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## The optimal rainfall thresholds and probabilistic rainfall conditions for a landslide early warning system for Chuncheon, Republic of Korea

**Abstract** The purpose of this study is to establish the criteria for a landslide early warning system (LEWS). We accomplished this by deriving optimal thresholds for the cumulative event rainfall–duration (ED) and identifying the characteristics of the rainfall variables associated with a high probability of landslide occurrence via a Bayesian model. We have established these system criteria using rainfall and landslide data for Chuncheon, Republic of Korea. Heavy rainfall is the leading cause of landslides in Chuncheon; thus, it is crucial to determine the rainfall conditions that trigger landslides. Hourly rainfall data spanning 1999 to 2017 from seven gauging stations were utilized to establish the ED thresholds and the Bayesian model. We used three different calibration periods of rainfall events split by 12, 24, 48, and 96 non-rainfall hours to calibrate the ED thresholds. Finally, the optimal threshold was determined by comparing the results of the contingency table and the skill scores that maximize the probability of detection (POD) score and minimize the probability of false detection (POFD) score. In the LEWS, by considering the first level as “normal,” we developed subsequent step-by-step warning levels based on the Bayesian model as well as the ED thresholds. We propose the second level, “watch,” when the rainfall condition is above the ED thresholds. We then adopt the third level, “warning,” and the fourth level, “severe warning,” based on the probability of landslide occurrence determined via a Bayesian model that considers several factors including the rainfall conditions of landslide vs. non-landslide and various rainfall variables such as hourly maximum rainfall and 3-day antecedent rainfall conditions. The proposed alert level predicted a total of 98.2% of the landslide occurrences at the levels of “severe warning” and “warning” as a result of the model fitness verification. The false alarm rate is 0% for the severe warning level and 47.4% for the warning level. We propose using the optimal ED thresholds to forecast when landslides are likely to occur in the local region. Additionally, we propose the ranges of rainfall variables that represent a high landslide probability based on the Bayesian model to set the landslide warning standard that fits the local area’s characteristics.

**Keywords** Rainfall threshold · Landslide early warning system · Bayesian model · Probabilistic method · Landslide warning levels

### Introduction

Rainfall-induced landslides can result in damage to life and property. On a global scale, 4862 landslides were recorded between 2004 and 2016, causing 55,997 fatalities (Petley 2012; Froude and Petley 2018). The majority of human losses to landslides occur in Asia, usually in the summer months of the Northern Hemisphere (Petley 2012). Chuncheon is located in the northern central part of South Korea in eastern Asia, and the major cause of landslides is

the heavy rainfall that occurs in the summer monsoon season. For instance, on 27 July 2011, landslides in Chuncheon caused by heavy rainfall resulted in approximately 37 casualties (Sung 2012) and approximately 4 million USD in property damage according to the historical records in the National Disaster Management System for Chuncheon City. Therefore, it is of great importance to obtain predictions and alerts for landslides considering their causes and probability of occurrence to issue timely landslide hazard warnings to prevent similar tragedies. To determine the alarm level of landslide occurrence, it is necessary to define the rainfall threshold for the initiation of landslides and identify the rainfall conditions associated with a high probability of landslide occurrence.

Researchers have studied the relationship between rainfall and landslides, ever since Caine (1980) proposed the rainfall intensity–duration (ID) thresholds by analyzing 73 rainfall events related to shallow landslides and debris flows around the world. Guzzetti et al. (2008) revised and supplemented ID thresholds to suggest a minimum rainfall threshold for landslide initiation on a global scale which identifies changing trends in rainfall intensity at 48 h of rainfall duration, and to calculate regional rainfall thresholds according to the Köppen climatic regions. In addition to the ID threshold, research on ED thresholds is based on the conditions of rainfall events that caused landslides in the past (Innes 1983; Wiczorek 1987; Crosta 1998; Kanji et al. 2003). Gariano et al. (2015) recently calculated and verified ED thresholds in Italy. Piciullo et al. (2017) also calculated ED thresholds in Italy and applied the same verification method to the study of a local landslide early warning model. Peruccacci et al. (2017) derived the 5th percentile ED threshold curve for rainfall-induced landslide in Italy as well as the ED thresholds for each local area according to environmental conditions such as geomorphic setting, geology, soil, land cover, climatic region, and average annual rainfall.

Studies on the rainfall thresholds at which landslides begin typically focus on ID and ED thresholds (Guzzetti et al. 2008; Segoni et al. 2018b). Since the ID and ED thresholds are based on rainfall events, the definition of a rainfall event has a significant effect on the threshold setting. A rainfall event is divided by a non-rainfall period in an objective way to separate the case whether the rainfall event affects the landslide. In general, studies distinguish rainfall events based on a 24-h non-rainfall period (Guzzetti et al. 2008; Saito et al. 2010; Chen et al. 2015; Kim et al. 2013; Oh and Park 2014; Hong et al. 2016; Kang and Kim 2016; Lee and Kim 2017; Park et al. 2018). Brunetti et al. (2010) separated rainfall events based on a non-rainfall period to account for different meteorological regimes, 48-h periods without rainfall during the dry and warm season (May–September), and 96-h periods without rainfall during the wet and cold season (October–April). Hong et al. (2016) analyzed ID rainfall thresholds for landslide occurrence depending

on the various kinds of rainfall events, split by 6, 12, 24, 48, 72, and 96 h without rainfall.

The ID and ED thresholds are deterministic methods and can be used to determine the critical threshold values for the initiation of landslides. Deterministic methods can clearly distinguish rainfall thresholds for debris flows (Berti and Simoni 2005; Coe et al. 2008; Berti et al. 2012). However, in most cases, landslides can be affected not only by rainfall but also by time-related factors such as soil moisture (Valenzuela et al. 2018), the distribution of pore water pressure, the weathering and binding of materials, and long-term changes in local stress fields (Fell et al. 2000; Leroueil 2001). Slope failure is challenging to predict based only on rainfall, and it can be more easily identified using a combination of related factors. There are certain cases where a landslide does not occur even when the rainfall thresholds are exceeded. Thus, the probability of landslide occurrence should be estimated based on more specific rainfall variables.

Studies of ID and ED thresholds (Guzzetti et al. 2008; Saito et al. 2010; Lee and Sung 2018; Gariano et al. 2015; Piciullo et al. 2017; Peruccacci et al. 2017; Gariano et al. 2020) using the quantile regression analysis method or frequentist method can provide the percentile regression equation for each percentile. However, ID and ED thresholds have a limit in that they are established using only the characteristics of rainfall events that cause landslides. Rainfall intensity is the average value of cumulative rainfall divided by rainfall duration, and cumulative rainfall is the sum of the hourly precipitation in a rainfall event. Therefore, both rainfall variables do not directly reflect the hourly maximum rainfall. Gariano et al. (2020) pointed out that ED thresholds are preferable to ID thresholds as the two variables measure independent quantities. That is why we calibrate only the ED thresholds. However, the ED thresholds do not provide rainfall characteristics with a probability of landslide occurrence when rainfall conditions are above the rainfall thresholds. They also do not reflect the amount of antecedent rainfall before the rainfall event since their thresholds are set according to each rainfall event's rainfall variables. Antecedent rainfall is crucial to the landslide occurrence mechanism due to the increase of pore water pressure and the deterioration of slope stability (Crozier 1999; Iverson 2000; Glade et al. 2000; Segoni et al. 2018b; Valenzuela et al. 2018). Wicki et al. (2020), Rosi et al. (2020), Kim et al. (2020), Yang et al. (2020), and Ponziani et al. (2012) highlighted the necessity of using antecedent rainfall or other proxies to account for more complex hydrological conditions.

To overcome these limitations, after Berti et al. (2012), we first analyzed the probability of landslide occurrence using a Bayesian method, including rainfall events that caused landslides and rainfall events that did not cause landslides. Second, we considered the antecedent rainfall and the hourly maximum rainfall in the Bayesian model. Finally, we analyzed the probability of a landslide occurrence by the interval range of rainfall variable values using one-dimensional and two-dimensional Bayesian methods in which to determine the landslide early warning system (LEWS) criteria.

This study aims to establish the criteria for a warning model within a LEWS. We propose to derive ED threshold equations and use them as thresholds for the second level of landslide warning. Furthermore, to establish the third and fourth warning levels (the second-highest and highest levels, respectively), the Bayesian model determines the probability of landslide occurrence based on the

interval of rainfall variables, including rainfall intensity, cumulative event rainfall, rainfall duration, antecedent rainfall, and hourly maximum rainfall.

### Study area

Chuncheon (1116.83 km<sup>2</sup>) is located in the central northern part of the Republic of Korea (Fig. 1). According to the Köppen–Geiger climate classification, Chuncheon belongs to the Dwa (monsoon-influenced hot-summer humid continental climate) region with dry winters and intense rainfall in the summer (Peel et al. 2007). The average annual rainfall in Chuncheon is 1312.9 mm and the average monthly rainfall is 19.6 mm in January (winter). The average monthly rainfall (maximum rainfall) in the typical monsoon period (June, July, August, and September) in Chuncheon is 128.4 (459.6) mm, 375.3 (932.5) mm, 299.8 (785.2) mm, and 144.2 (491.9) mm, respectively. Chuncheon has not been hit by an earthquake with a magnitude greater than 2.0 for 40 years, and therefore the area is fit for investigating rainfall-triggered landslides. Chuncheon has a basin surrounded by a mountainous topography with elevations ranging from 5.2 to 1437.5 a.s.l. Its main geomorphic feature is this basin that has been affected by differential erosion. The basin's interior is composed of biotite granite (the Chuncheon granite), and the mountainous area is mainly composed of gneiss and schist. Lee et al. (2020) analyzed the geo-environmental variables that represent this highly susceptible area in Chuncheon characterized by an elevation of 100~200 m, a slope of 15~25°, concave curvature, high stream power index, a distance of 100~200 m to the river, young timber age, loose timber density, artificial forest, coniferous forests, a soil depth of 50~100 cm, and sandy loam soil. The main types of landslides that occur in Chuncheon include translational slides (debris slides, earth slides, and debris block slides), rotational slides (debris slump and earth slump), and flows (debris flows and earth flows) (Lee et al. 2020). The typical sizes of the landslides tend to have a length of 20 to 200 m and a width of 3 to 20 m from the landslide investigation reports in 2013 by Chuncheon City.

### Data

#### Rainfall data

Hourly rainfall data were collected using seven tipping-bucket rain recorders installed by the Han River Flood Control Office (HRFCO) of the Korean Ministry of Land, Infrastructure, and Transport (MLIT). We used data from gauging stations (Jichon, Hwaak, Gapyeong 2, Cheonjeon, Bukbang, Chuncheon, and Seomyeon) in Chuncheon. The analysis period spanned 19 years from 1999 and 2017 for all stations but Jichon, where the analysis spanned from 2003 to 2017 due to different starting dates of rainfall measurement. Although there is uncertainty in defining rainfall events that caused landslides, they can be defined consistently by distinguishing them based on the specific period of non-rainfall (Guzzetti et al. 2008; Brunetti et al. 2010; Berti et al. 2012). We constructed rainfall variables according to the definition of four types of rainfall events split by 12 h, 24 h, 48 h, and 96 h of non-rainfall. As only the dates of the heavy rainfall that caused landslides in Chuncheon were available, we defined cumulative rainfall for an event in the three different ways as follows:

First, the “total cumulative amount of rainfall” refers to the sum of all hourly rainfalls within one rainfall event. For instance, if

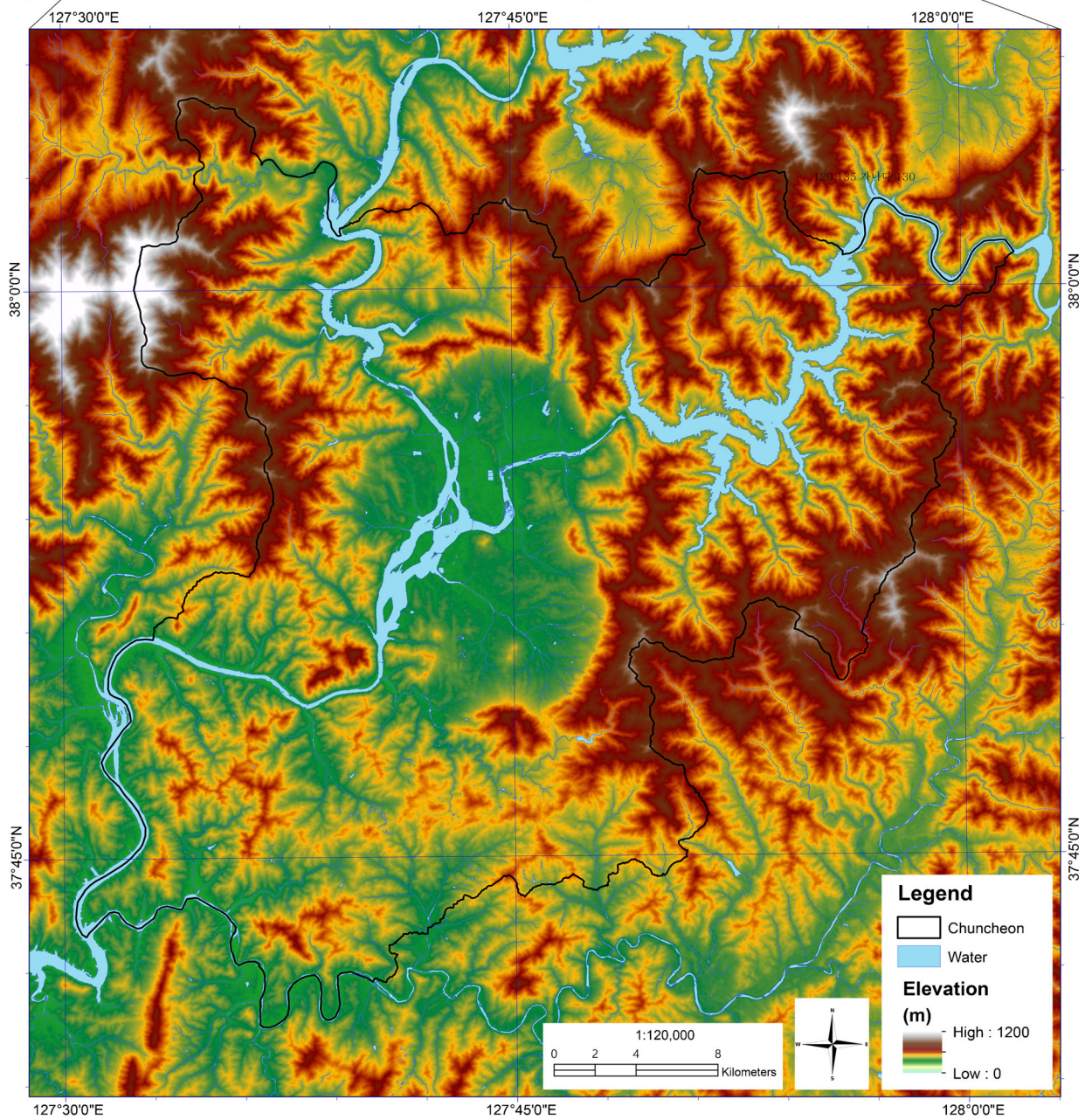


Fig. 1 Location of Chuncheon City and its geomorphic setting

we divide the rainfall event by 12 h of the non-rainfall, the starting point of cumulative event rainfall is after over the 12 h of non-rainfall period, and the ending point of cumulative event rainfall is just before over the 12-h non-rainfall period. Second, the “amount accumulated up to the point of the hourly maximum rainfall” means that the starting point of the cumulative event rainfall is the same as the starting point of the “total cumulative amount of rainfall,” and the ending point of cumulative event rainfall is the hourly maximum rainfall of the rainfall event since, according to some authors, in specific conditions many landslides tend to occur at the highest recorded hourly rainfall (Wieczorek 1996; Chen et al. 2015). If the same hourly maximum rainfall occurs twice, we used the most recent hourly maximum rainfall value as the classification criterion. Third, the “amount accumulated up to 3 hours after the point of the hourly maximum rainfall” means that the ending point of cumulative event rainfall is 3 h after the hourly maximum rainfall in a rainfall event. This is due to the fact that the cumulative rainfall after the peak rainfall can affect landslide occurrence (Kim et al. 2013; Chen et al. 2015). Based on these definitions, we constructed three versions of the rainfall duration, cumulative event rainfall, and rainfall intensity. Besides, we established rainfall variables such as hourly maximum rainfall, 3-day antecedent rainfall, and 14-day antecedent rainfall according to the four types of rainfall event for the Bayesian model.

#### Landslide data

We obtained the landslide occurrence area from Chuncheon City’s disaster register data for 19 years between 1999 and 2017. Of these years, 757 landslides occurred at the seven distinct heavy rainfall events in 1999, 2002, 2006, 2009, 2011, 2013, and 2016. We constructed point data as a center of parcel data in all the years except 2013. In particular, in 2013, Chuncheon City recorded relatively accurate landslide location information on the updated landslide occurrence list. For this reason, we compared landslide locations in 2013 with orthophotos from the National Geographic Information Institute (NGII) and digital aerial photographs provided on an Internet portal (<http://map.daum.net>). Thiessen polygons were created based on rainfall station data, and altitude data and administrative area maps were overlaid and analyzed to determine the range of influence for each station (Fig. 2) (Tiranti et al. 2019; Wu and Yeh 2020). We then aggregated landslide occurrence points with each influential range of the seven stations where rainfall data were collected.

#### Methodology

##### Cumulative event rainfall–duration thresholds

To calculate the rainfall threshold for landslide initiation with cumulative event rainfall and duration (ED) data, we first conducted a quantile regression analysis (Koenker 2009) using the R programming language to establish a threshold of second percentiles. The expression for the ED threshold is as follows:

$$E = \alpha D^{\beta} \quad (1)$$

where  $\alpha$  is a constant representing the threshold curve and is the intercept value of the cumulative event rainfall amount  $E$  when the rainfall duration  $D$  is equal to 1. Since  $\beta$  is a positive value, the

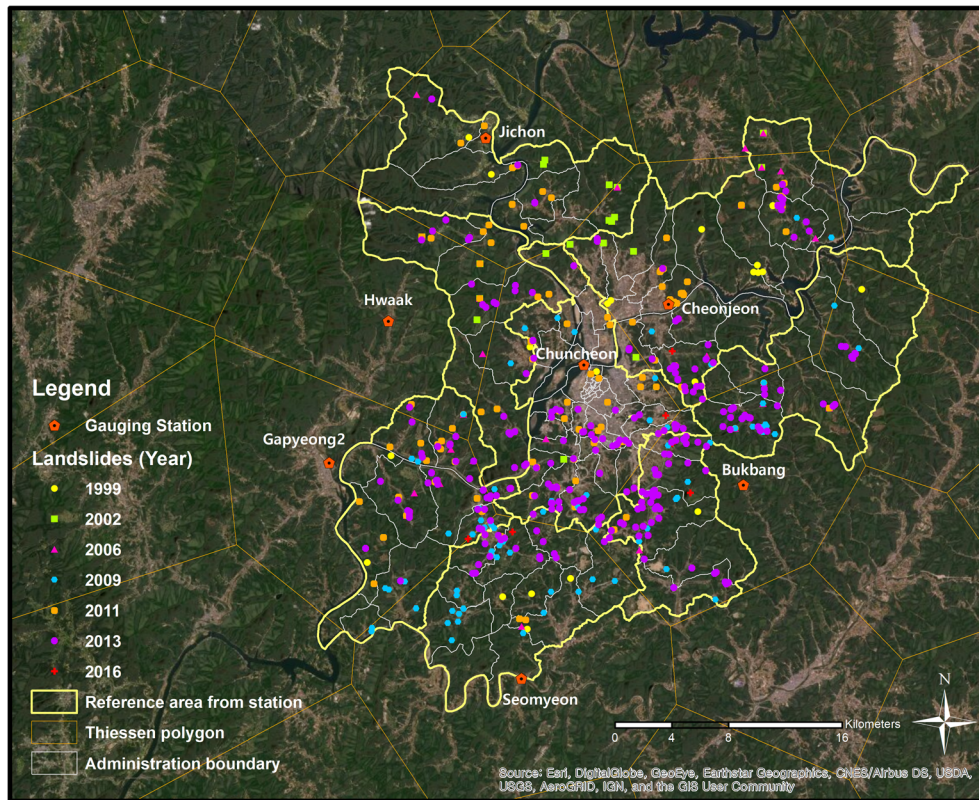
larger the value of  $\beta$ , the steeper the slope of the threshold equation.

##### Verification of ED thresholds

Gariano et al. (2015) utilized a validation method using a contingency table and skill score of rainfall-induced landslide thresholds, and this method was later used in the research of Piciullo et al. (2017) and Lee and Kim (2017). The basic concepts of contingencies include whether the event occurs or not and whether the model predictions are correct or wrong (Wilks 2011; Accadia et al. 2003; Frattini et al. 2010; Staley et al. 2012). Contingencies (true positives [TPs], false positives [FPs], false negatives [FNs], true negatives [TNs]) can be obtained based on the rainfall conditions, which are either lower or higher than the rainfall thresholds, and whether a landslide occurred or did not occur (Table 1). The definition of the contingencies is as follows. TPs indicate that the rainfall variable condition is higher than the threshold and that one or more landslides occurred. FNs are when the rainfall conditions are lower than the rainfall thresholds and one or more landslides occurred. FPs are when rainfall conditions are above the thresholds but no landslides occurred or were reported. TNs refer to cases where rainfall conditions are below the threshold and no landslides occurred or were reported. From the values of contingencies, we can calculate the probability of detection (POD), the probability of false detection (POFD), the probability of false alarm (POFA), and the Hanssen and Kuipers (1965) (HK) skill score (Table 2). Among them, the HK skill score (also known as Peirce’s skill score) is defined as the POD minus the POFD (Peirce 1884; Hanssen and Kuipers 1965). Besides, the Euclidean distance from optimal classification ( $\delta$ ) is calculated by adding SQRT to the sum of the square of POFD and the square of 1 minus POD (Table 2). The higher the HK skill score, and the lower the  $\delta$  value, the higher the accuracy of the landslide prediction. Based on these skill scores, this study verified the adequacy of the ED thresholds for landslide occurrence and established the optimal threshold for a landslide early warning system.

##### Bayesian model for landslide probability

Probabilistic methods, such as Bayesian analysis, have the following advantages (Berti et al. 2012). First, they can be used to numerically evaluate more reliable thresholds for landslides since they incorporate variability and uncertainty. For instance, existing thresholds, such as ED thresholds, do not provide the probability of landslide occurrence when rainfall exceeds the thresholds. This causes uncertainty about how many times a landslide will occur according to the interval of rainfall variables. However, probabilistic analysis can consider the distribution of rainfall that does not result in landslides, which makes it much more informative and assigns reliability to a given threshold. Second, probabilistic methods can help in estimating extreme events by providing a distribution of the probability of landslide occurrence. The categorized forecast levels can be derived from the results of landslide probability according to the rainfall conditions. Meanwhile, deterministic methods can only split rainfall cases into a landslide occurred case or no landslide occurred one based on the rainfall thresholds. Finally, the probabilistic approach, which is generally used for quantitative risk assessment, determines the confidence level of the prediction (Refice and Capolongo 2002; Berti et al. 2012).



**Fig. 2** The reference area from seven gauging stations and the locations of landslide occurrences between 1999 and 2017 in Chuncheon, Republic of Korea

The Bayesian theorem utilizes conditional probabilities, and we can determine the probability of “A” occurring under the conditions of “B.” In the one-dimensional model, the conditional probability is obtained through the relationship between an event “A” and a specific condition “B.” The formulation of the one-dimensional Bayesian model is as follows:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (2)$$

where *A* refers to landslides and *B* refers to rainfall conditions. *P*(*A*) is the prior probability that landslide (*A*) occurs with or without *B*-scale rainfall conditions. *P*(*B*) is the probability that *B*-scale rainfall is observed regardless of the occurrence of landslides (*A*). *P*(*B*|*A*) refers to the likelihood of a *B*-scale rainfall condition when landslides (*A*) occur. *P*(*A*|*B*) is the conditional probability that landslides (*A*) will occur when there is a *B*-scale rainfall

condition. To identify the probability of landslide occurrence under certain rainfall conditions, we analyzed cumulative event rainfall, rainfall duration, rainfall intensity, hourly maximum rainfall, 3 days of antecedent rainfall, and 14 days of antecedent rainfall according to the one-dimensional Bayesian model.

In the two-dimensional model, conditional probabilities are obtained from the relationship between event *A* and the two conditions *B* and *C*. The equation of the two-dimensional Bayesian model is as follows:

$$P(A|B, C) = \frac{P(B, C|A) \times P(A)}{P(B, C)} \quad (3)$$

where *P*(*A*) is the prior probability that landslide *A* will occur regardless of the *B* and *C* rainfall conditions. *P*(*B*,*C*) refers to the probability that *B*- and *C*-scale rainfall is observed regardless of the occurrence of landslides (*A*). *P*(*B*,*C*|*A*) represents the

**Table 1** Contingencies used for landslide occurrence and rainfall thresholds

Predicted landslides		Occurred (+)	Observed landslides	Did not occur (–)
Rainfall thresholds	Above the threshold (+)	TP (+   +)		FP (+   –)
	Below the threshold (–)	FN (–   +)		TN (–   –)

**Table 2** Definitions and formulas for skill scores

Skill score	Definition	Formula
The probability of detection score (POD)	Percentage of rainfall variables above the threshold when landslides occur	$POD = TP/(TP + FN)$
The probability of false detection score (POFD)	Percentage of rainfall variable values above the threshold when no landslide occurred or was reported	$POFD = FP/(FP + TN)$
The probability of false alarm score (POFA)	Percentage of no landslide occurred or was reported when the rainfall variables are above the threshold	$POFA = FP/(TP + FP)$
The Hanssen and Kuipers (1965) skill score (HK)	The probability of detection score minus the probability of false detection score	$HK = \{TP/(TP + FN)\} - \{FP/(FP + TN)\} = POD - POFD$
$\delta$	The Euclidean distance from the perfect classification	$\delta = \text{SQRT}\{(POFD)^2 + (1 - POD)^2\}$

SQRT, square root

likelihood of *B*- and *C*-scale rainfall conditions during landslide *A*.  $P(A|B,C)$  is the conditional probability that landslide *A* will occur under *B*- and *C*-scale rainfall conditions. In this study, to determine the probability of landslide occurrence under two rainfall variable conditions, we analyzed “cumulative event rainfall and rainfall duration,” “rainfall intensity and rainfall duration,” “cumulative event rainfall and hourly maximum rainfall,” and “cumulative event rainfall and 3-day antecedent rainfall” using the two-dimensional Bayesian model. The analysis results were displayed in the form of a 3D bar graph using the Origin Evaluation 2020b software (OriginLab, Northampton, MA, USA).

## Results

### ED thresholds

The ED threshold equations for rainfall events, with non-rainfall periods of 12 h, 24 h, 48 h, and 96 h, are calculated as shown in Table 3 and Fig. 3 according to the three types of rainfall events.

The slopes of the ED thresholds were relatively gentle under the various types of rainfall events (12ED<sub>total</sub>, 24ED<sub>total</sub>, 96ED<sub>max3</sub>, and 96ED<sub>max</sub>), which shows that the longer the rainfall duration, the smaller the rate of increase in the cumulative event rainfall that resulted in landslides. The absolute value of  $\beta$  in the ED thresholds (12ED<sub>total</sub> and 24ED<sub>total</sub>), based on the total cumulative rainfall, had a minimum value of 0.205 (Table 3, Fig. 3). Additionally, the absolute values of  $\beta$  in the ED thresholds (96ED<sub>max3</sub> and 96ED<sub>max</sub>) were 0.328 and 0.375, respectively. The effect of the difference in cumulative event rainfall is more important than the rainfall duration since the rate of change of cumulative event rainfall is low compared to the rainfall duration.

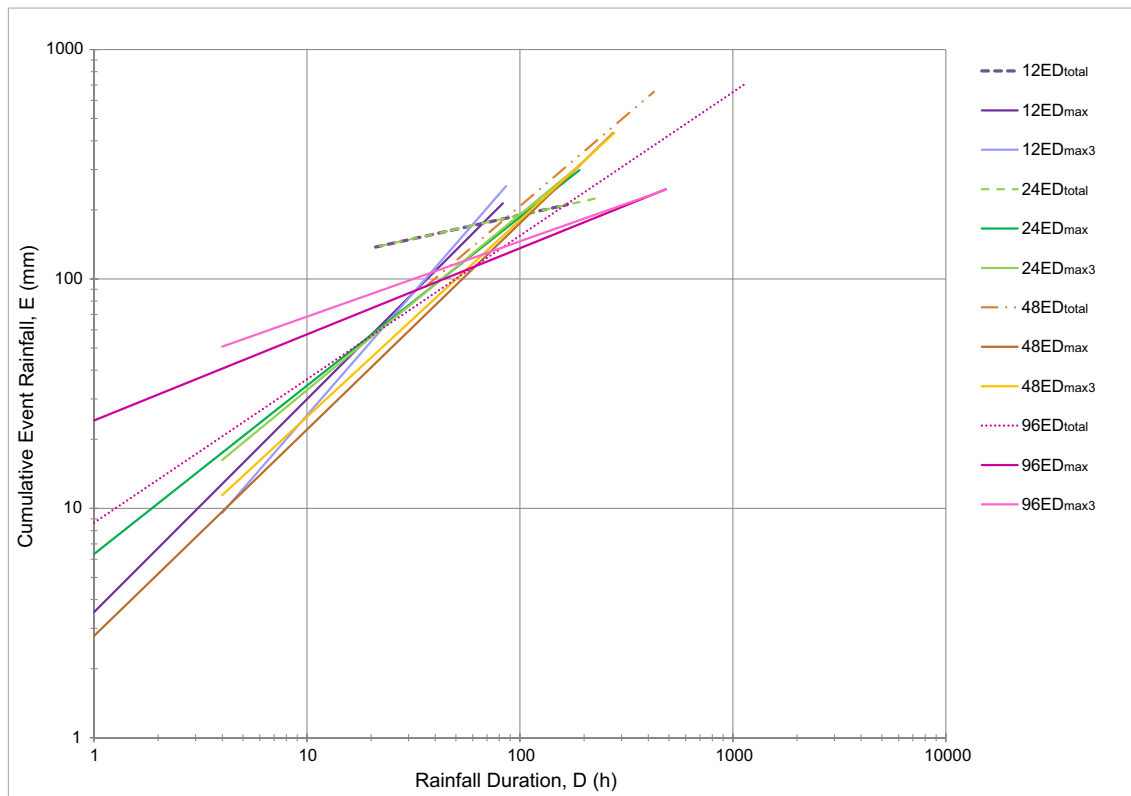
### Verification of ED thresholds

We calibrated the ED threshold equation from the rainfall conditions of 42 rainfall events in which a landslide occurred during the 19 years between 1999 and 2017 in Chuncheon and constructed a contingency table with all the rainfall events to verify the ED

**Table 3** Cumulative event rainfall duration (ED) threshold formulations based on the definition of various types of rainfall events

Types of rainfall events with different non-rainfall periods	ED threshold equation	$\alpha$	$\beta$
12ED <sub>total</sub>	$E = 73.915D^{0.2046}$ ( $21 \leq D \leq 167$ )	73.91476	0.2045692
12ED <sub>max</sub>	$E = 3.5313D^{0.9285}$ ( $1 \leq D \leq 83$ )	3.531283	0.9284508
12ED <sub>max3</sub>	$E = 2.1745D^{1.0685}$ ( $4 \leq D \leq 86$ )	2.174461	1.0685249
24ED <sub>total</sub>	$E = 73.915D^{0.2046}$ ( $22 \leq D \leq 231$ )	73.91476	0.2045692
24ED <sub>max</sub>	$E = 6.3178D^{0.7343}$ ( $1 \leq D \leq 190$ )	6.317764	0.7342732
24ED <sub>max3</sub>	$E = 5.6283D^{0.7652}$ ( $4 \leq D \leq 193$ )	5.628273	0.7652164
48ED <sub>total</sub>	$E = 5.4002D^{0.7926}$ ( $36 \leq D \leq 425$ )	5.400179	0.7925535
48ED <sub>max</sub>	$E = 2.7804D^{0.8994}$ ( $1 \leq D \leq 274$ )	2.780397	0.8993965
48ED <sub>max3</sub>	$E = 3.4756D^{0.8577}$ ( $4 \leq D \leq 277$ )	3.475571	0.8576778
96ED <sub>total</sub>	$E = 8.6545D^{0.6257}$ ( $108 \leq D \leq 1135$ )	8.654464	0.6257138
96ED <sub>max</sub>	$E = 24.147D^{0.3753}$ ( $1 \leq D \leq 483$ )	24.14699	0.3752865
96ED <sub>max3</sub>	$E = 32.185D^{0.3283}$ ( $4 \leq D \leq 486$ )	32.18534	0.3283282

In the abbreviations in the first column, the first two numbers denote the non-rainfall periods as the criteria for dividing the event rainfalls, and the suffixes total, max, and max3 indicate different durations of cumulative rainfall, namely total cumulative rainfall, cumulative rainfall until the time of hourly maximum rainfall, and cumulative rainfall until the 3 h after the time of hourly maximum rainfall, respectively. In the second column,  $D$  refers to the rainfall duration of the rainfall event and  $E$  refers to the cumulative event rainfall.  $\alpha$  means a constant and  $I$ -intercept value, and  $\beta$  is the slope value for the threshold curve



**Fig. 3** ED threshold curves according to the types of rainfall event. In the abbreviations, the first two numbers denote the non-rainfall periods as the criteria for dividing the event rainfalls, and the suffixes total, max, and max3 indicate different durations of cumulative rainfall, namely total cumulative rainfall, cumulative rainfall until the time of hourly maximum rainfall, and cumulative rainfall until the 3 h after the time of hourly maximum rainfall, respectively

threshold. The  $12ED_{total}$  threshold had the highest hit rate for landslide occurrence in terms of the HK skill score and Euclidean distance. The skill score analysis of the ED threshold equations showed that the HK skill scores from the formulas of  $12ED_{total}$ ,  $24ED_{total}$ , and  $96ED_{max3}$  were 0.979, 0.977, and 0.923, respectively (Table 4). The Euclidean distance values from the optimal points at  $12ED_{total}$ ,  $24ED_{total}$ , and  $96ED_{max3}$  were close, namely 0.021, 0.023, and 0.058. When non-rainfall periods for the criterion for a rainfall event were 12, 24, and 48 h, the thresholds with the total cumulative rainfall obtained the highest skill scores. However, the 96ED thresholds with cumulative rainfall up until the 3 h after the hourly maximum rainfall had the highest skill score among the three different cumulative rainfall definitions.

### Bayesian model

**One-dimensional Bayesian model** We analyzed six rainfall variables—cumulative event rainfall, rainfall duration, rainfall intensity, hourly maximum rainfall, 3-day antecedent rainfall, and 14-day antecedent rainfall—based on the rainfall event split by the over 12 h of non-rainfall which has the highest skill score. The results of analyzing the probability of landslide occurrence using the intervals of rainfall variables with the 1-D Bayesian model are as follows.

First, when the cumulative event rainfall exceeded 450 mm (0.2% marginal probability of rainfall), the probability of landslide occurrence was 100%. However, when the cumulative event rainfall

was less than 150 mm, no landslide occurred. As the cumulative event rainfall increased, the probability of landslide occurrence tended to increase (Fig. 4(a)). Second, when the rainfall duration was 4–5 days (96–120 h) (0.2% marginal probability of rainfall), the probability of landslide occurrence was the highest, at 73.3%. When the rainfall duration was 3–4 days (72–96 h; 0.6% marginal probability of rainfall), the probability of landslide occurrence was the second highest, at 23.3% (Fig. 4(b)). Third, when the rainfall intensity was 8–10 mm/h, the probability of landslide occurrence was the highest, at 13.4%. The highest landslide probability for rainfall intensity was lower than the highest landslide probability for cumulative event rainfall, rainfall duration, hourly maximum rainfall, and 3-day antecedent rainfall conditions (Fig. 4(c)).

Fourth, when the hourly maximum rainfall amount exceeded 40 mm, the probability of landslide occurrence was more than 20%. Meanwhile, when the hourly maximum rainfall was less than 20 mm, the probability of landslide occurrence was 0%. Therefore, hourly maximum rainfall thresholds of 40 mm or more and 20 mm or less can be significant factors for predicting landslide occurrence (Fig. 5(a)). Fifth, when the 3-day antecedent rainfall exceeded 300 mm, the probability of landslide occurrence was the highest, at 25% (Fig. 5(b)). Although the 3-day antecedent rainfall ranged from 200 to 300 mm, the probability of landslides was low as the rainfall variables (such as cumulative event rainfall, rainfall duration, and rainfall intensity) of the rainfall event that are directly related to landslide triggering are more significant than

**Table 4** The values of contingencies and skill scores for the various types of rainfall threshold

Type of rainfall threshold	TP	FN	FP	TN	POD	POFD	POFA	HK	$\delta$
12ED <sub>total</sub>	42	0	145	6799	1	0.021	0.775	0.979	0.021
12ED <sub>max</sub>	40	2	1782	5162	0.952	0.257	0.978	0.696	0.261
12ED <sub>max3</sub>	40	2	1915	5029	0.952	0.276	0.980	0.677	0.280
24ED <sub>total</sub>	42	0	135	5633	1	0.023	0.763	0.977	0.023
24ED <sub>max</sub>	40	2	965	4803	0.952	0.167	0.960	0.785	0.174
24ED <sub>max3</sub>	42	0	998	4770	1	0.173	0.960	0.827	0.173
48ED <sub>total</sub>	40	2	444	4127	0.952	0.097	0.917	0.855	0.108
48ED <sub>max</sub>	42	0	1450	3121	1	0.317	0.972	0.683	0.317
48ED <sub>max3</sub>	40	2	1042	3529	0.952	0.228	0.963	0.724	0.233
96ED <sub>total</sub>	40	2	210	2682	0.952	0.073	0.840	0.880	0.087
96ED <sub>max</sub>	40	2	152	2740	0.952	0.053	0.792	0.900	0.071
96ED <sub>max3</sub>	41	1	153	2739	0.976	0.053	0.789	0.923	0.058

TP, the number of landslide occurrences when the rainfall was higher than the threshold; FN, the number of landslide occurrences when the rainfall did not exceed the thresholds; FP, the number of cases when a landslide did not occur when the rainfall exceeded the threshold; TN, the number of cases when a landslide did not occur when rainfall was lower than the threshold; POD, the probability of detection score; POFD, the probability of false detection score; POFA, the probability of false alarm score; HK, the Hanssen and Kuipers skill score;  $\delta$ , Euclidean distance from the perfect classification

the 3-day antecedent rainfall. Sixth, when the 14-day antecedent rainfall was 300–350 mm, the probability of landslide occurrence was the highest, at 5.5% (Fig. 5c). This indicates that the 14-day antecedent rainfall was not an essential variable for landslide occurrence since the probability of a landslide occurring for all values of 14-day antecedent rainfall was the lowest compared to the other rainfall variables.

As the values of event rainfall duration, rainfall intensity, and hourly maximum rainfall increased, the trend of landslide probability did not increase consistently and slightly decreased (Fig. 4(b, c), Fig. 5(a)). This trend was either because we have considered only one rainfall variable or because there were not many rainfall events that caused landslides. Therefore, in the 2D Bayesian analysis, the probability of landslides is determined by considering the two rainfall variables.

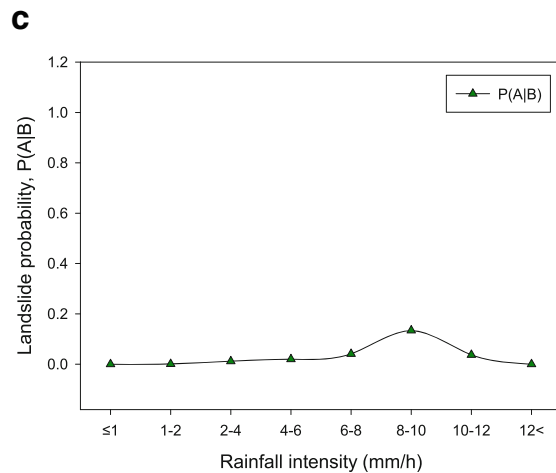
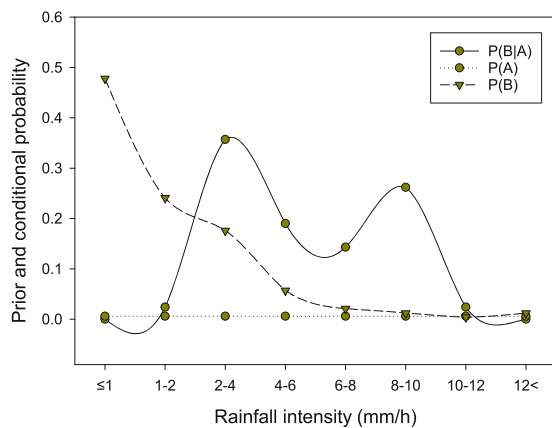
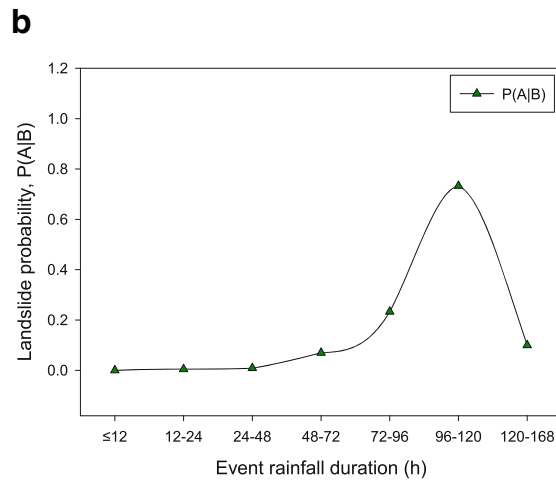
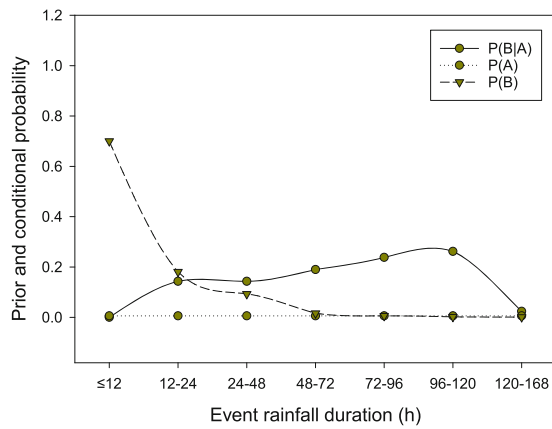
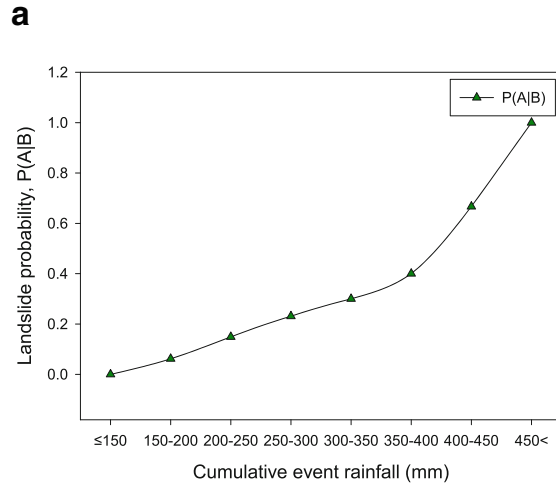
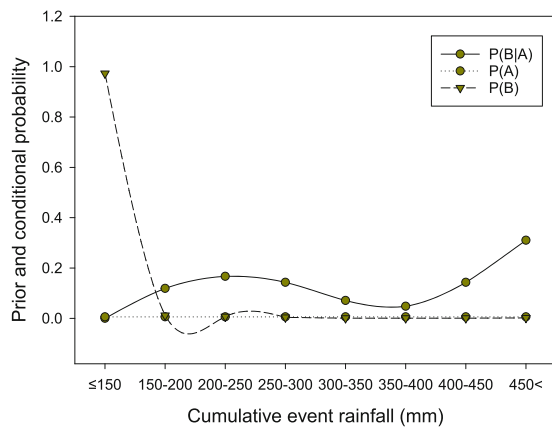
*Two-dimensional Bayesian model* In the two-dimensional Bayesian model, we selected two rainfall variables among five variables—the cumulative event rainfall, rainfall duration, rainfall intensity, hourly maximum rainfall, 3-day antecedent rainfall. (The 14-day antecedent rainfall was not considered as it was not crucial in the one-dimensional Bayesian model.) In other words, the two-dimensional Bayesian model derived landslide probabilities based on rainfall events which are defined by over 12 h of inter-event time: cumulative event rainfall and rainfall duration, rainfall intensity and rainfall duration, cumulative event rainfall and hourly maximum rainfall, and cumulative event rainfall and 3-day antecedent rainfall.

The landslide probabilities for cumulative event rainfall and rainfall duration determined using the two-dimensional Bayesian model are as follows (Table 5, Fig. 6). In the case of cumulative event rainfall and rainfall duration, when the cumulative event rainfall exceeded 450 mm (0.014–0.086% marginal probability of rainfall), it was found that the probability of landslide occurrence

was 100% when the rainfall duration was more than 48 h. Furthermore, when the rainfall duration was 96–120 h (0.04–0.057% marginal probability of rainfall), the probability of landslide occurrence was 100% when the cumulative event rainfall exceeded 250 mm. For a rainfall duration of 48–72 h (0.01% marginal probability of rainfall), the probability of landslide occurrence was 100% even when the cumulative event rainfall was 400–450 mm. When the rainfall duration was short (24–48 h), the probability of landslide occurrence was 100% when the cumulative event rainfall was 300–350 mm (0.01% marginal probability of rainfall). Furthermore, for shorter rainfall durations (12–24 h), the probability of landslide occurrence was 57.1% when the accumulated rainfall amount was 200–250 mm (0.1% marginal probability of rainfall).

Second, the two-dimensional Bayesian model of rainfall intensity and duration shows the characteristics of the rainfall-induced landslide in Chuncheon. The main characteristics of the results are that landslides occur when there is a long rainfall duration and mild rainfall intensity and when there is a short rainfall duration and high rainfall intensity. The two-dimensional Bayesian probabilities of rainfall intensity and duration are as follows (Table 6, Fig. 7). For rainfall durations of 48–72 h (2–3 days), the probability of landslide occurrence was 100% when the rainfall intensity was 6–10 mm/h (0.029% marginal probability of rainfall). When the rainfall duration was 96–120 h (4–5 days), the probability of landslide occurrence was 100% when the rainfall intensity was 4–8 mm/h (0.014–0.043% marginal probability of rainfall); and when the rainfall intensity was 2–4 mm/h (0.1% marginal probability of rainfall), the probability of landslide occurrence was 85.7%. When the rainfall duration is 4–7 days, there will likely be a long period of soil moisture saturation as there are only 12 non-rainfall periods during the rainfall event. Thus, landslides can occur even with low rainfall intensity.

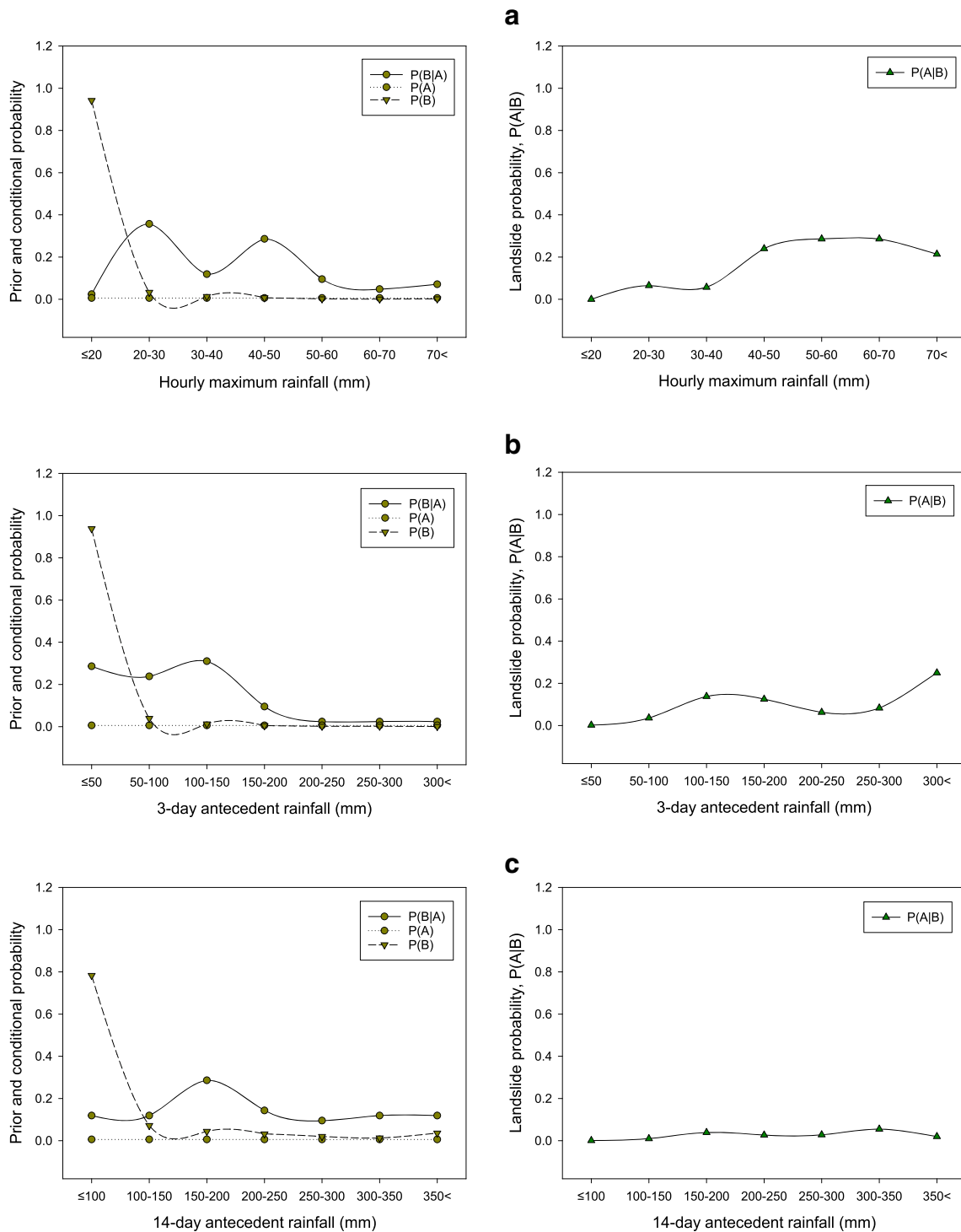




**Fig. 4** Results of the one-dimensional Bayesian analysis of the Chuncheon landslide dataset for cumulative event rainfall, event rainfall duration, and rainfall intensity. Plots in the left column show the prior landslide probability  $P(A)$ , the prior rainfall probability  $P(B)$ , and the conditional probability of  $P(B|A)$ . A comparison between the frequency distributions of triggering rainfall versus overall rainfall is possible by comparing  $P(B|A)$  and  $P(B)$ . Plots in the right column illustrate the landslide probability  $P(A|B)$  for different ranges of the considered rainfall variable

Third, the Bayesian two-dimensional model was used to determine the probability of landslide occurrence by the interval of the hourly

maximum rainfall according to the cumulative event rainfall (Table 7, Fig. 8). When the cumulative event rainfall exceeded 450 mm (0.04–



**Fig. 5** Results of the one-dimensional Bayesian analysis of the Chuncheon landslide dataset for hourly maximum rainfall, 3-day antecedent rainfall, and 14-day antecedent rainfall. Symbols are the same as in Fig. 4

0.057% marginal probability of rainfall), the probability of landslide occurrence was 100% when the hourly maximum rainfall amount exceeded 20 mm/h. When the cumulative event rainfall exceeded 400–450 mm, the probability of landslide occurrence was 100% when the hourly maximum rainfall exceeded 20 mm/h, except for hourly maximum rainfall range 30–40 mm, because the hourly maximum

rainfall reflects only the hourly rainfall when the peak hourly rainfall appears so that it may be affected by other rainfall variables. The probability of landslide occurrence was 100% when the cumulative event rainfall was 350–400 mm and the hourly maximum rainfall was 30–40 mm/h (0.04% marginal probability of rainfall). The two-dimensional Bayesian analysis of cumulative event rainfall and hourly maximum

**Table 5** Results of the two-dimensional Bayesian model for different rainfall durations and cumulative event rainfall

$(P(A B,C))$		Rainfall duration (h)						
		≤ 12	12–24	24–48	48–72	72–96	96–120	120–168
Cumulative event rainfall (mm)	≤ 150	0	0	0	0	0	0	No data
	150–200	0	0.118	0.063	0	0	0.333	0
	200–250	No data	0.571	0.143	0.077	0	0	0
	250–300	No data	0	0.167	0	0.4	1	0
	300–350	No data	0	1	0	0.5	1	No data
	350–400	No data	No data	0	No data	0.5	1	0
	400–450	No data	No data	No data	1	0.4	1	No data
	> 450	No data	No data	No data	1	1	1	1

rainfall helped to identify not only the normal state of rainfall but also the threshold of peak hourly rainfall with the potential to trigger landslides.

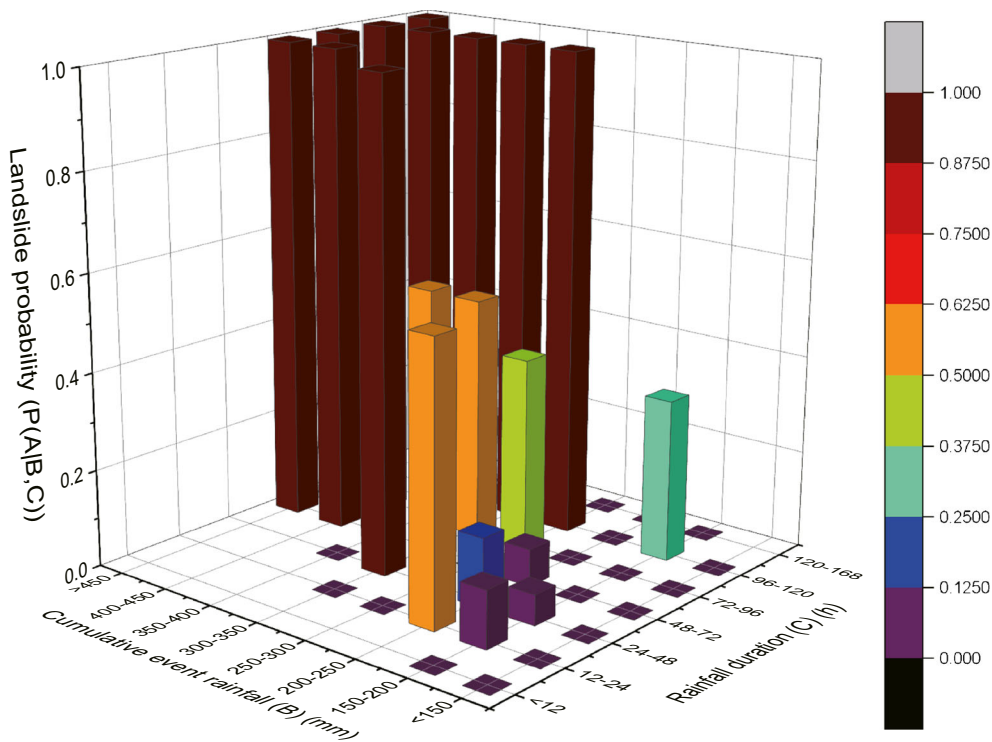
Fourth, the Bayesian two-dimensional model was used to determine the probability of landslide occurrence for different cumulative event rainfall and 3-day antecedent rainfall (Table 8, Fig. 9). When the cumulative event rainfall exceeded 300 mm, the probability of landslide occurrence was 100% when the 3-day antecedent rainfall exceeded 100 mm (0.04–0.029% marginal probability of rainfall). In the case of cumulative event rainfall of 200–250 mm, the probabilities of landslide occurrence were 100% and 50%, respectively, at 3-day antecedent rainfalls of 100–150 mm and 150–200 mm. When the cumulative event rainfall was small (150–200 mm), the probabilities of

landslide occurrence were 100% and 66.7% at 3-day antecedent rainfalls of 250–300 mm (0.04% marginal probability of rainfall) and 100–200 mm, respectively. These results suggest that cumulative event rainfall and 3-day antecedent rainfall are significant in that they not only reflect the characteristics of rainfall events but also take into account the prior rainfall associated with the soil moisture content before the rainfall event.

### Discussion

#### ED thresholds for landslide early warning system

According to the United Nations International Strategy for Disaster Reduction (UNISDR) (UNISDR 2009), an early warning system



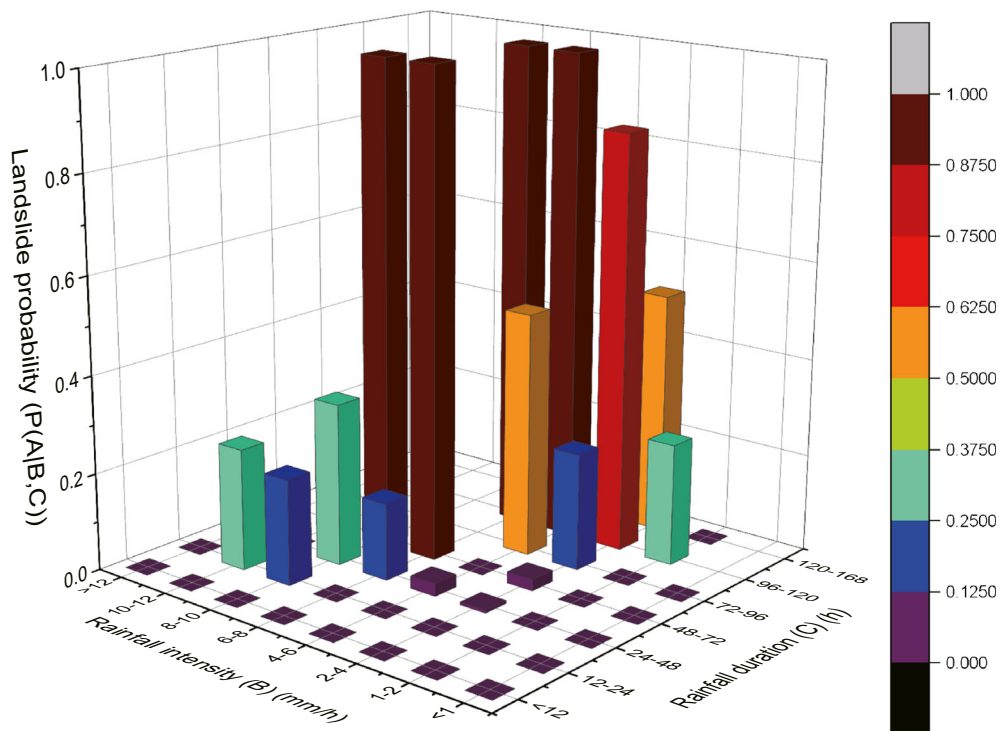
**Fig. 6** Graph showing the results of the two-dimensional Bayesian model for different cumulative event rainfalls and rainfall durations

**Table 6** Results of the two-dimensional Bayesian model for different rainfall durations and rainfall intensities

$(P(A B,C))$		Rainfall duration (h)						
		$\leq 12$	12–24	24–48	48–72	72–96	96–120	120–168
Rainfall intensity (mm/h)	$\leq 1$	0	0	0	0	0	No data	No data
	1–2	0	0	0	0	0	0.25	0
	2–4	0	0	0.006	0.024	0.24	0.857	0.5
	4–6	0	0	0.026	0	0.5	1	No data
	6–8	0	0	0.158	1	No data	1	No data
	8–10	0	0.217	0.333	1	No data	No data	No data
	10–12	0	0.25	0	No data	No data	No data	No data
	$> 12$	0	0	No data	No data	No data	No data	No data

refers to “the set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities and organizations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss.” Intrieri et al. (2013) described four main processes of a landslide early warning system, namely design, monitoring, forecasting, and education. The design part involves defining geological and meteorological geo-indicators according to the mechanism of landslide triggering and defining rainfall events that affect landslide initiation. The monitoring part mainly includes measuring rainfall in the case of rainfall-induced landslides. This study focused on which rainfall thresholds can be applied as criteria for warning levels and for issuing an accurate landslide alert at the appropriate time (forecasting).

It is not easy to consistently define the duration of a rainfall event which affects landslides since it is difficult to obtain accurate information about the exact occurrence time of landslides, which is essential for obtaining accurate forecasts of landslide occurrence (Brunetti et al. 2010; Gariano et al. 2015; Guzzetti et al. 2020). Hence, in this study, it was possible to define the rainfall event with the highest hit ratio of the ED thresholds among the various rainfall event conditions based on the non-rainfall period (12, 24, 48, 96 h). The 12ED<sub>total</sub> threshold has the highest skill score among the ED thresholds and is based on the rainfall event definition that corresponds to “the total cumulative amount of rainfall, which is defined by an over 12-hour inter-event time.” Figure 10 graphically illustrates the formulation of  $E = 73.915D^{0.2046}$  ( $21 \leq D \leq 167$ ). This is a meaningful result because the optimal threshold was defined with a 12-h break between consecutive rainfalls, whereas in most of

**Fig. 7** Graph showing the results of the two-dimensional Bayesian model for different rainfall durations and rainfall intensities

**Table 7** Results of the two-dimensional Bayesian model for different hourly maximum rainfall and cumulative event rainfall

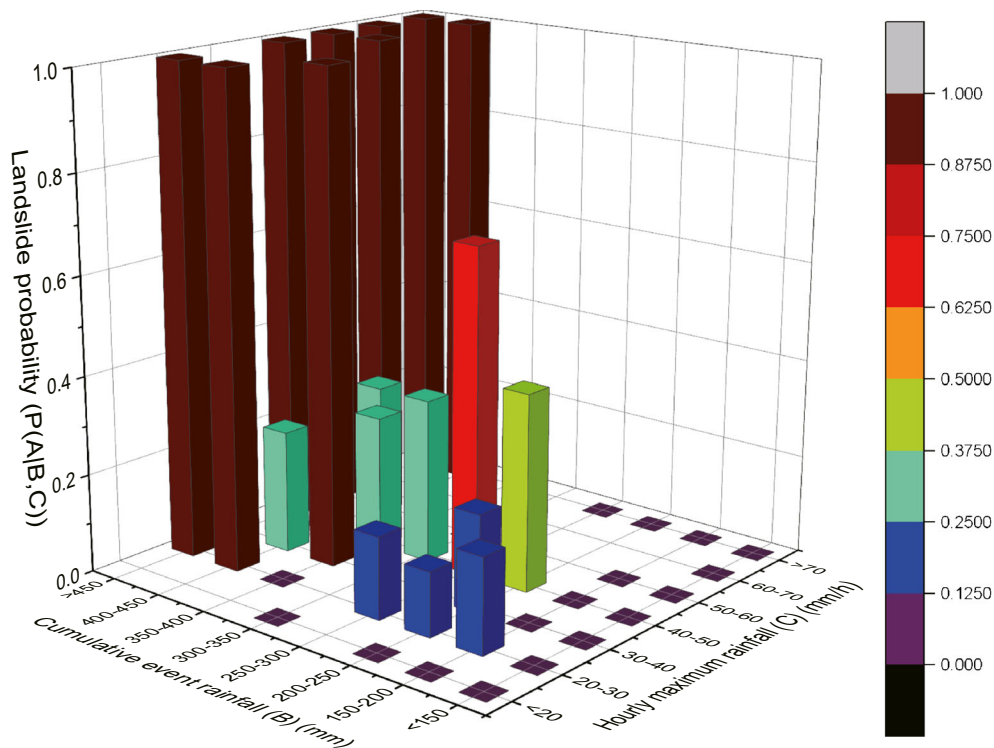
$(P(A B,C))$		Hourly maximum rainfall (mm/h)						
		$\leq 20$	20–30	30–40	40–50	50–60	60–70	$> 70$
Cumulative event rainfall (mm)	$\leq 150$	0	0	0	0	0	0	0
	150–200	0	0.192	0	0	0	No data	0
	200–250	0	0.13	0.2	0.4	No data	No data	0
	250–300	No data	0.167	0	0.667	0	No data	0
	300–350	0	No data	0.333	0.333	0	No data	No data
	350–400	No data	0	1	0.333	No data	No data	No data
	400–450	No data	1	0.25	No data	1	No data	1
	$> 450$	No data	1	No data	1	1	1	1

the literature, a 24-h break is taken into account (Saito et al. 2010; He et al. 2020). The short time, such as a 12-h break, was chosen due to high permeability soil characteristics such as sandy loam and the topographical features of the landslide occurrence area consisting of a steep slope of 15° or more.

To determine the level of “watch” as the basis for predicting landslides, it is possible to use ED thresholds as the initial condition for causing landslides since these thresholds are the lower envelope of the rainfall events (Table 9). Guzzetti et al. (2020) reported that few methods or techniques are available to determine thresholds for landslide early warning systems. Most previous studies developed a threshold for local characteristics as a rainfall-induced landslide threshold for each ED threshold. However, in this study, it was possible to derive rainfall thresholds that show the optimal rainfall conditions with high skill scores by

varying the definition of rainfall events. We propose to use  $12ED_{total} (E = 73.915D^{0.2046})$  as a basis for “watch”-level landslide forecasting for practical application in LEWSs because it represents the two-percentile regression curve and lower envelope of ED thresholds. In future studies, we will discuss the detailed criteria for producing landslide alerts, including strategies for the cross-use of rainfall forecasts and observations.

According to Guzzetti et al. (2020) and Intrieri et al. (2012), experts in landslides should conduct detailed monitoring of rainfall and landslide occurrences when the second level, namely the “watch” or “attention” level, is issued (Table 9). At this second level, residents and administrators need to prepare a disaster protection strategy for the level of the third level, “warning,” and the “watch” level is different from the first and lowest level, “normal” in which landslides rarely occur. For instance,



**Fig. 8** Graph showing the results of the two-dimensional Bayesian model for different hourly maximum rainfall and cumulative event rainfall

**Table 8** The results of the two-dimensional Bayesian model for different 3-day antecedent rainfall and cumulative event rainfall

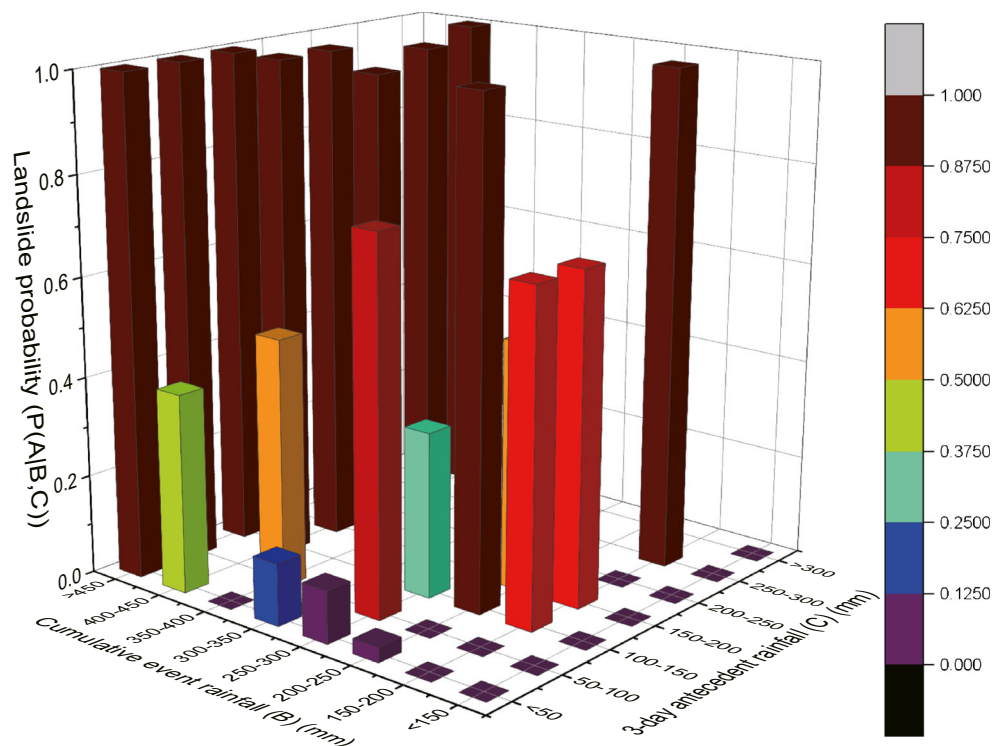
$P(A B,C)$		3-day antecedent rainfall (mm)						
		$\leq 50$	50–100	100–150	150–200	200–250	250–300	$> 300$
Cumulative event rainfall (mm)	$\leq 150$	0	0	0	0	0	0	0
	150–200	0	0	0.667	0.667	0	1	No data
	200–250	0.03	0	1	0.5	No data	No data	No data
	250–300	0.105	0.75	0.333	No data	No data	No data	No data
	300–350	0.125	No data	1	No data	No data	No data	No data
	350–400	0	0.5	No data	No data	1	No data	No data
	400–450	0.4	No data	1	1	No data	No data	1
	$> 450$	1	1	1	No data	No data	No data	No data

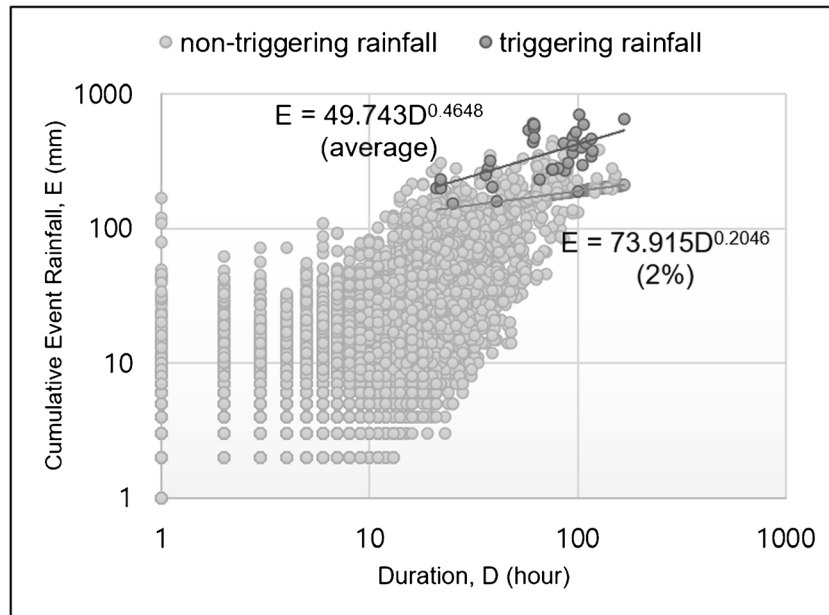
approximately 2–19 landslides (Martelloni et al. 2012; Lagomarsino et al. 2013; Segoni et al. 2015a, b, 2018a) or local occurrences of landslides (Tiranti and Rabuffetti 2010; Tiranti et al. 2013, 2014) can be observed at the “watch” level. However, there are cases where landslides did not occur, even in conditions that exceeded the ED threshold (Fig. 10). When constructing LEWSs, other variables conveying useful information about the potential onset of landslides could be also the antecedent rainfall and the hourly maximum rainfall. However, the ED threshold values do not incorporate these two rainfall variables. In this study, we identified

the rainfall conditions with a high probability of landslide occurrence and used these levels to classify the warning levels. The level of “warning” and “severe warning” in the LEWS crisis alerting phase can be set using the Bayesian method (Table 10).

#### Bayesian results of rainfall conditions for the landslide early warning system

Previous studies used a one-dimensional Bayesian model to examine cumulative event rainfall, rainfall duration, rainfall intensity, 14-day antecedent rainfall, and 30-day antecedent rainfall based

**Fig. 9** Graph showing the results of the two-dimensional Bayesian model for different 3-day antecedent rainfall and cumulative event rainfall



**Fig. 10** ED threshold ( $12ED_{total}$ ) for landslides in Chuncheon

on the daily rainfall (Berti et al. 2012; Robins 2016; Gonzalez and Caetano 2017; Dikshit et al. 2018; Do and Yin 2018). In this study, rainfall intensity, the hourly maximum rainfall, and the 3-day antecedent rainfall, which are highly correlated with landslide occurrence, were added to the two-dimensional Bayesian model, while the 30-day antecedent rainfall, which was not highly correlated with landslide occurrence, was excluded. In previous studies, the two-dimensional Bayesian model was only used for calculating the probability of landslide occurrence with the specific rainfall conditions of rainfall intensity vs. duration or cumulative event rainfall vs. duration. However, in this study, we tried to reflect the extreme condition of event rainfall and the initial condition of event rainfall by using hourly maximum rainfall and antecedent precipitation, so the two-dimensional Bayesian model dealt with cumulative event rainfall vs. hourly maximum rainfall and cumulative event rainfall vs. 3-day antecedent rainfall (Table 11).

The ED threshold based on rainfall-triggered landslide shows the rainfall characteristics when landslides begin to occur. The Bayesian model can identify the rainfall variable's range with a high probability of landslide under conditions above the ED threshold. The Bayesian model results have the advantage of providing the "warning" and "severe warning" levels for a landslide early warning system. The study areas of Berti et al. (2012) (the Emilia-Romagna region, Italy) and Robins (2016) (Papua New Guinea) were more extensive than this study

area, and their time unit was daily rainfall, not an hourly basis. In particular, Berti et al. (2012) used the probabilities of landslide occurrence of 5% and 10% or more as the landslide predictive warning level. In this study, we used hourly rainfall data instead of daily rainfall data. Furthermore, we determined a high probability of landslide occurrence using rainfall variables, including "the rainfall intensity vs. duration" and "the cumulative event rainfall vs. duration," as well as "the hourly maximum rainfall vs. cumulative event rainfall" and "the 3-day antecedent rainfall vs. the cumulative event rainfall." The results shown in Table 10 suggest that landslide occurrence probabilities of 40–90% and 90–100% should be classified as the "warning" and "severe warning" levels, respectively.

Determining the probability of landslide occurrence based on rainfall conditions for local regions, as was performed in this study, can increase the detail and accuracy of landslide crisis alerts. By applying all the rainfall conditions with 90–100% and 40–90% probabilities of landslide occurrence, as shown in Table 10, we accurately hindcasted 743 out of the 757 landslides (98.2%) that occurred in Chuncheon between 1999 and 2017. However, this study is limited in that the model fit evaluation was conducted with the same dataset used for the threshold definition. For this reason, we must conduct model prediction performance for further study by using future data that is not utilized for the model construction. When all the cases satisfy either of the rainfall

**Table 9** A four-level scheme for a landslide early warning system

Level	Names used for the level	Thresholds
Lowest level	"Normal"	When it starts in the summer season and under the $12ED_{total}$ thresholds
Second level	"Watch"	Over the $12ED_{total}$ thresholds
Third level	"Warning"	40–90% probability of landslide occurrence (refer to Table 10)
Highest level	"Severe warning"	90–100% probability of landslide occurrence (refer to Table 10)

**Table 10** Probability of landslide occurrence depending on rainfall variables

Rainfall variable	40–90% probability of landslide occurrence: warning	90–100% probability of landslide occurrence: severe warning
Cumulative event rainfall	$350 \text{ mm} < E \leq 450 \text{ mm}$	$450 \text{ mm} < E$
Cumulative event rainfall—rainfall duration	$200 \text{ mm} < E \leq 250 \text{ mm}$ and $12 \text{ h} < D \leq 24 \text{ h}$ $250 \text{ mm} < E \leq 450 \text{ mm}$ and $72 \text{ h} < D \leq 96 \text{ h}$	$250 \text{ mm} < E$ and $96 \text{ h} < D \leq 120 \text{ h}$
Rainfall intensity—rainfall duration	$2 \text{ mm/h} < I \leq 4 \text{ mm/h}$ and $96 \text{ h} < D \leq 168 \text{ h}$ $4 \text{ mm/h} < I \leq 6 \text{ mm/h}$ and $72 \text{ h} < D \leq 96 \text{ h}$	$4 \text{ mm/h} < I \leq 8 \text{ mm/h}$ and $96 \text{ h} < D \leq 120 \text{ h}$ $6 \text{ mm/h} < I \leq 10 \text{ mm/h}$ and $48 \text{ h} < D \leq 72 \text{ h}$
Cumulative event rainfall—hourly maximum rainfall	$200 \text{ mm} < E \leq 300 \text{ mm}$ and $40 \text{ mm} < M_h \leq 50 \text{ mm}$	$400 \text{ mm} < E \leq 450 \text{ mm}$ and $50 \text{ mm} < M_h$
Cumulative event rainfall—3-day antecedent rainfall	$250 \text{ mm} < E \leq 400 \text{ mm}$ and $50 \text{ mm} < A_3 \leq 100 \text{ mm}$ $150 \text{ mm} < E \leq 250 \text{ mm}$ and $100 \text{ mm} < A_3 \leq 200 \text{ mm}$	$300 \text{ mm} < E$ and $100 \text{ mm} < A_3$ $150 \text{ mm} < E \leq 200 \text{ mm}$ and $250 \text{ mm} < A_3 \leq 300 \text{ mm}$

conditions corresponding to the “warning” and “severe warning” levels shown in Table 10, we refer to the “warning and severe warning” levels shown in Table 12. As a result of analyzing the POD and the POFA for “warning and severe warning” levels, the POD is 0.976, but the POFA is 0.397 (Table 12). If these two warning levels are separated, the POD and POFA are 0.714 and 0.474 for the “warning” level, and 0.571 and 0 for the “severe warning” level, respectively. If a Bayesian probability model is applied to locations where the leading cause of landslides is rainfall, the rainfall conditions with a high probability of landslide occurrence could serve as the criteria for the “warning” level or “severe warning” level in landslide early warning systems.

### Conclusion

This study analyzed ED thresholds for predicting landslides and determined the rainfall conditions with a high probability of landslide occurrence. We propose the ED thresholds to be used to set the level of the landslide warning. First, to improve the hit ratio of predictive alarms, the ED thresholds with the highest skill score were identified. Using the two optimal equations, we determined the level of “watch” for the LEWS. Thus, when the rainfall

condition is above the ED threshold the “watch” level is issued. However, this case was identified only using the characteristics of rainfall events when landslides occurred, and we noted that landslides did not occur even though the rainfall was above the threshold. A probabilistic method, such as a Bayesian model, can overcome this limitation.

Second, we identified the probability of landslide occurrence as one-dimensional and two-dimensional Bayesian models by including not only the rainfall conditions of the landslide but also the rainfall conditions of non-landslides. The Bayesian model can reflect the rainfall intensity, rainfall duration, and cumulative event rainfall, which are directly related to the occurrence of landslides, as well as the 3-day antecedent rainfall and hourly maximum rainfall. Therefore, the “warning” and “severe warning” levels are proposed based on the rainfall conditions with 40–90% and 90–100% probabilities of landslide occurrence, respectively. As a result of model fit verification, it was possible to discern 98.2% of the landslides that occurred in Chuncheon, Republic of Korea, between 1999 and 2017 by using the “warning” and “severe warning” levels. The false alarm rates are 47.4% and 0% in the “warning” level and the “severe warning” level, respectively.

**Table 11** Rainfall variables used for the Bayesian model

Reference	Identification of rainfall event	Rainfall variables	
		1D Bayesian model	2D Bayesian model
Berti et al. (2012)	Interpretation by the authors (Aleotti 2004)	$E$ (mm), $D$ (days), $I$ (mm/day), $A_{14}$ (mm), $A_{30}$ (mm)	$I$ (mm/day) and $D$ (mm)
Robins (2016)	The use of multiple time frames (Frattini et al. 2009)	$E$ (mm), $D$ (days)	$E$ (mm) and $D$ (days) $I$ (mm/day) and $D$ (days)
González and Caetano (2017)	Not mentioned	$I$ (mm/day)	$I$ (mm/day) and $D$ (days)
Dikshit et al. (2018); Dikshit and Satyam (2019)	Total number of consecutive days of rainfall	$E$ (mm), $D$ (days), $I$ (mm/day)	$I$ (mm/day) and $D$ (days)
Do and Yin (2018)	Interpretation by the authors (Aleotti 2004)	$I$ (mm/day)	$I$ (mm/day) and $D$ (days)
This study	Non-rainfall used as criterion to truncate the rainfall sequence (Brunetti et al. 2010)	$E$ (mm), $D$ (hours), $I$ (mm/h), $M_h$ (mm), $A_3$ (mm), $A_{14}$ (mm)	$E$ (mm) and $D$ (hours) $I$ (mm/h) and $D$ (hours) $E$ (mm) and $M_h$ (mm), $E$ (mm) and $A_3$ (mm)

$M_h$ , hourly maximum rainfall in a rainfall event;  $A_3$ , 3-day antecedent rainfall before a rainfall event;  $A_{14}$ , 14-day antecedent rainfall;  $A_{30}$ , 30-day antecedent rainfall



**Table 12** The values of contingencies and skill scores for three warning levels of LEWS

Warning level	TP	FN	FP	TN	POD	POFD	POFA	HK	$\delta$
Watch level	42	0	145	6799	1	0.021	0.775	0.979	0.021
Warning level	30	12	27	6917	0.714	0.004	0.474	0.71	0.286
Severe warning level	24	18	0	6944	0.571	0	0	0.571	0.429
Warning and severe warning level	41	1	27	6917	0.976	0.004	0.397	0.972	0.024

This study is meaningful in that it proposes to apply the ED thresholds and Bayesian probability models to categorize warning levels of a landslide early warning system. The results of this study may inspire the collective use of deterministic and probabilistic methods to construct such early warning systems. The same research methodology can be applied to other regions in future studies.

### Acknowledgments

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