



DEWS: A QGIS tool pack for the automatic selection of reference rain gauges for landslide-triggering rainfall thresholds

Omar F. Al-Thwaynee^{a,b,*}, Massimo Melillo^a, Stefano Luigi Gariano^a, Hyuck Jin Park^b, Sang-Wan Kim^b, Luigi Lombardo^c, Paulo Hader^d, Meriame Mohajane^e, Renata Pacheco Quevedo^f, Filippo Catani^g, Ali Aydda^h

^a Research Institute for Geo-Hydrological Protection IRPI, Italian National Research Council, Perugia, Italy

^b Department of Energy and Mineral Resources Engineering, Sejong University, South Korea

^c Department of Earth Systems Analysis (ESA), University of Twente, Enschede, Netherlands

^d School of Engineering, Department of Civil and Environmental Engineering, São Paulo State University (UNESP), Bauru, Brazil

^e Construction Technologies Institute ITC, Italian National Research Council, Polo Tecnologico di San Giovanni a Teduccio, 80146, Napoli, Italy

^f Earth Observation and Geoinformatics Division, National Institute for Space Research, São José dos Campos, Brazil

^g Department of Geosciences, University of Padova, Padova, Italy

^h Department of Geology, University Ibn Zohr – Agadir, Agadir, Morocco

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ABSTRACT

Several studies on empirical rainfall thresholds for landslide occurrence depend on the measurements of nearest rain gauges to the landslides, without taking in consideration the morphological and hydrological settings of the areas. Therefore, we introduce the DEWS (Distance, Elevation, Watershed, and Slope unit) QGIS software tool, for selecting representative rain gauges, a relevant step in the definition of empirical rainfall threshold models. DEWS set with default parameter values for non-expert users. DEWS employs four filters: Distance, Elevation, Watershed, Slope unit, and requires only three data inputs (digital elevation model, landslides inventory, rain gauge locations). Reliability was tested using 223 landslides and 328 rain gauges with the CTRL-T (Calculation of Thresholds for Rainfall-induced Landslides) tool applied in South Korea. Consequently, the amount of rain gauges used was optimized and reduced by 33% using DEWS from using CTRL-T alone, while the shape of the threshold curve and uncertainty values were maintained.

1. Introduction

The definition and analysis of rainfall thresholds for landslide triggering play the foremost role in hazard reduction and especially in regional-scale early warning system design (Guzzetti et al., 2020; Segoni et al., 2018a). Two different approaches are generally adopted to define rainfall thresholds (Guzzetti et al., 2022), namely physically-based (e.g., Medina et al., 2021) and empirical/statistical (e.g., Jordanova et al., 2020) approaches. This work is focused on empirical thresholds considering triggering rainfall. An important step in the definition of empirical rainfall threshold consists in associating each landslide to its relative triggering conditions, usually defined on the basis of rainfall series measured by rain gauges (Althwaynee et al., 2018). Therefore, it's crucial to find the appropriate techniques to select the reference station (most common data provider than radar or satellite systems);

however, there is no consensus on which is the most suitable approach (Gariano et al., 2020b; Segoni et al., 2018b).

In their review, of 107 articles published in the period 2008–2016, including a total number of 115 thresholds, Segoni et al. (2018b) stated that, “Surprisingly, in about 25% of the analyzed thresholds, a clear description of the method adopted for the rain gauge selection is missing.”. In the same review, 72 research study cases adopted different methods for the selection of rain gauges, including: automatic (10%), manual/expert judgment (9%), nearest (16%), reference rain gauge (5%), single rain gauge (18%), Thiessen polygons (4%), mixed or not specified (35%), and rest were not even specified (Segoni et al., 2018b).

The criteria of these different algorithms depend on analyzing the record of each rain gauge first and then selecting that or those locations which perform better in terms of return times, weights, and skill scores (Iadanza et al., 2016). However, these methods require testing all the

* Corresponding author. Research Institute for Geo-Hydrological Protection IRPI, Italian National Research Council, Perugia, Italy.

E-mail address: omar.faisel@gmail.com (O.F. Al-Thwaynee).

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existing rain gauges first, and then the rainfall records are collected. The rules for deciding on the most relevant station must be very specific if the automatic analysis process is to avoid selecting the nearest stations or stations with different watersheds of the landslide or if any among those with similar topographic and morphological landslide event settings. Other crucial steps in the threshold definition are the approach used for the definition of rainfall values (or events) responsible for landslides - e.g., manual drawing, statistical, probabilistic, physically-based - and the selection of threshold parameters - e.g., event-based variables as mean event intensity, cumulated event rainfall, and event duration, or antecedent conditions with fixed duration (Segoni et al., 2018b).

In a recent work, Gariano et al. (2020b), classified and analyzed fifty articles that discussed landslide threshold analyses in Italy that included a rain gauge selection procedure. Overall, fifteen cases adopted an automatic selection (geographical features and the characteristics of the rainfall events), ten relied on expert judgment (subjective), eight used a single representative rain gauge, seven chose the nearest gauges and three opted for a Thiessen polygon criterion. The common element among these examples is that they all essentially overlooked the influence of the landscape characteristic. However, landslides are the result of a complex system of interplaying factors, encompassing hydrological, geomorphological, topographical and triggering influences to the failure mechanism. Therefore, we argue here that part of these influences should also be reflected in the selection of the most representative rain gauge record used to estimate landslide occurrence probabilities.

Specifically, the disadvantage of the “nearest station” selection is clearly shown when more than one rain gauge is available, and particularly in case of complex morphological settings (Althwaynee et al., 2015; Segoni et al., 2018b). Such situations call for capturing the triggering rainfall and suitably reflect the convective storm dynamics. In addition to the physiographic considerations required to select a representative station, another element that makes this problem even more complex is the collection of comprehensive records from a large number of stations, especially if the data are not publicly available or hydrologically and geomorphologically dependent.

Therefore, Gariano et al. (2015) applied certain constraints, like the distance (7–15 km) and difference in elevation between the landslides and rain gauge, depending on the complexity of the terrain. Along the same research lines, Valenzuela et al. (2019) recommended including new correlation criteria that consider the geographical, geomorphological, and climatic conditions of the study area.

An alternative selection criterion is often based on Thiessen polygons generated from a set of rain gauges (to define an area of influence around sample points represented by a polygon, so that the sample points are closer to each other than any other points out of this polygon). However, the Thiessen polygon method boils down to another distance-dependent approach that ignores the physiographic context where landslides take place. It can be considered as a basic automatic selection concept that when equal distances need to be considered as a search area from the landslides (center of polygon). This method again ignores other factors such as elevation, between landslide and rain gauges (similar elevation; Gariano et al., 2015), and the slope direction (aspect) or the same valley, or other significant parameters such as the dominant wind direction in the area. This latter factor is rarely considered (Aleotti, 2004).

In addition, several studies have examined which factor in rain gauge selection criteria (elevation or distance) is the most significant. A study carried by Peruccacci et al. (2012), mentioned that for a few landslides, elevation was considered more important than geographic distance to the landslide. However, it concluded that “For most of the landslides, the representative rain gauge was the one closest to the landslide, in the set of rain gauges located in the same valley”. Consequently, the study recommended that more factors, such as hydrological-related watershed and slope units, should be considered.

Watershed (either as small as a footprint or a large surface area that

drains all the streams and rainfall to a common outlet such as a reservoir) is mostly used as an independent hydrological surface that can be used to delineate landslide-dependent incidents. Consequently, any rain gauge that falls outside the watersheds in which the landslides are mapped should be removed (Althwaynee et al., 2021). This is explained from a hydrological point of view because a landslide is a geo-hydrological hazard and the watershed encloses the features that share similar conditions of soil moisture content and basin volume flow. Moreover, this makes it possible to address upstream–downstream linking issues such as landslides (Dolidon et al., 2009). Jan et al. (2007) examined the influence of the rainfall period when the rainfall amount outside the surface watershed is considerably larger than the rainfall amount within the surface watershed over the same period. The authors concluded that the rainfall occurring in the nearby surface watersheds may also cause variations in groundwater level; however, low rainfall intensity with a long duration can induce a greater groundwater level variation than high rainfall intensity with a short duration. In addition, the common watershed that encloses the landslide events and rain gauges is considered first, before considering stations located in different watersheds.

Slope unit (SUs; Amato et al., 2019; Hua et al., 2021), based on the curvature watershed approach, relate to physiographic elements that partition any terrain into half sub-catchments computed at different scales (Yu and Chen, 2020), making the process subjective and time-consuming (Wang et al., 2017). SUs, which mainly refer to morphological elements, are usually generated based on hydrological analysis output and digital elevation model (DEM) derivatives (Duman et al., 2005). Moreover, SUs represent actual slope shapes; therefore, these units can be considered as the smallest homogeneous surfaces that are highly relevant when addressing any hydrological and morphological differences within the surface, and they reduce the mentioned differences within the features included (rain gauges and landslides).

The method adopted of Rain gauges selection influences the results of the rainfall threshold calculation and the operational applications; Several empirical thresholds based on rainfall conditions have been defined through statistical analysis as well as physically-based approaches. The most used are the ID (rainfall mean intensity–rainfall duration) and the ED (cumulated event rainfall–rainfall duration) rainfall thresholds. Even if the two approaches are analytically equivalent, being $I = E/D$, from a theoretical point of view, it is preferable to define ED thresholds, in which the two variables measure independent quantities (Gariano et al., 2020a). Consequently, we adopted the CTRL-T tool (Calculation of Thresholds for Rainfall-induced Landslides Tool; Melillo et al., 2018) used by many authors in various environmental settings (e.g., Distefano et al., 2022; Lin et al., 2022; B. Zhao et al., 2022; Brunetti et al., 2021; Jordanova et al., 2020; Melillo et al., 2020; Teja et al., 2019) for the automatic calculation of thresholds for rainfall-induced landslides.

In this work, a new free tool pack named DEWS (Distance, Elevation, Watershed, and Slope unit) was built in the QGIS software environment (open-source free and offline GIS packages), for extracting rain gauges referring to landslide locations, in line with previous works dealing with similar topics as e.g. Bragagnolo et al. (2020) and Guo et al. (2022). DEWS employs four spatial filters, with minimum input data and parameters by the user. The tool was tested for validity on a regional scale that covers major areas of South Korea. DEWS can be considered a supplementary procedure for the tool proposed by Melillo et al. (2018), introducing new criteria to apply multiple filters to automatically select the representative rain gauge (i.e., the most representative measuring station that is appropriate to reconstruct the landslide-triggering rainfall). However, it can be also independently used.

2. Description of DEWS models and parameters

DEWS is a supplementary tool pack that conducts preprocessing selection analysis to produce a more relevant group of rain gauge

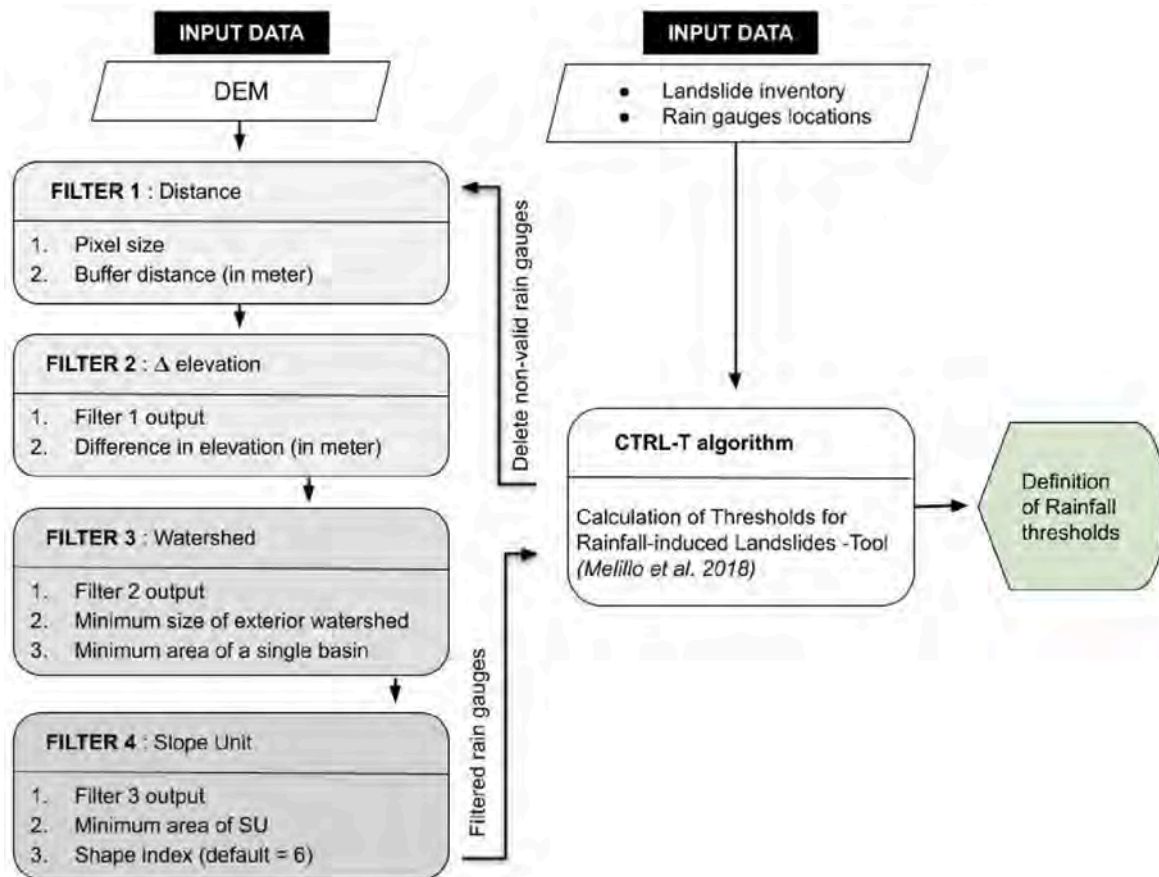


Fig. 1. DEWS general framework.

locations, and eventually act as a supplementary and complementary analysis step to rainfall thresholds models. It is a supplement because it works on a macro-to-micro basis of spatial components between the landslides and surrounding rain gauges within a distance that is more than or equal to the maximum permissible distance between the representative rain gauge and the landslide. Therefore, the current objective is to have a minimum number of rain gauges related to each landslide within a specific distance. However, DEWS provides spatial complementary analysis, in other words, it does not carry rain gauge attribute analysis for the rain events records that might trigger the landslides, and consequently this is not served in the tool pack. Fig. 1 illustrates the general framework of the tool pack structure and its possible link with CTRL-T. To test the efficiency of DEWS, CTRL-T was chosen in this research for calculating objective and reproducible rainfall thresholds. The input data are composed of: (1) parameters of the filter's algorithm, (2) rain gauge locations, (3) landslide locations, (4) DEM. The settings of the parameters are simple and supported by default values for non-expert users. The tool pack is divided into four filters (Filter 1 and 2: Geographical; Filter 3: Hydrological; Filter 4: Geomorphological) and a final block. Fig. 2 shows the user interface of the QGIS processing toolbox, with the four panels of requested input data and parameters.

Filter 1 selects rain gauges within a specified buffer distance from the landslide locations using the setting parameters and the inventories of the landslides and rain gauges. Then, using the optimized locations of rain gauges and landslides provided by the Filter 1 section, Filter 2 uses the DEM to extract the elevation of the rain gauges and the landslides and then calculates the differences within each buffer circle. Consequently, each landslide is associated with a group of rain gauges within the buffer around this landslide and then the filter removes the rain gauge elevation values closest to each landslide using the allowable

elevation difference defined by the parameter's settings. The study area extent and resampled DEM were extracted in the current filter to optimize the running time cost in each filter.

The rain gauge features falling in the watershed that contains the landslide locations are extracted by means of Filter 3. The parameter settings are the minimum size of the exterior watershed (default: 1500 in cells) and the minimum area of a single basin (default: 1000 m²). The *r. watershed* algorithm (<https://grass.osgeo.org/grass82/manuals/r.watershed.html>) is the main processed model; however, using different values of exterior watershed size (rather than the default value) has a significant impact on altering the size/behavior of the resultant watershed.

Filter 4 represents SU, which is the smallest and most focused filter, uses the "LaGRiSU" (Landslide grid and slope unit extraction) tool pack (https://github.com/Althwaynee/LaGRiSU_Landslide-Grid-and-Slope-Units-QGIS_ToolPack). It is modified here to extract the slope units associated with each landslide. Consequently, only the rain gauges falling within these slope units are selected. It is noteworthy that Filter 4 does not require any parameter settings, given that all settings are integrated internally.

In the following sections, we describe in detail the algorithms used for selecting the rain gauges of each filter (see Fig. 3).

2.1. Filter 1, 2 (distance and elevation)

In the literature, the selection of the representative rain gauges rarely includes an analysis of the elevation (Gariano et al., 2020b; Segoni et al., 2018b). However, the elevation needs to be taken into account, given that it plays the main role in the amount of rainfall received by an area (Arnone et al., 2021). In some scenarios, close objects distance on plan might have a wide difference in elevation compared to distant objects.

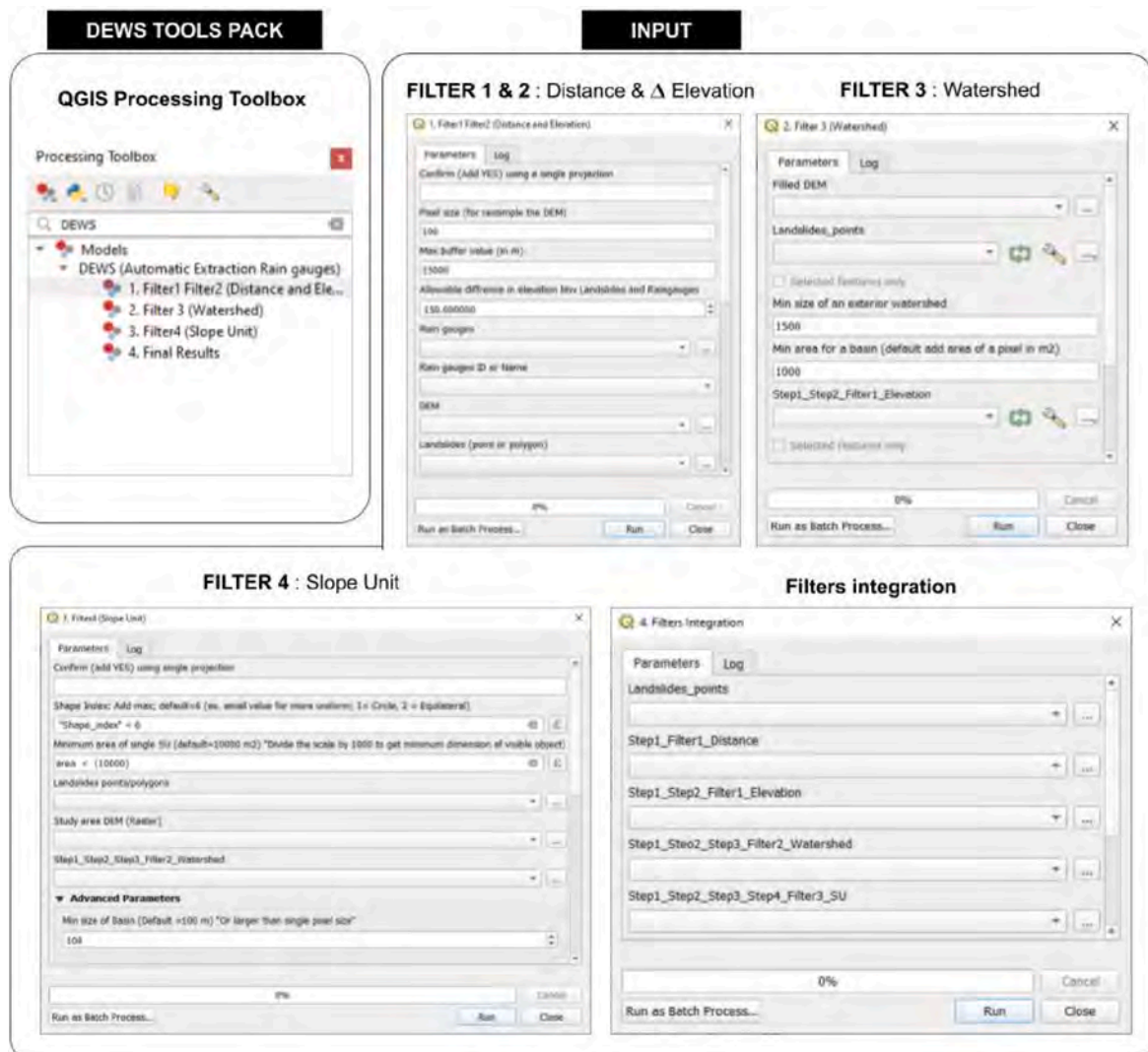


Fig. 2. GUI of the DEWS QGIS tool pack.

That's to say, the distance component cannot be the only driving factor.

Firstly, for better representation, all features are represented by their centroid, thus, a constant buffer distance (referring to morphological settings and rain gauge density) is thus generated around the landslides using the input parameter values. Here, 15 km is assigned as the maximum default value. However, in regions with a low rain gauge density, the user may increase or reduce this value, especially when dealing with abrupt changes in altitude.

Later, the DEM raster is used to extract the value of altitude for landslides and rain gauges. Then, we apply a certain condition to select only the difference in elevation value (as maximum limit) that matches with user defined value. The default value of difference in elevation is set to 150 m as default; however, that value greatly depends on morphological settings. And there is no clear standard procedure to determine the best value.

If we have a close landslide-rain gauges distance (<15 km) with more rain gauges related to these landslides, the filter deals with each landslide as an independent feature, assuring that each landslide has a minimum of a single station near to it. If the buffer around these landslides has more than one rain gauge, all rain gauges serve all landslide locations.

2.2. Filter 3. watershed filter

The watershed filter is more focused on the area around landslides and addresses the homogeneity in terms of hydrological conditions related to landslides that occur. Boundary of the watershed, reflected by high mountains or complex terrain, has a significant effect on the amount of rainfall that can reach the slopes. In different watersheds, the settings vary, as described in the following paragraphs.

The filter mainly consists of *r.watershed* (QGIS function) to calculate hydrological parameters and RUSLE factors, developed by the GRASS development team) to calculate the set of hydrological parameter maps, including flow accumulation, drainage direction, location of streams, and watershed basins.

The default value for the threshold option, which specifies the minimum size of an exterior watershed basin in cells, is 1500, as recommended by QGIS software tutorial. This value is adjustable within the current filter tool pack; however, low threshold values dramatically increase the run time and generate more detailed basin results and stream segment maps. *"The minimum size of drainage basins, defined by the threshold parameter, is only relevant for those watersheds with a single stream having at least the threshold of cells flowing into it. (These watersheds are called exterior basins.) Interior drainage basins contain stream segments below multiple tributaries. Interior drainage basins can be of any size because the length of an interior stream segment is determined by the distance between*

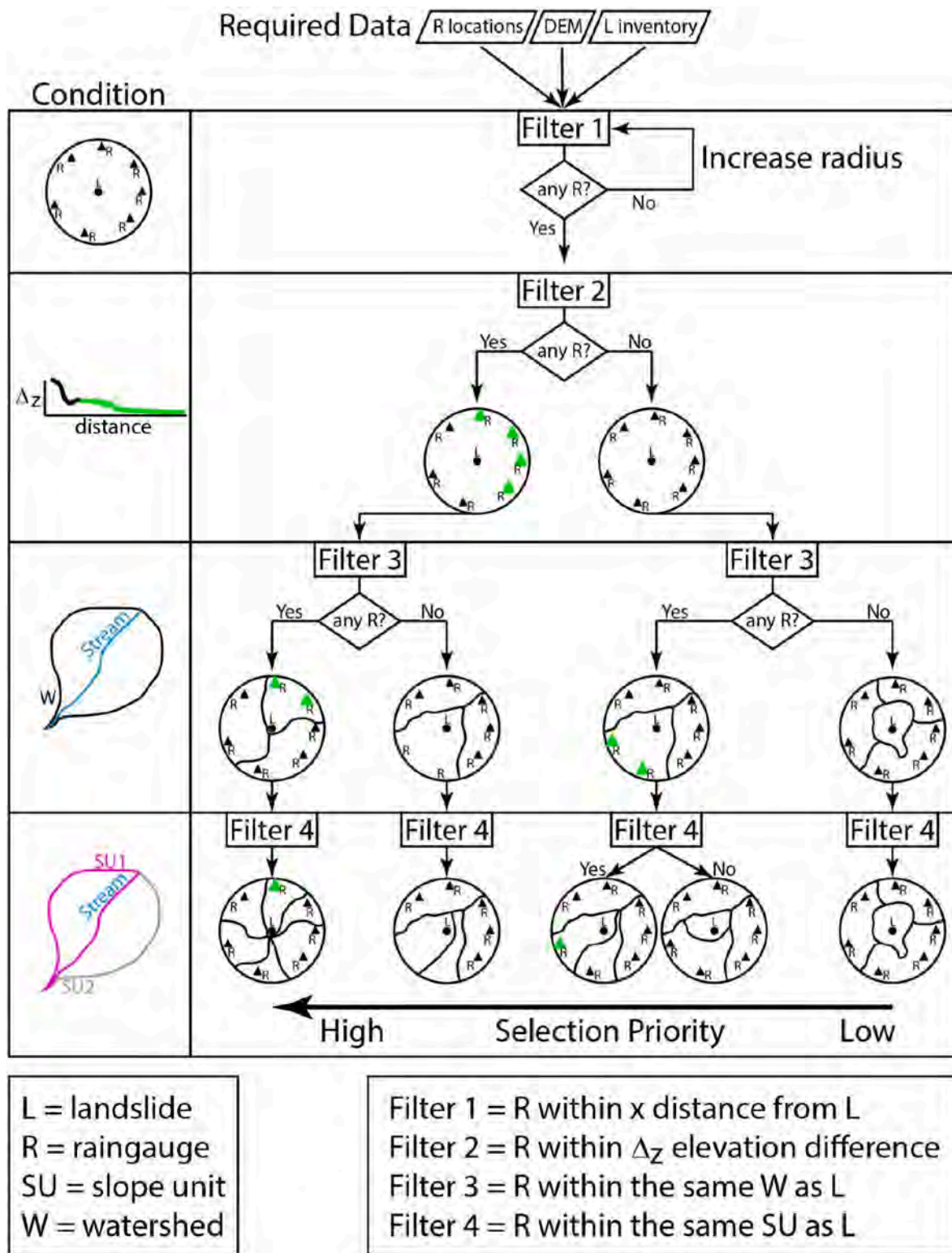


Fig. 3. Logical framework of DEWS process.

the tributaries flowing into it" (<https://grass.osgeo.org/grass78/manuals/r.watershed.html>).

Another parameter is the minimum basin size, which can be set to the area of a single pixel in the used DEM; however, the user must consider a value in terms of the minimum surface area that can collect water. Here, we assign 1000 m² as a default to be justified by the user.

As a result, a watershed smaller or along the buffer distance was

created, and the features within these areas were extracted from Filter 2. The landslides that did not have a minimum single rain gauge, were skipped, and kept the previous filter points (Fig. 3).

2.3. Filter 4. slope unit

The slope unit filter consists of multiple steps of hydrological and

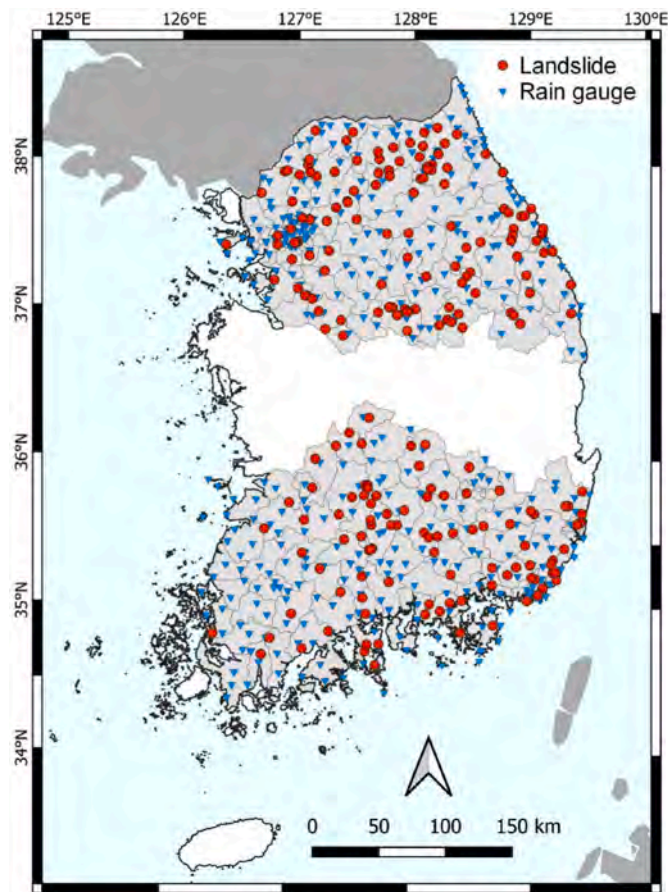


Fig. 4. Map of the study area (two selected regions of South Korea) showing the landslides and the rain gauges used in this work.

spatial analysis using one input feature (DEM) only and by using the LaGRISU tool pack that was designed by some authors of this article. In the catchment basin, the SU is considered as half of its area, resulting in two SUs separated by the valley line. The drainage network generated with a given threshold of the contributing area can be arbitrarily dense. Commonly, there are two approaches to extracting SUs: the bottom-up approach and the top-down approach. The bottom-up approach starts from a fine partition of the slopes and then groups together similar units. It is typically based on image (aspect) classification. The top-down approach is based on a pure hydrologic partition into half-basins, with a smaller contributing area providing a finer partition (adopted in the current study). In this step, the method presented by Wang et al. (2017) for the construction process of the SUs was followed, based on the following steps.

1. Hydrological analysis; to produce the catchment basin in positive relief; therefore, the drainage network is extracted as a valley line using DEM data;
2. Turn the highest point into the lowest point and vice versa; therefore, the DEM is inverted; then, using negative relief, the negative drainage network and consequently the catchment basin, were extracted.

Positive and negative relief catchment basins are superimposed and merged; as a result, two SUs in catchment basins are generated.

Smaller threshold values (minimum area required to initiate and maintain a channel) result in more extensive stream networks and vice versa. However, to determine the channel initiation area threshold, there is very little guidance regarding an appropriate method to follow (Engelen and Kloosterman, 2012). In different regions of the study area,

different contributing thresholds are needed, i.e., the threshold value is unique for each landscape and data set, including source and grid resolution (Palamakumbure et al., 2015). In contrast, the half-basins associated with the drainage network become arbitrarily small with an increasing accumulation threshold. As such, the threshold is frequently determined either by examining map or imagery data or by experimentation until a suitable or desirable channel network is identified. Therefore, to simplify the tool processing within a QGIS environment and to accomplish as much as possible for the SU aspect to be homogeneous, the mean value contributing area was used as the given threshold for the generation of a drainage network. Consequently, this represents a disadvantage of the current module by considering the single value for the thresholds and that should attract more attention, especially when the results mean that the uncertainty of flow accumulation threshold impacts the hydrology modeling (Luo et al., 2008).

The slope unit filter, considering the slope faces and slope direction, is mainly effective in areas where there is a high density of rain gauges and complex terrain areas, and less effective for flat to semi-flat surfaces.

3. CTRL-T tool settings

After the DEWS process, CTRL-T (Melillo et al., 2018) is used for threshold calculation. Input data is composed by continuous sets of hourly rainfall data (usually gathered from rain gauges), and on a landslide database, consisting of geographic coordinates and accurate dates of occurrence. Specific regional parameters need to be set, such as the maximum permissible distance between the representative rain gauge and the landslide, and the minimum dry (i.e., with no rain) interval between two consecutive rainfall events. Moreover, the length of the minimum dry period can change in the “warm” (CW) and “cold” (CC) seasons, whose length should be set. The determination of the two seasons is based on a monthly soil–water balance (MSWB) model, which exploits monthly rainfall and temperature data and allows estimating the average monthly potential (PET) and real (RET) evapotranspiration. Depending on the local seasonal and climatic conditions, the length of the CW and CC periods may vary and may lead RET to vary accordingly (Thorp, 1986). The aridity index (AI), i.e., the ratio between the average monthly rainfall (E_m) and the average monthly potential evapotranspiration (PET_m), is used to define the length of the two seasons for each of the two regions. The warm/dry season has $AI < 1$, while in the cold/rainy season $AI \geq 1$ (equation (1)).

$$AI_m = E_m / PET_m \quad (1)$$

PET was calculated using the MODIS 16 data product of MOD16A2 for Evapotranspiration/Latent Heat Flux product.

Melillo et al. (2018) recommended that further improvements might be addressed in CTRL-T to the weight evaluation by including orographic and geomorphological parameters, such as the elevation difference between landslide and rain gauge. That was addressed by applying DEWS as a preprocessing step as follows.

1. Rain gauges record and landslide inventory comma delimited value (.csv) files were processed to meet with CTRL-T algorithm input settings.
2. Using the entire rain gauges and landslide inventory as input, CTRL-T first block one (reconstruction of rainfall events) was run to test the valid rain gauges (if any extensive missing record or non valid stations locations).
3. In QGIS, two regions of study area were selected with the related rain gauges and landslides, and non-valid rain gauges (based on previous step) were deleted.
4. Using landslide and rain gauges data of the first region, the CTRL-T algorithm was run entirely to produce what so called rainfall threshold with no DEWS input. For each failure, nearby rain gauges are located in a circular area (buffer) centered on the landslide

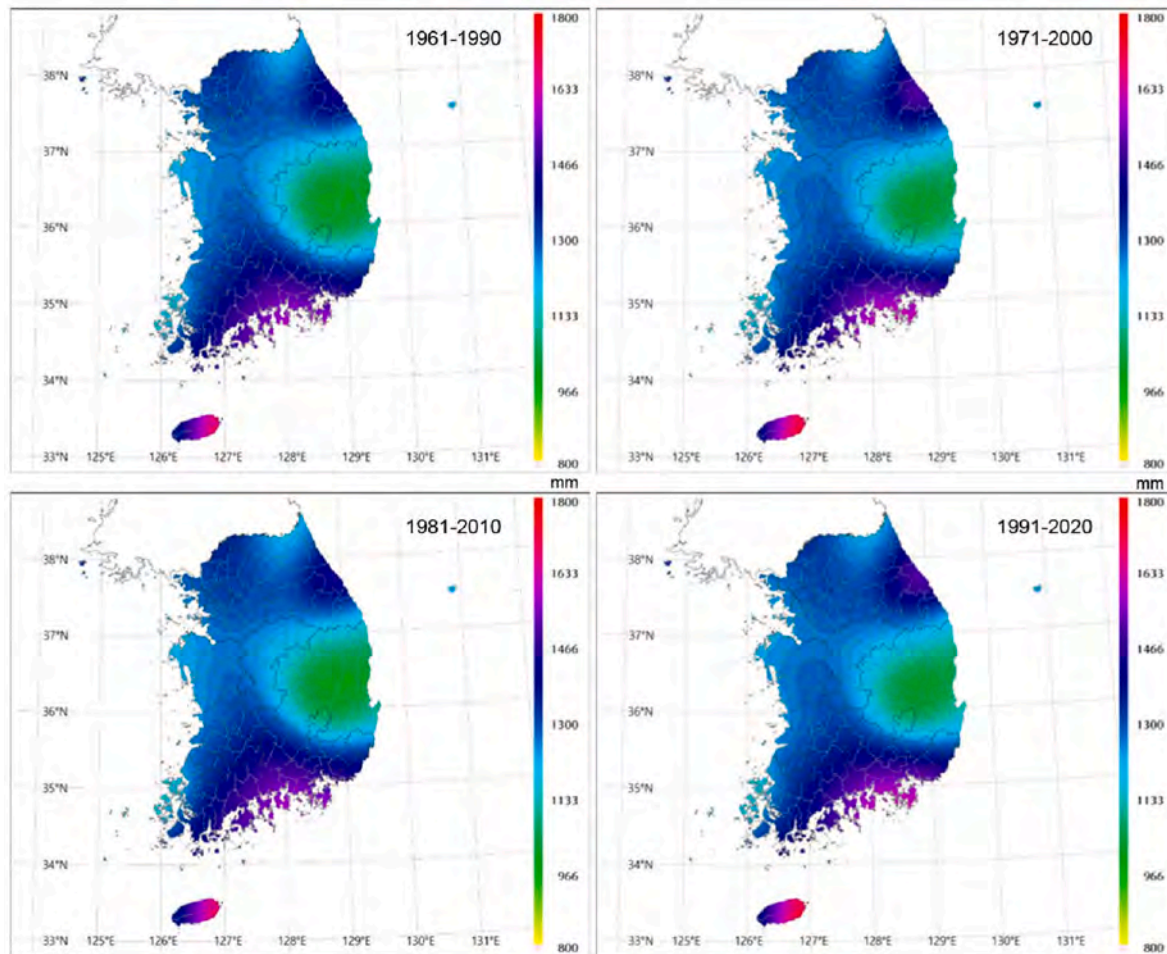


Fig. 5. Maps of average annual rainfall (mm) for the period between 1961 and 2020; a) 1961–1990; b) 1971–2000; c) 1981–2010; d) 1991–2020. Source (data.kma.go.kr, n.d.):

location and with a parametrized radius we used buffer distance of 20 km as to avoid the coincidence with DEWS that run distance filters of defined buffer distance (15 km).

- Finally run DEWS with different sets of data (CTRL-T only and CTRL-DEWS for two regions).

Later, the selection of single or multiple rainfall conditions (MRC) that are most likely responsible for the slope failures will be carried. Each MRC is assigned a weight to select the representative rain gauge and the rainfall conditions associated with the landslide. The weight is equal to the ratio between the cumulated rainfall (E) times the mean rainfall intensity (I) divided by the square of the distance between the rain gauge and the landslide.

Last step is the calculation of cumulated event rainfall–rainfall duration (ED) thresholds at different non-exceedance probabilities (NEPs), and the associated uncertainties, where the MRC with the maximum weight for each failure (MPRC, Maximum Probability Rainfall Condition) are selected. The thresholds are defined using a frequentist approach and have a power law form linking E to D (Eq. (2)):

$$E = (\alpha \pm \Delta\alpha) D^{(\gamma \pm \Delta\gamma)} \quad (2)$$

where α is the scaling parameter and γ is the shape parameter, i.e., the intercept and slope of the power law curve respectively; $\Delta\alpha$ and $\Delta\gamma$ represent the relative uncertainties of the two parameters.

4. South Korea as the regional-scale study area

South Korea has a high percentage of mountainous regions, where many residences and infrastructure are in piedmont areas, and major landslides disasters are common in mountainous areas and are caused by typhoons. The mean annual temperature and mean annual precipitation in this area are in the ranges 6.6–16.6 °C and 825.6–2007.3 mm, respectively, with substantial regional variations (data.kma.go.kr). Forest lands cover about 63.7% of the territory. However, this value has decreased over time because of urbanization and road construction, and likely leads to slope disturbance and thus to an increased hazard risk. The most common types of landslides are shallow transitional slides that occur dominantly in granite and metamorphic rocks, which represent 42.6% of country geology (Kim et al., 2021; Yoo et al., 2012; Kim and Chae, 2009), and are relatively small, i.e., typically less than 2 m in depth, 20 m in width, and 100 m in length, on average (Kim et al., 2021). The 2002, 2003, 2006, and 2011 typhoons caused damage occurring around residential areas in the metropolitan area and large-scale debris flows that occurred in urban areas because of sediments from Mts. Woomyeon and Chuncheon and following intensive rainstorms (Kim et al., 2021; Lee et al., 2022).

In the current research, a landslide inventory (mostly transitional shallow landslides, with many mobilized into debris flows; Althwaynee et al., 2021; Vasu and Lee, 2016) for the period between 1999 and 2011 (on average 15 effective landslides per year) is used. Inventoried landslides occurred mainly during the period from June to September and mostly in the regions of Gangwon, Gyeongsang, Chungcheong, and

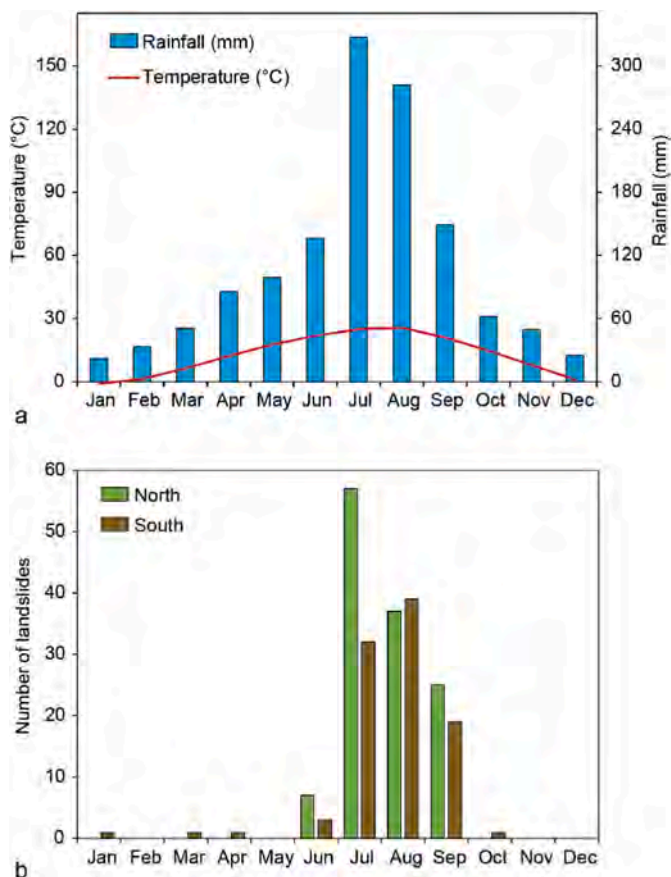


Fig. 6. a) Ombrothermic diagram for the 30-year period 1991 to 2020. b) Number of collected landslides in the northern and southern part of the study area.

Jeolla.

A total of 223 landslides (with temporal attributes information of daily level details) were classified mainly as shallow landslides with low percentage represent transitional as debris flow with scar depth less than 3 m and scar area of less than 2000 m², were selected in landslide cluster zones of northern (126 landslides) and southern (97 landslides) parts of South Korea (areas in center of republic were excluded as the density of landslides is rationally low). This research considers the mainland excluding the islands.

In addition, each landslide in the inventory is surrounded by a dense network of rain gauges. The main stations use a tipping bucket and automatically correct the 1-min rainfall accumulation in heavy rainfall situations. Overall, 328 automatic weather stations are distributed throughout the two highlighted regions (Fig. 4). Additionally, there are 65 automated surface observing systems, which are automated sensors that serve as a primary climatological observation network.

Rain gauges are however unevenly distributed over the country (data.kma.go.kr) and are concentrated on its urban areas and active landslide areas (high density of gauges around Seoul, the capital, and around coastal regions). Since the rain gauges record was available before and after the inventory occurrence dates, with no significant missing records, there was no need for any spatial interpolation of rain gauges records.

5. Results and discussions

5.1. Climate characteristics

Fig. 5 shows four maps of average annual rainfall (mm) in the areas for the periods 1961–1990, 1971–2000, 1981–2010, and 1991–2020.

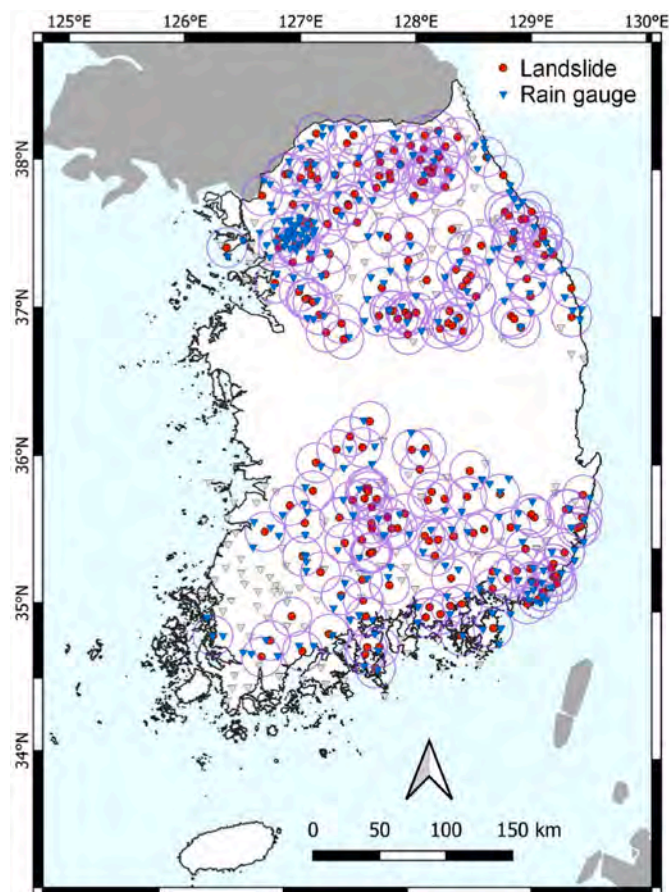


Fig. 7. Output of Filter (1, 2); Red dots: landslide inventory; Blue triangle: selected (filtered) rain gauges distance; Gray triangles: ignored rain gauges, on the mainland of South Korea.

Similar rainfall features can be observed in the northern and southern part of Korea, contrarily to the central part. The climate of active and non-active landslides regions is wet throughout the year as shown in the Ombrothermic diagram (Fig. 6a). The climate is characterized by the extended rainfall amplitudes during the summer (20 June to 20 September), and with less than 10% of rain falls during the rest of the year. The absolute maximum rainfall reaches 330 mm and 270 mm in summer for active and non-active landslides regions, respectively. On the contrary, ice and frosts during winter are common phenomena, however they do not threaten the slopes up to failure limits.

Between 28 July and 11 August 2020, extreme rainfall lasting for 2 weeks resulted in 1938 landslides, covering an area of 1271 km², with approximate damage cost around 181,500,000 KRW (\$ 159,000). In current research, a limited inventory (223 records) that contain the exact date of occurrence for the period 1999 to 2011 is used. And that constraint, leaves us with limited options to decide to have no more than two zones, northern and southern, with 126 and 97 landslide records, respectively.

Referring to annual rainfall map for the period between 1961 and 2020 (Fig. 5) and comparing to landslide temporal distribution (Fig. 6b) and landslide distribution map without temporal attribute of date of occurrence and with temporal attribute (Fig. 4) we notice that landslides spatially clustered in the northern and southern part of the country, leaving us well informed that landslides are purely rainfall dependent in the study area.

5.2. DEWS tool pack

The DEWS tool pack simplified in a way that each step was

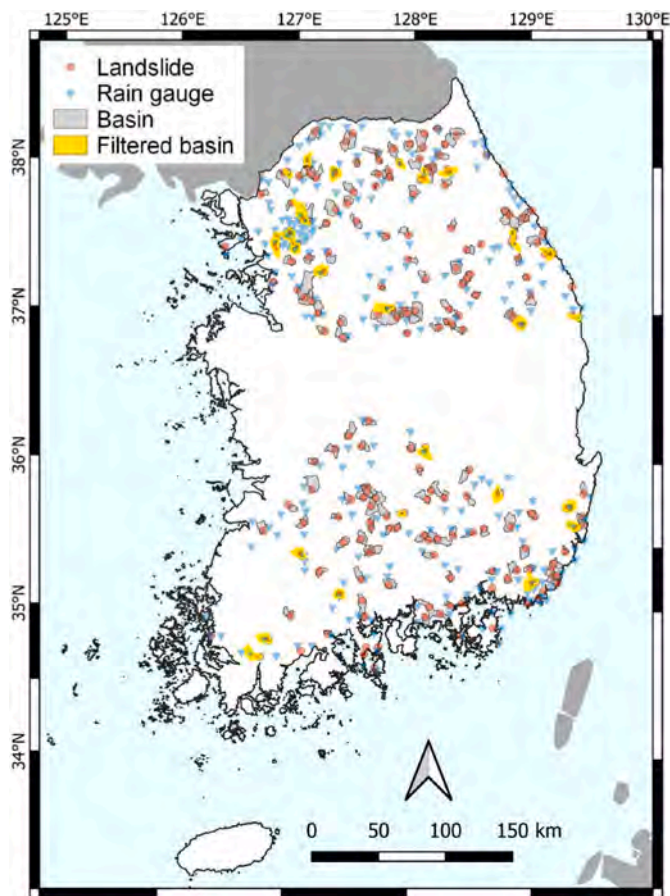


Fig. 8. Output of Filter 3 (watershed): orange dots: landslide inventory; Green triangles: resultant (selected) rain gauges; Blue triangles: ignored rain gauges; Gray areas: watersheds without rain gauges; Yellow areas: watersheds with a minimum of 1 rain gauges.

represented by a single graphical user interface (GUI) and were sorted logically (Fig. 2). Input represents a total of 40 and 25 automated surface observing systems and 115 and 173 automatic weather stations, and 97 and 126 landslide locations for northern and southern regions, respectively.

Filter 1 (distance) is used to first remove duplicate geometrical attributes of the rain gauges. After assuming the effective parameter of distance from landslides, the filter produces a new area represented by a buffered polygon (not dissolved to assure that each resultant polygon represents a single landslide). The polygon area now represents the extent of these polygons and consequently, the landslides with no station within this buffer are not included in the following analysis.

By running Filter 2 (elevation), the relevant stations and landslide elevation values are extracted, and differences in elevation between the landslides are computed within a specific polygon. As a result, rain gauges were extracted that complied with a condition that if the elevation difference was more than a defined limit (150 m), then the related stations were deleted. We then analyzed the difference in elevation using a statistical summary, and we found that the mean (μ) value was 106 m and the standard deviation (SD) was 153 m; therefore, a value between 110 and 250 m was acceptable, keeping in mind that values in the 1st quartile were close to 24 m and those in the 3rd quartile were less than 118 m. Therefore, keeping the parameter as more than the 3rd quartile and $SD + \mu$ preserves some stations that meet the mentioned criteria. Finally, in the case that no station qualifies based on the assumed criteria, then the stations of Filter 1 are selected based on Filter 2.

Filter 3 (watershed), the parameter of “Min area for a basin (default:

add the area of a pixel in m^2)” is used to first reduce the high density of small (non-logical) basin areas, and by default represents the area of a single pixel in the DEM. Therefore, the resampling algorithm of DEM was included to resample the raster for resolution reduction, as the high spatial resolution unnecessarily increased the processing time (Arnone et al., 2021). As mentioned earlier, the minimum size of an exterior watershed must be within a specific range to assure a moderate density of watershed basins (Fig. 7). Therefore, using the default value (1500) generates a watershed of the study area and keeps 164 units (containing 77 rain gauges) that cover the landslide bodies for the area from 10,687,500 to 268,447,500 m^2 . In addition, 38% of the extracted watersheds contain 1 to 11 rain gauges, while the other watersheds only contain landslides. In addition, like Filter 1, landslides with watersheds with rain gauges in Filter 2 (Fig. 8) were preserved (to avoid overlap), while other landslides without rain gauges in Filter 2 keep the Filter 1 results.

Filter 4 extracts rain gauges within slope units, is more focused, and is essentially required especially where there is a high density of rain gauges as well as when the wind speed and wind direction are significant factors for rainfall distribution (L. Zhao et al., 2022). Here, the feature within single slopes has the highest accuracy with regard to the amount of falling rainfall as well as the slope aspect (which is recommended in the literature as being an aspect that requires consideration) and other meteorological factors. A total of 218 SUs (single-pixel areas up to 8,505,000 m^2) were extracted containing the entire landslide inventory. The SU filter extracts only two rain gauges that share a similar slope unit with landslide events. This is because moderate to small landslides in the study area do not cover large areas (Fig. 9).

However, the very large areas of slope units are caused by the consequences of having inaccurate landslide locations. When the landslide center falls within the valley and not within the slope body, the function considers the adjacent slopes as the represented slope units, and as a consequence, there may be more than one slope along the mountain chain, or a shallow and continuous slope. In contrast, we notice a smaller and focused SU is the opposite of the conditions noted above and where the landslide inside the slope body is represented with steep slopes (Fig. 9).

Once the filter outputs are completed, the last step before they are merged ensures that there is no overlap in the results of each filter (Fig. 10). In other words, as mentioned, Filter 1 is mandatory, and the rest of the filters are optional and are used to limit the number of stations that do not meet the criteria in each filter.

5.2. Rainfall threshold calculation

To show the validity and effectiveness of the proposed filters, 10 thresholds were prepared for the north and south of the study area using 10 different filtering settings combinations (Table 1). We then implemented CTRL-T using the output presented in the previous sections. Rain gauges are entered with landslide inventory to produce the empirical thresholds at several exceedance probabilities.

From June to August (rainy season and warm) and from November to February (dry season and cold) witness the highest PET (Fig. 11 a,c). While other months come with the lowest PET with no rain. This is a typical semi tropical climate and RET will not differ much from PET due to rainfall availability during warm seasons. Thus, we proposed two scenarios, first the area with high PET will be assigned a minimum dry period of 24 h, and others 48 h (since the landslides only occurred during the June to October, rainy and warm with low aridity for the two regions). Aridity index map (Fig. 11b), was derived using monthly rainfall for 2010 collected by the north and south region separately. Consequently, we assigned the starting of the warm season in June and the end of the warm season in September.

As shown in Fig. 10, not all landslides were included in the development of threshold analysis (automatically excluded by CTRL-T), and that due to the pre-set of the time delay parameter between the end of the rainfall condition and the occurrence of the landslide exceeded the

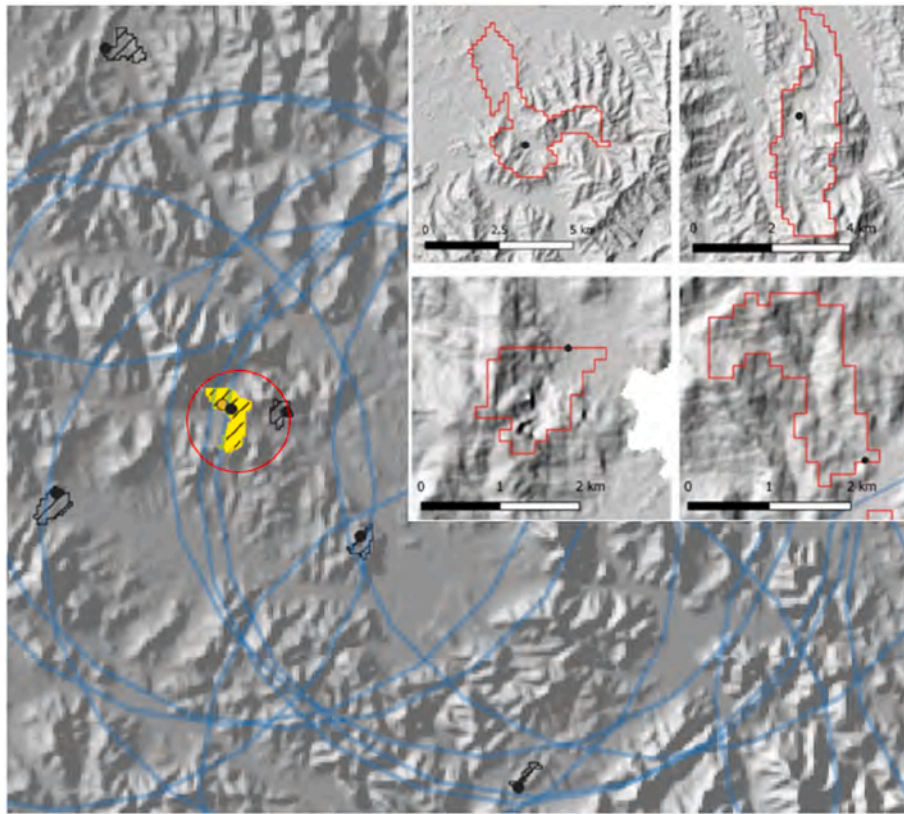


Fig. 9. Output of Filter 4: landslides (black dots), resultant rain gauges (yellow dots), watersheds without rain gauges (transparent areas), and watersheds with a minimum of one rain gauge (highlighted areas). Different areas of slope units (un-uniform red polygons) due to uncertain landslides locations using different pixel sizes of original DEM raster. Fine pixel size produce small SU, coarse pixel size produce small SU.

set parameter. In addition, accurate landslide information or rainfall data were lacking. CTRL-T selects only the rainfall condition corresponding to the first triggered landslide. As a result, the included landslide inventory, those with valid rainfall events that might be responsible for the landslide occurrence.

As mentioned earlier, CTRL-T includes the geographical search (distance) for the reference rain gauge; similarly, this option is represented also by filter 1 in DEWS (Filter 1 was considered to give DEWS option to be used with other thresholds models). Thus, To check the validity of preprocessing using DEWS with CTRL-T and DEWS (including distance of buffer value of filter 1 in DEWS and default search radius in CTRL-T), a total set of 10 thresholds were generated (Table 1). To test the efficiency of DEWS, we assumed 15 km as default buffer distance for filter 1 (distance), while 20 km for the CTRL-t buffer around landslides locations. As anticipated, even though the included rain gauges within 20 km distance to landslide using CTRL-T (no DEWS), included a higher amount of rain gauges than CTRL-T with DEWS considering a buffer of 15 km. However, a similar amount of rainfall events that might be responsible for the landslide's occurrence was reconstructed.

In 4th, 6th, 8th and 10 combinations (for both study regions) with active watershed and slope units options and with 50m–400m difference in elevations. One may comment that having a wider range of elevation limit in case 10, will increase the possibility of including more rain gauges, and logically to have better representation for unique rain gauges. This sentence can be accepted in case of the 9th combination. However the improvement was noticed in the 10th combination when the hydrological (watershed) and geomorphological (slope) filters were involved (Fig. 12). Also, when looking at the amount of MPRC at ED plot (Fig. 13), we get similar pairs, even though the amount of rain gauges selected using DEWS to produce the threshold represents 65 and 69% of the total amount of rain gauges for south and northern regions, respectively.

The reduction applied using the filters reduced the input amount of rain gauges by 67% see the values of the unique rain/total amount of rain gauges (F column in Table 1), while interestingly, the unique rain gauges was not affected, and consequently, the constructed threshold still has similar limits of non exceeding probability. That confirms the improvement of using DEWS, it is not always having more stations will result in more unique rain gauges, while selecting less rain gauges using the DEWS filters criteria will successfully relate more rainfall events to referred landslides (Fig. 12).

The range value of the cumulated rainfall, E, for the 10 thresholds is 20–110 mm for $3 \leq D \leq 110$ h. In particular, the equations of the 10 thresholds obtained for the MPRC data sets in Table 1 reveal that the thresholds are statistically indistinguishable if considering the uncertainties associated with the fitting curves. Fig. 13 shows the thresholds in log-log coordinates. Since the number of rainfall conditions used to determine the thresholds is close to 75 (average 68), which is the minimum number to obtain stable α and γ parameters (Peruccacci et al., 2017), we acknowledge that the two curves are very similar even in terms of uncertainties. Since the MPRC data sets of Curves are the corresponding 5% frequentist thresholds are close to each other, we ignore adding more results, and keep this as the most significant outcome of CTRL-T.

Values of α and γ are high (30% for α and 15% for γ), due to the large scale our analyses was performed at (mainland of South Korea). In addition to this, the limited amount of landslides contained within the inventory may have played a role. Using such large area was unavoidable (albeit the uncertainty was anticipated), but that is due to limited landslide data on local scale (contain temporal information on events daily occurrence).

In Fig. 12, 4th, 6th and 10th used less rain gauges compare to 1st (CTRL-T only), and that in many cases might increase the uncertainty, i. e, using less data leads to high uncertainty, however, the structured

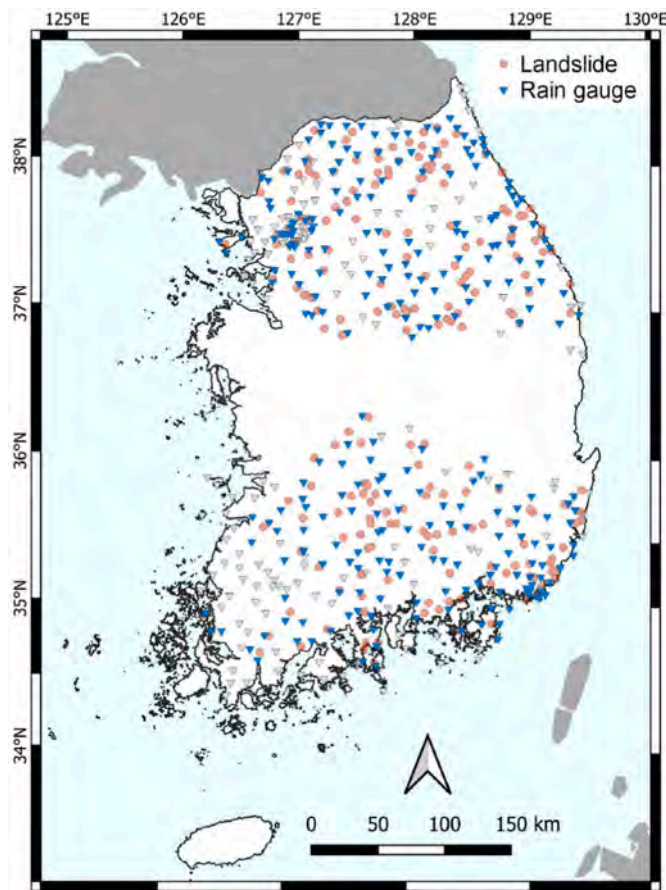


Fig. 10. Final selected rain gauges, orange dots: landslide inventory; Blue triangles: resultant (selected) rain gauges; Gray triangles: ignored rain gauges.

filters lead to stability in range of uncertainty ($\Delta\alpha$ and $\Delta\gamma$) significantly for the cases with lower amount of stations.

In order to elaborate the effectiveness of having structured the selection of rain gauges, we included the additional set of results represented by the southern region, using similar 10 combinations of CTRL-T and DEWS filters. As anticipated, the ED thresholds associated with uncertainties were rationally similar.

After the 1st combination of CTRL-T only, the amount of included rain gauges dramatically decreased when the 2nd combination (distance reduced from 20 to 15 km) in the southern region. However, if this linear behavior of reducing the distance will result in a better unique station, then the northern region should act the same. But, to agree with the research hypothesis, the 2nd combination in the northern region did not result in significant reduction of rain gauges, but instead, it reacted significantly by tuning up and down the elevation value limit. And that confirms that choosing the representative rain gauge with DEWS has much more advantages even though the included rain gauges is less than the set of rain gauges in thresholds without DEWS by 30%. As a result, the thresholds in the log-log plane show higher steepness and less area of uncertainty. On the other hand, whenever we activate the watershed and slope units (4th,6th, 8th and 10th), we get more reduction in the included station, and this is normal as these filters are adding more constraint to selection degree of freedom.

CTRL-T with DEWS integration aims at producing thresholds with focus on preprocessing and post processing, that aims to identify the optimized representative rain gauge as well as reducing the computational time of the single steps, and reconstruction and analysis of the rainfall conditions responsible for the failure. CTRL-T carries automatic selection of all the available stations within a given distance from the landslide. And mainly through a weight, which is a function of both

Table 1

Equations of the rainfall thresholds for the possible initiation of landslides in South Korea for MPRC data sets varying the 10 combinations of CTRL-T and DEWS filters. (bold text represent the best combination in term of reduction in rain gauges; F is the unique rain/total amount of rain gauges).

Region	Model	Model combination	F	Threshold 5%
North	1st	N_CTRL20	34.8	$E = (14.1 \pm 4.8) \wedge D (0.49 \pm 0.08)$
	2nd	N_CTRL20_D15_E0W0S0	33.8	$E = (14.8 \pm 5.5) D (0.47 \pm 0.08)$
	3rd	N_CTRL20_D15_E50W0S1	40.5	$E = (15.8 \pm 4.9) D (0.46 \pm 0.07)$
	4th	N_CTRL20_D15_E50W1S1	48.9	$E = (15.9 \pm 4.9) D (0.46 \pm 0.07)$
	5th	N_CTRL20_D15_E100_W0S1	40.5	$E = (15.7 \pm 4.9) D (0.47 \pm 0.07)$
	6th	N_CTRL20_D15_E100_W1S1	50.4	$E = (15.7 \pm 4.9) D (0.47 \pm 0.07)$
	7th	N_CTRL20_D15_E200_W0S1	40.5	$E = (15.8 \pm 4.8) D (0.46 \pm 0.07)$
	8th	N_CTRL20_D15_E200_W1S1	50.4	$E = (16.0 \pm 4.8) D (0.46 \pm 0.07)$
	9th	N_CTRL20_D15_E400W0S1	40.7	$E = (15.9 \pm 4.9) D (0.46 \pm 0.07)$
	10th	N_CTRL20_D15_E400W1S1	51.2	$E = (16.2 \pm 5.0) D (0.46 \pm 0.07)$
South	1st	S_CTRL20	32.8	$E = (7.2 \pm 2.9) D (0.58 \pm 0.09)$
	2nd	S_CTRL20_D15_E0W0S0	47.1	$E = (7.3 \pm 3.1) D (0.58 \pm 0.1)$
	3rd	S_CTRL20_D15_E50W0S1	47.1	$E = (7.3 \pm 3.0) D (0.57 \pm 0.1)$
	4th	S_CTRL20_D15_E50W1S1	49.2	$E = (7.3 \pm 3.0) D (0.58 \pm 0.1)$
	5th	S_CTRL20_D15_E100W0S0	47.1	$E = (7.3 \pm 2.9) D (0.57 \pm 0.1)$
	6th	S_CTRL20_D15_E100W1S1	52.9	$E = (7.1 \pm 2.8) D (0.57 \pm 0.1)$
	7th	S_CTRL20_D15_E200W0S1	47.1	$E = (7.2 \pm 3.0) D (0.58 \pm 0.1)$
	8th	S_CTRL20_D15_E200W1S1	52.9	$E = (6.8 \pm 2.7) D (0.58 \pm 0.1)$
	9th	S_CTRL20_D15_E400W0S1	47.1	$E = (7.2 \pm 2.9) D (0.58 \pm 0.1)$
	10th	S_CTRL20_D15_E400W1S1	53.8	$E = (7.0 \pm 2.8) D (0.58 \pm 0.1)$

geographical (distance between landslide and rain gauge) and hydrological (cumulated rainfall and duration of the rainfall event) characteristics, associated with the selected stations. With the proposed weight, the closest rain gauges are selected in almost 80% of the cases. In the current study, we added the distance, watershed, and slope unit to prioritize the selection based on these criteria with referring to landslide location. The results prove the validity of this integration compared to using the CTRL-T alone by comparing the ratio of uncertainty, adopting a bootstrap technique (Peruccacci et al., 2017) before and after integration.

6. Conclusion

We have introduced an automatic rain gauge selection procedure (DEWS) as an effective supplementary tool pack for rainfall threshold modeling. In this study, a previously developed algorithm, CTRL-T, was selected (due to its highly efficiency and proven validity) to produce ED thresholds for landslide triggering in South Korea. The DEWS filtering analysis focuses on selecting the rain gauges representative for landslide triggering, based on four criteria (filters). The current tool pack works under a QGIS environment (open-source, offline GIS software) whereby the information is used as input for the CTRL-T algorithm to be used in the R programming environments. Calculating thresholds at different non-exceeding probabilities could be used in probabilistic schemes to produce more reliable warning levels for landslide occurrences.

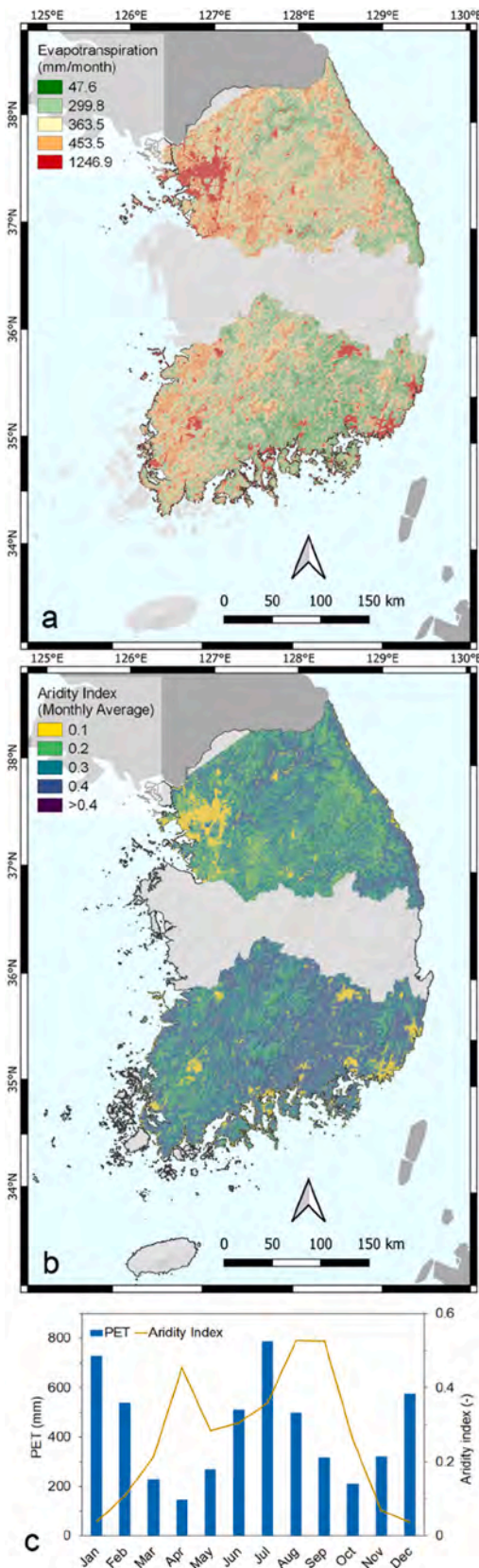


Fig. 11. (a) Monthly average PET (Potential evapotranspiration (mm/month) for 2001,2005,2010, South Korea, (b) 2010 monthly average aridity index for study area, (c) PET and Aridity index of monthly average of 3 years (2001, 2005, and 2010) of active landslides in southern regions in South Korea.

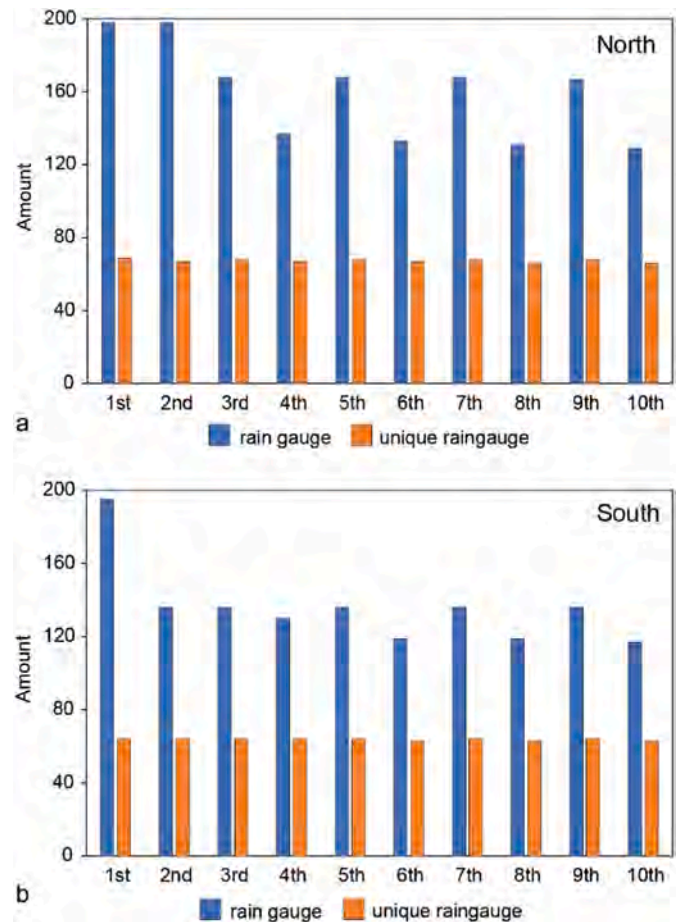


Fig. 12. Amount of rain gauges included vs. the unique rain gauges used to construct the rainfall events (a) northern region, (b) southern region.

However, a national landslide detailed inventory (with precise spatial and temporal attributes) is highly demanded, especially when comparing the inventory that carry the spatial location compared to scarce inventories with uncertain temporal attributes. Thresholds for different geological classes could be moreover determined. This feature can be considered as an indicator of the rainfall conditions responsible for landslide occurrences.

The advantages of the current supplementary procedure are.

- the DEWS unit addresses spatial components between the landslides and surrounding rain gauges, and it does not require extensive attribute analysis for the rainy days preceding the landslides;
- DEWS successfully recognize the effective stations within topographical and hydrological units of landslides, and that was confirmed by rainfall events produced by CTRL-T that yield landslide;
- ranges of uncertainty were stabilized and reduced using CTRL-T with DEWS integration, even though the implemented rain gauges amount in the integration model was 33% lower than the stations amount used with CTRL-T only;
- the tool pack can be used by non-experts because it works on the front end of the GUI with no programming skills needed; open-source package (open-source, offline GIS software);
- both CTRL-T and DEWS allow fast processing of a large amount of data and aim at reducing the subjectivity in the whole process of reconstructing rainfall conditions responsible for the landslides.

For future work, the DEWS tool pack will be fully written in R code (instead of two steps, QGIS and R). That will assure more flexibility in

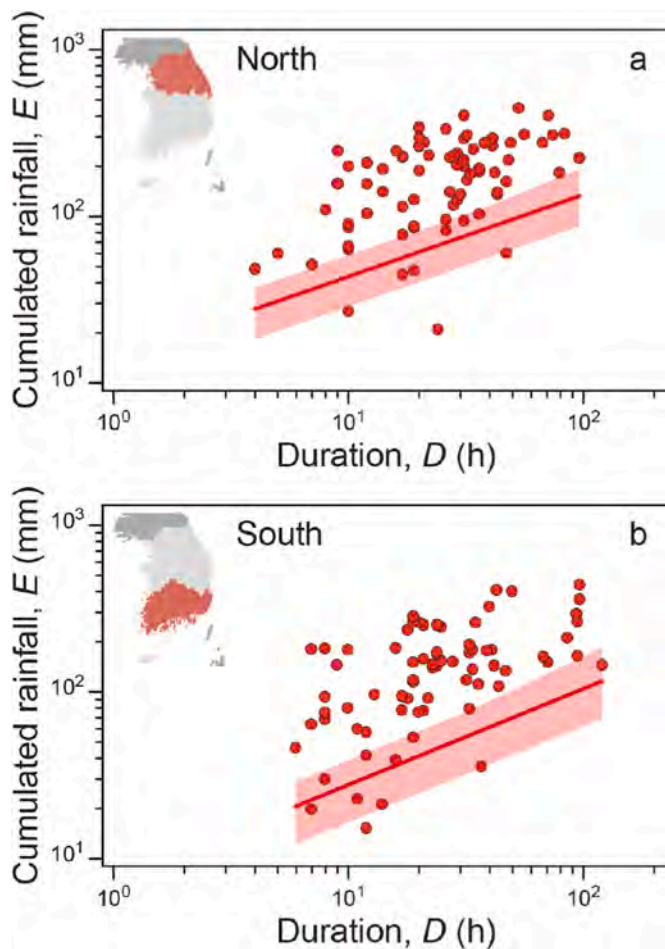


Fig. 13. Log-log plot with the cumulated event rainfall E (mm) vs. rainfall duration D (h) conditions that have resulted in landslides in the study area reconstructed by CTRL-T, and corresponding 5% ED threshold ($T_{5, \text{MPRC}}$), with associated uncertainty (shaded areas). (a) North and (b) south of study area.

parameter adjustment and add a loop function that might choose the best input of DEWS based on CTRL-T output validity.

Software availability

Name: DEWS (distance, elevation, watershed, and slope) unit for rainfall-induced landslide reference station selection Developer: Omar F. Althwaynee, omar.faisel@gmail.com.

Software required: QGIS versions 3.8.0.

Availability: Free of charge, public;

Integrated development environment suggested: Open-source QGIS (geographic information software); DEWS Tool pack repository: <https://github.com/Althwaynee/DEWS-Distance-Elevation-Watershed-and-slope-unit>.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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