYUDO-BEDADUNG	LUMAJANG	Rawan Longsor				8,13	108,84	21,79	75,43
833	WS BONDOYUDO-BEDADUNG	LUMAJANG	Rawan Longsor				8,13	108,84	21,79	75,43
843	WS BONDOYUDO-BEDADUNG	PROBOLINGGO	Rawan Longsor				8,13	108,84	21,79	75,43
847	WS BRANTAS	BLITAR	Rawan Longsor	Rawan Longsor	Rawan Longsor		55,86	145,59	27,41	110,75
854	WS BRANTAS	BLITAR	Rawan Longsor	Rawan Longsor	Rawan Longsor		55,86	145,59	27,41	110,75
855	WS BRANTAS	BLITAR	Rawan Longsor				41,01	105,90	23,71	86,17
862	WS BRANTAS	JOMBANG	Rawan Longsor				41,01	107,88	29,99	86,17
863	WS BRANTAS	KEDIRI	Rawan Longsor	Rawan Longsor	Rawan Longsor		55,86	145,59	27,41	110,75
864	WS BRANTAS	KEDIRI	Rawan Longsor	Rawan Longsor	Rawan Longsor		55,86	145,59	27,41	110,75
865	WS BRANTAS	KEDIRI	Rawan Longsor	Rawan Longsor	Rawan Longsor		55,86	145,59	27,41	110,75
866	WS BRANTAS	KEDIRI	Rawan Longsor	Rawan Longsor	Rawan Longsor		55,86	145,59	27,41	110,75
867	WS BRANTAS	KEDIRI	Rawan Longsor				41,01	105,90	23,71	86,17
868	WS BRANTAS	KEDIRI	Rawan Longsor				41,01	107,88	29,99	86,17
870	WS BRANTAS	KOTA BATU	Rawan Longsor				41,01	105,90	23,71	86,17
871	WS BRANTAS	LUMAJANG	Rawan Longsor				8,13	108,84	21,79	75,43
886	WS BRANTAS	MALANG	Rawan Longsor				8,13	108,84	21,79	75,43
888	WS BRANTAS	MALANG	Rawan Longsor				41,01	105,90	23,71	86,17
890	WS BRANTAS	MALANG	Rawan Longsor				8,13	108,84	21,79	75,43
891	WS BRANTAS	MALANG	Rawan Longsor				8,13	108,84	21,79	75,43

Figure 6. An example of detailed LEWS information displayed on the Balai Litbang Sabo (BLS) website.

At present, the results of the TRIGRS model simulation for areas that are predicted to have a very high landslide hazard level (red exclamation mark) are not shown on the BLS website. We run the TRIGRS model manually, as it is not encapsulated into the Delft–FEWS platform yet. In addition, the results of TRIGRS are still used by the internal members of BLS to determine the detailed locations of landslide occurrence and to support the decision-making process.

3.2. Examples of the Capability of LEWS to Detect Landslides

The results of LEWS (warning maps) and the TRIGRS model simulation (FS maps) have been saved since the LEWS system became operational at the end of 2017. We must admit that there have been several false alarms, hits, and misses produced by our system. In this study, however, we only provide two examples of landslide events occurring on Java Island; in particular, in the Pacitan region, east Java and in the Brebes region, central Java. In these areas, the soil samples had been collected and analyzed in the BLS laboratory before the landslides occurred. The impact of landslides in these areas has been severe. A number of people have been killed and some infrastructures have been damaged.

3.2.1. Landslide in Pacitan

The landslide in Pacitan, east Java province killed nine people on 28 November 2017. The type of the landslide is translational slides. In this region, the soil is dominated by fine particles and loose rocks (clay and marl). Before the landslide, heavy precipitation occurred over two consecutive days, with a total precipitation of 352 mm. The heavy precipitation caused the building up of high pore pressure at the soil/rock interface [53]. Thus, the soil may collapse due to overburden stress, when the water fills the void between soil and rock. The BLS team observed this soil type during field inspection after the landslide occurred.

BLS, via the LEWS website and a Whatsapp group consisted of various Indonesian government institutions, had already announced a landslide early warning information from 28 November to 30 November 2017, before the landslide occurred. The LEWS showed that the Pacitan region was categorized as having a very high probability of landslide occurrence (red exclamation mark, Figure 7). Moreover, there were other locations that also were predicted as having a high probability of landslide occurrence at the same level as Pacitan, such as west Java and Sulawesi Island. Although there were three locations that were predicted as having a very high potential landslide hazard, the landslide occurred only in Pacitan. This indicates that LEWS produced a false alarm for the other locations.

The simulation of slope stability using the TRIGRS model was carried out to identify the landslide-prone locations around the Pacitan area. The precipitation data used for simulation were the precipitation data on the day and before the landslide occurred. The data needed to run the TRIGRS model, such as soil properties and DEM, were previously collected. The slope gradient of this location is divided into three classes; namely, low slope ($0^\circ <$ slope $\leq 20^\circ$), medium slope ($20^\circ <$ slope $\leq 40^\circ$), and high slope (slope $> 40^\circ$).

From the field survey, it was noticed that the landslides occurred in regions that have medium to high slopes. The small-scale up to large-scale landslides were spotted upstream of the Brungkah river, with the biggest landslide thickness about 15 m. The simulation results showed that a high probability of landslide occurrence was identified on the hills downstream of the Tukul reservoir (Figure 8), which was in agreement with the field survey. It can also be seen that many areas have factor of safety values (FS) less than 0.8 (orange shading), associated with landslide-prone areas.

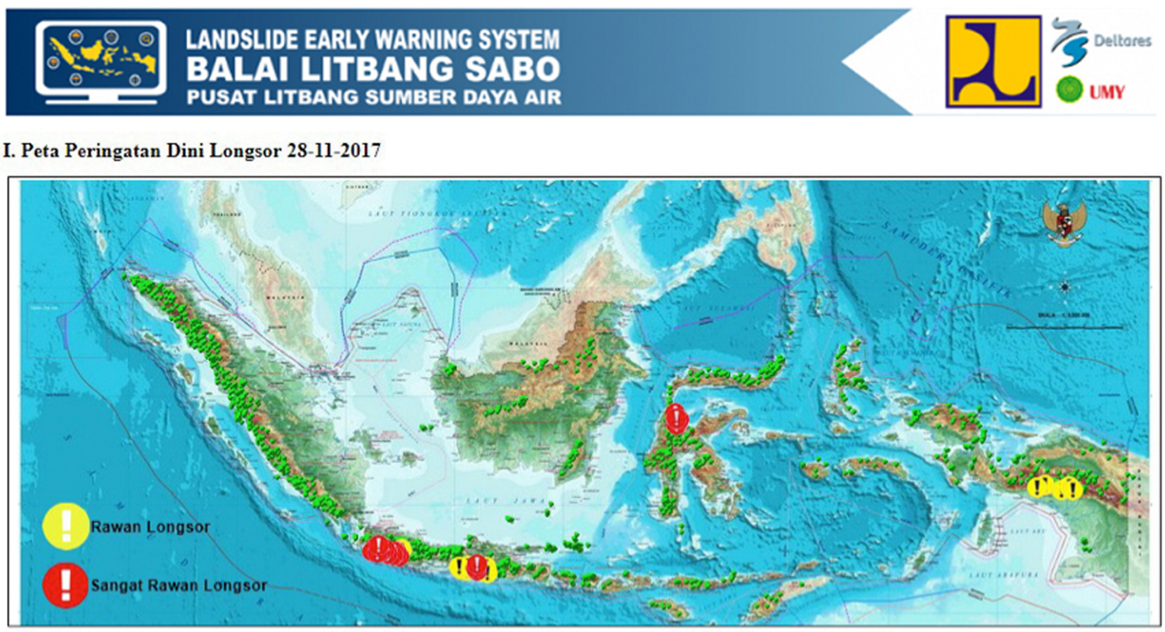


Figure 7. The warning signals issued by the Balai Litbang Sabo Landslide Early Warning System (BLS LEWS) for 28 November 2017.

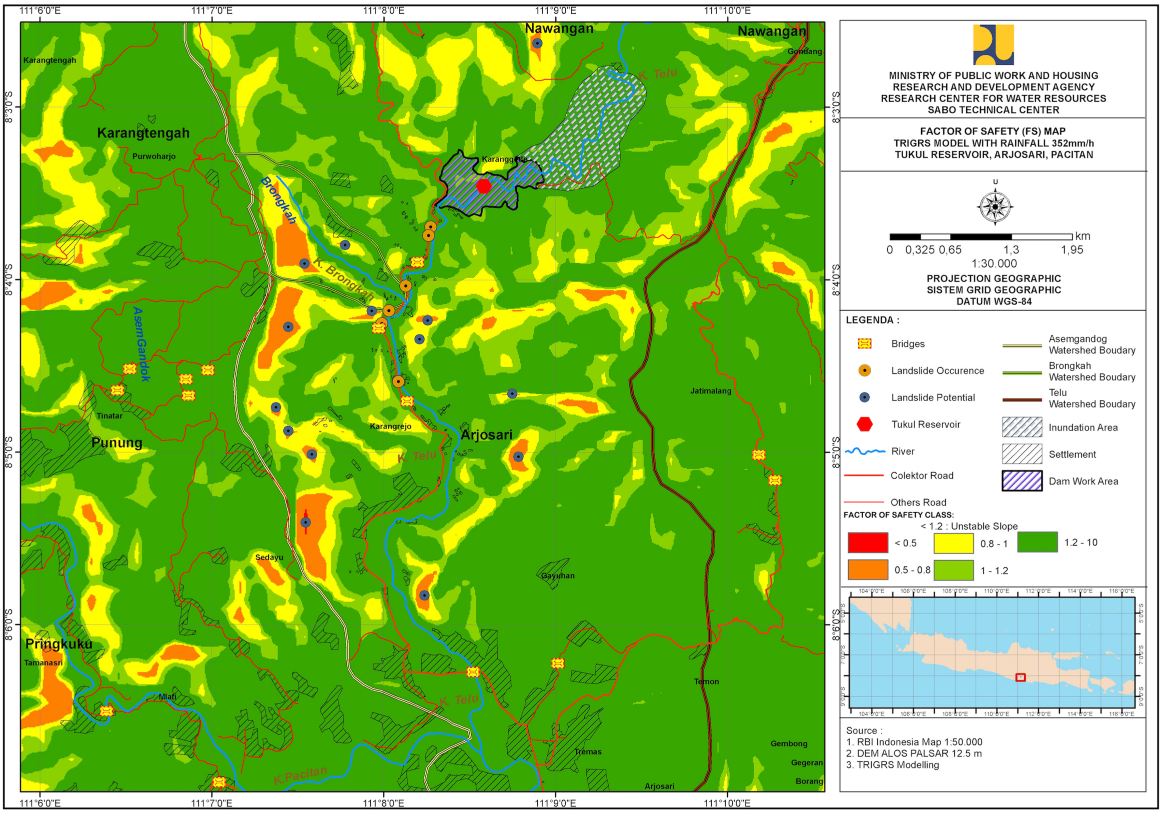


Figure 8. A factor of safety map for Pacitan region simulated using the Transient Rainfall Infiltration and Grid-based Regional Slope-stability (TRIGRS) model on 28 November 2017.

3.2.2. Landslide in Brebes

On 22 February 2018, a landslide occurred in Pasir Panjang village, Salem sub-district, Brebes. From the drone photography taken by BNPB, the landslide crown was located on the tiptop Gununglio Mountain, with land cover of high-density forest. There was no settlement in the upstream part, whereas the paddy fields were located in the downstream areas. The width of the landslide crown was about 120 m. The thickness of landslide, along its 1 km length, was 5–20 m, while the landslide volume was 1.5 million m^3. Similar to the landslide in Pacitan, the type of the landslide in the Brebes region is translational slides. The causes of the landslide were steep slope, loose and crumbly soil structure, marl rock material at the bottom of the slip plane, and heavy precipitation.

Similar to the landslide in Pacitan, BLS provided early warning information from 20 February until 22 February 2018, through the BLS website and the Whatsapp group. Brebes region was categorized as having a very high probability of landslide occurrence (red exclamation mark, Figure 9). Locations with very high landslide hazard warnings were only predicted in the Brebes region and its surroundings, while other locations, such as Sumatera, Kalimantan, Sulawesi, and Papua Islands, were predicted as having moderately high landslide hazards (yellow exclamation mark). Landslide early warnings issued from 20 February until 22 February 2018 showed that there was no false alarm produced by the LEWS system. Warnings of moderately high landslide hazards (yellow exclamation mark) in Sumatera, Kalimantan, Sulawesi, and Papua Islands on 20 February 2018 were not categorized as false alarms in our evaluation. We only count red exclamation marks in our evaluation of false alarms.

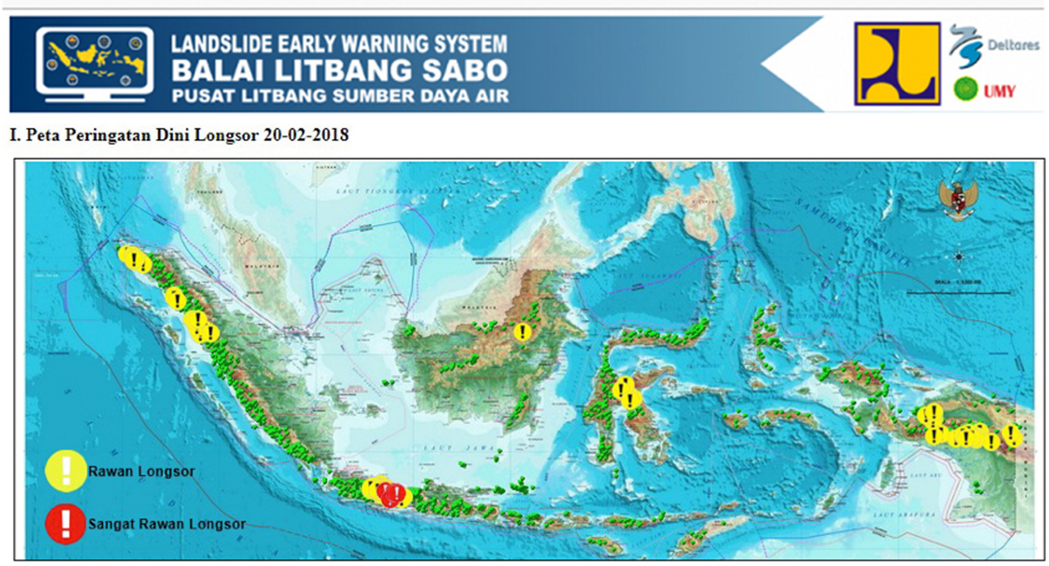


Figure 9. The warning signals issued by the Balai Litbang Sabo Landslide Early Warning System (BLS LEWS) for 20 February 2018.

Slope stability analysis using the TRIGRS model was carried out in the Brebes region, as seen in Figure 10. The TRIGRS model produced FS values in the range of 0.8–1 for some areas (i.e., prone to landslide hazard occurrence). For a few locations, the FS value simulated by the TRIGRS model was less than 0.8 (red areas in Figure 10). The location of the landslide incident was laid on the orange zone (FS 0.8–1, blue dot in Figure 10).

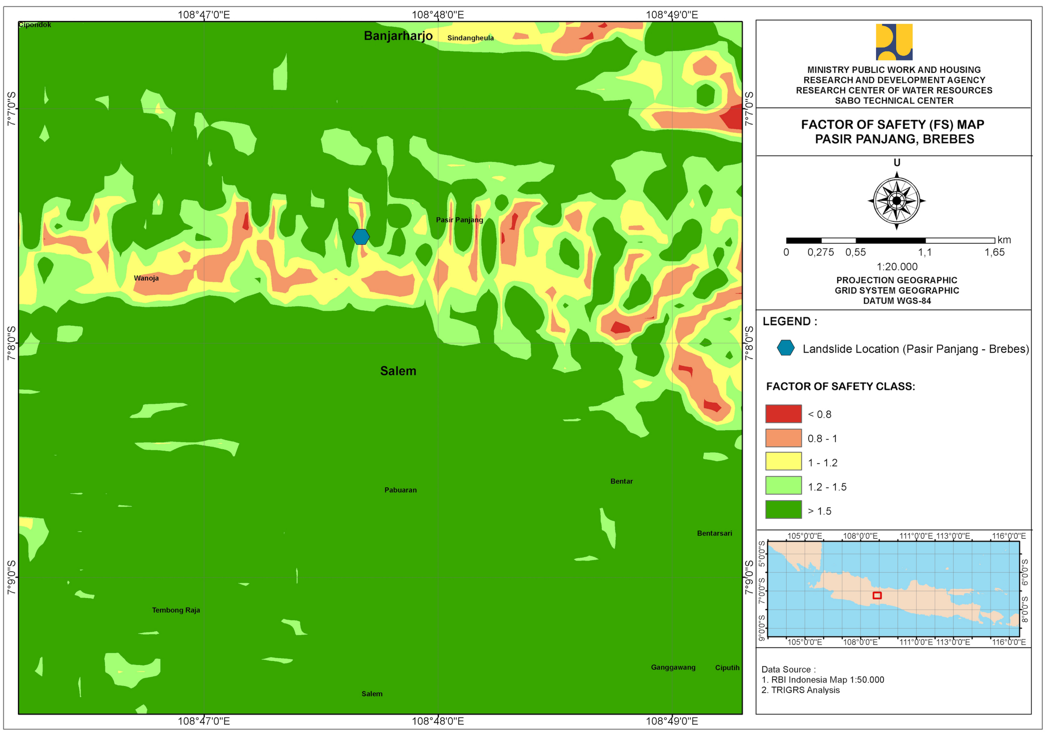


Figure 10. A factor of safety map for Brebes region simulated using the Transient Rainfall Infiltration and Grid-based Regional Slope-stability (TRIGRS) model on 20 February 2018.

3.3. Discussion and Future Improvements

BLS LEWS was developed based on observed and forecasted precipitation data; thus, the accuracy of the LEWS is strongly influenced by the uncertainty of the precipitation data (see Figure 4). BLS LEWS also produces false alarms and misses for landslide hazard predictions, for instance giving a hazard alarm for no hazard occurrence or no hazard alarm for landslide occurrence. Some of the landslide events could not be predicted by LEWS because the forecast only produced a small precipitation amount (below the rainfall threshold). However, landslides did occur; for example, the landslide event in Cianjur, west Java in October 2017. The landslide occurrence in Cianjur was not detected by LEWS, since the forecast only showed a small precipitation amount, located far below the rainfall threshold. For the time being, we are collecting information of hits, false alarms, and misses from the local authorities, such as the river basin authority and local disaster relief agency, through the Whatsapp group. In addition, we have also been collecting such information from the news, such as from television, the Internet, and the newspaper. One should keep in mind that BLS does not have a responsibility to disseminate and communicate the warnings at the field level. Thus, feedback from the local authorities, who are the stakeholders, are important for the evaluation of our LEWS. Further adjustment of the rainfall threshold line will be made based on the evaluation results of hits, false alarms, and misses.

BLS LEWS also has other limitations; for example, it cannot detect landslide events due to human interference [54,55], such as slope cutting for road or mining purposes, and landslides induced by the earthquakes [56,57]. For improvement of the prediction accuracy, the precipitation threshold line needs to be updated; this work is still ongoing as a part of a verification study [58]. The rainfall threshold line is based on numerous landslide events occurred mostly in Java Island [24,25]. The precipitation threshold employed in LEWS still refers to 1-day and 3-day cumulative precipitation data of 61 mm and 91 mm, respectively. These numbers were selected from a range of 83 rainfall-induced landslide data, based on median values and major landslide events. However, the threshold of the rainfall-induced landslide in Java may differ from other islands, due to spatial variation in rainfall intensity for each region in Indonesia [19,59,60]. For example, the western part of Indonesia has higher precipitation intensity than the eastern part of Indonesia, especially on Nusa Tenggara Island. Therefore, the use of different critical lines for every island or even for every province should be encouraged [46]. As a result, the prediction of LEWS is expected to be more accurate. In addition, the resolution of the TRMM and precipitation forecast data from BMKG ($0.25° \times 0.25°$) is not suitable for catchment-scale landslide prediction.

The TRIGRS model for slope stability analysis simulates the factor of safety (FS) value, which is influenced by precipitation, topography, and the soil physics, especially soil permeability. Soil permeability is an important factor in the alteration of the slope FS [53,61,62]. For high soil permeability (sandy soil), the change of slope FS is significantly affected by time, while it is almost unchanged for low soil permeability (clay). Less infiltration occurs during precipitation events in the case of low soil permeability, and thus the FS value remains relatively stable [63].

For future improvement, BLS will encapsulate the TRIGRS model into the Delft–FEWS system for all landslide-prone areas in Indonesia. Thus, the LEWS can generate fast and accurate landslide early warning information through the calculation of multiple hazard evaluations with different approaches (the precipitation threshold method and slope stability model) [64]. Moreover, the results of the TRIGRS model will be overlaid on exposure maps (such as population maps), and thus information of landslide hazard prediction can be accurately distributed to villagers living upstream and downstream of predicted landslide hazard areas, through the responsible agencies. The main challenge to simulating the FS values using the TRIGRS model for landslide hazard prediction is obtaining the data required for running the TRIGRS model, such as soil properties, soil thickness, and groundwater level data. Taking these data for all landslide-prone areas in Indonesia, however, is costly and time-consuming.

4. Conclusions and Outlook

A LEWS, developed by BLS, has been operational since the end of 2017 and continues to provide landslide hazard warnings twice a week (updated every Tuesday and Friday). The advantage of this system, compared to others [28,29], is that it provides landslide prediction with a lead-time of four days. As a result, the responsible agencies have ample time for preparing disaster contingency actions. In terms of disaster management, the landslide early warning system provides vital information in supporting landslide mitigation and gives fast and early warning information to stakeholders and communities.

Slope stability analysis carried out in regions predicted to have a very high probability of landslide occurrence (red exclamation warning) can be used to support the decision-making process. The TRIGRS model produces simulation results that are quite close to the field conditions during landslide occurrence. The majority of landslides occurred in the areas that have steep slopes. It should be noted that the simulation results do not represent landslide-affected areas, but represent areas that may have a high probability of landslide occurrence. In fact, the locations that may be damaged by a landslide may be broader.

The BLS LEWS has been developed and will continually be improved to create a reliable and accurate LEWS by reducing false alarms and misses, as well as improving the correct predictions (hit) rate. Moreover, soil samples and rainfall data (especially that related to rainfall triggering landslides) will continually be collected. In the future, rainfall thresholds for each major Island in Indonesia will be discerned individually. The use of TRMM precipitation data will be replaced by another observation that has higher resolution. Indonesian LEWS is operational under BLS, and BLS will continue to support this system and to disseminate the landslide warning information to the stakeholders.

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