Risk-based analysis of monitoring time intervals for landslide prevention: A case study of low temporal resolution methods

Jongook Lee[1], Dong Kun Lee[2], Sung-Ho Kil[3], Ho Gul Kim[4]

[1]Interdisciplinary Program in Landscape Architecture, Seoul National University, Seoul, 08826, Republic of Korea
[2] Research Institute of Agriculture Life Science, Seoul National University, Seoul, 08826, Republic of Korea
[3]Department of Ecological Landscape Architecture Design, Kangwon National University, Chuncheon, 24341, Republic of Korea
[4]Urban Data and Information Center, Incheon Development Institute, Incheon, 22711, Republic of Korea

Correspondence to: Dong Kun Lee (dklee7@snu.ac.kr)

Abstract.

Landslides are one of the most dangerous types of disasters in terms of the frequency of their occurrence and the severity of their damage, as they may result in significant losses of human life and infrastructure. Monitoring methods based on low temporal resolution instruments, such as manually read inclinometers or piezometers, can be effective and cost-efficient solutions. The objective of this study was to analyse monitoring time intervals for low temporal resolution methods based on a risk study and to propose a plan for periodic landslide monitoring suitable for achieving equivalent risk reductions in areas with different hazard grades. For this purpose, an equation describing the probability of landslide occurrence was presented based on the concept of reliability, and the monitoring time interval was analysed quantitatively by calculating the average probability of landslide occurrence. A unit of relative temporal frequencies was used to characterise the frequency of landslide occurrence, as estimated by establishing a rainfall threshold. Pyeongchang County was selected as a case study site, because of the availability of landslide inventory data and the increases in population and infrastructure that have been observed since Pyeongchang became the host city of the 2018 Olympic Winter Games. Our results demonstrate that appropriate monitoring intervals can be determined by calculating the average probability of landslide occurrence, and resources for landslide prevention can then be allocated efficiently.

1 Introduction

Climate change has led to an increase in heavy precipitation events recently, and the risk to people, properties, and ecosystems from natural disasters such as storms, extreme precipitation events, and landslides has intensified, especially in conditions of insufficient infrastructure and services (IPCC, 2013). Landslides are one of the most dangerous types of disasters in terms of the frequency of their occurrence and the severity of their damage, as they may result in significant losses of human life and infrastructure (Petley, 2012;Kjekstad and Highland, 2009;Guzzetti, 2000;Salvati et al., 2010).

However, almost all countries find it challenging to allocate sufficient financial and human resources for major engineering works or comprehensive monitoring methods to mitigate disasters, such as the installation of costly measures to manage the risks posed by landslides (Guzzetti et al., 1999; Baroň and Supper, 2013). Monitoring and warning systems can substitute for expensive stabilization works or engineering solutions to prevent losses from landslides over large areas (Dai et al., 2002). Manually read monitoring methods with a low temporal resolution, such as conventional inclinometers to detect subsurface deformation and piezometers to monitor pore water pressure, can be effective solutions (Uhlemann et al., 2016). These methods can also be cost-efficient for controlling risks incurred by multiple areas that are susceptible to landslides over a broad region.

Nonetheless, continuous monitoring of landslide triggering parameters associated with rainfall has occasionally been sought due to time and cost restrictions (Springman et al., 2013). Uhlemann et al. (2016) briefly described the temporal resolution of landslide monitoring methods. In this study, we present a quantitative analysis of the monitoring time interval based on a risk analysis. In the Republic of Korea, the monitoring frequency of unstable slopes is regulated by law, through a simple requirement that they be monitored more than once per year. The objective of this study was to analyse monitoring time intervals for low temporal resolution methods based on a risk study and to propose a plan for periodic landslide monitoring suitable for achieving equivalent risk reductions in areas with different hazard grades.

Pyeongchang County was selected as a case study site because of the availability of landslide inventory data from the aftermath of Typhoon Ewiniar, caused intense rainfall that resulted in considerable loss of life and property in July 2006. Additionally, the population of Pyeongchang County has increased and its infrastructure has expanded since it became the host city of the 2018 Olympic Winter Olympic Games. The landslide hazard map produced by the Korea Forest Service (Korea Forest Service, 2012) was used to reflect the spatial probability of landslides based on a classification of landslide susceptibility. Temporal probability was incorporated into this study by estimating the frequency of landslide occurrence from the landslide inventory data.

To estimate the frequency of landslide occurrence, a descriptor of relative temporal frequencies was adopted as suggested by Corominas and Moya (2008) for conducting studies on a regional scale, and the number of landslide events was analysed along with the landslide hazard grades. Due to the lack of an accumulated inventory of landslide data in the study region, the frequency of landslide occurrence limited to an extreme weather event was estimated by establishing a rainfall threshold. The criteria for the rainfall threshold setting were determined by referring to local research results.

The concept of reliability was used to derive the formula for the probability of landslide occurrence in this study. This formula is the same as the equation presented by Crovelli (2000) based on a Poisson distribution model that is frequently employed to estimate the random events of natural hazards on a continuous timeline. The monitoring time intervals for reducing the landslide risk were calculated quantitatively by adopting the concept of time-average probability of failure. This concept is often used in reliability studies for safety instrumented systems (I.S.A., 2002) and has also been applied to structural safety for earthen dams (Su et al., 2012). This paper demonstrates that different monitoring time intervals need to be scheduled for distinct landslide hazard areas in order to achieve the same risk reduction effect. These results can be a useful basis for improving preventive landslide risk management through monitoring activities.

2 Methods

2.1 Study site

Pyeongchang is well known as the host city of the 2018 Olympic Winter Games, and most of the snow sports competitions will take place at nearby ski resorts. The county of Pyeongchang is located between 37°15’ and 37°50’ north latitude and 128°15’ and 128°45’ east longitude near a mountain range in Gangwon Province, South Korea, as displayed in Fig. 1. The total area of Pyeongchang is 1465 km^2, which accounts for 8.7% of the province’s area. Its elevation is generally high, with an average altitude of more than 600 m above sea level, and the northeast area is higher and includes steeper terrain than the southwest side. The bedrock of the Pyeongchang area is composed of Precambrian metamorphic sedimentary and granitic rocks, and Palaeozoic sedimentary rocks and Jurassic granite are distributed throughout the region (Kim et al., 1997). The soil cover in the study area is mainly sandy loam and clay loam, and sandy loam predominates in the mountainous areas where landslides have occurred (K.N.S.D.I.P., 2017). These topographic and geologic features make the study site prone to landslides.

The agricultural products are mainly from high altitude cultivation of maize, potato, and cabbage, and some crop fields are located on hillsides near the mountainous region. The population of Pyeongchang has been growing recently. The registered number of resident households has increased from 16251 in the year 2000 to 20745 in 2016 (Statistics Korea, 2017), which reflects the high demand for leisure and investment in the county. As a result, housing developments for permanent residences and for tourism are sprawling near mountainous areas, in locations that are relatively vulnerable to landslides. Furthermore, a previous study showed that the landslide hazard area in Gangwon Province will be increased by climate change impacts in the future, as estimated using representative concentration pathway (RCP) scenarios (Kim et al., 2014). Thus, a monitoring program with a proper management plan must be implemented in the county to prevent the potential loss of life and property due to landslides.

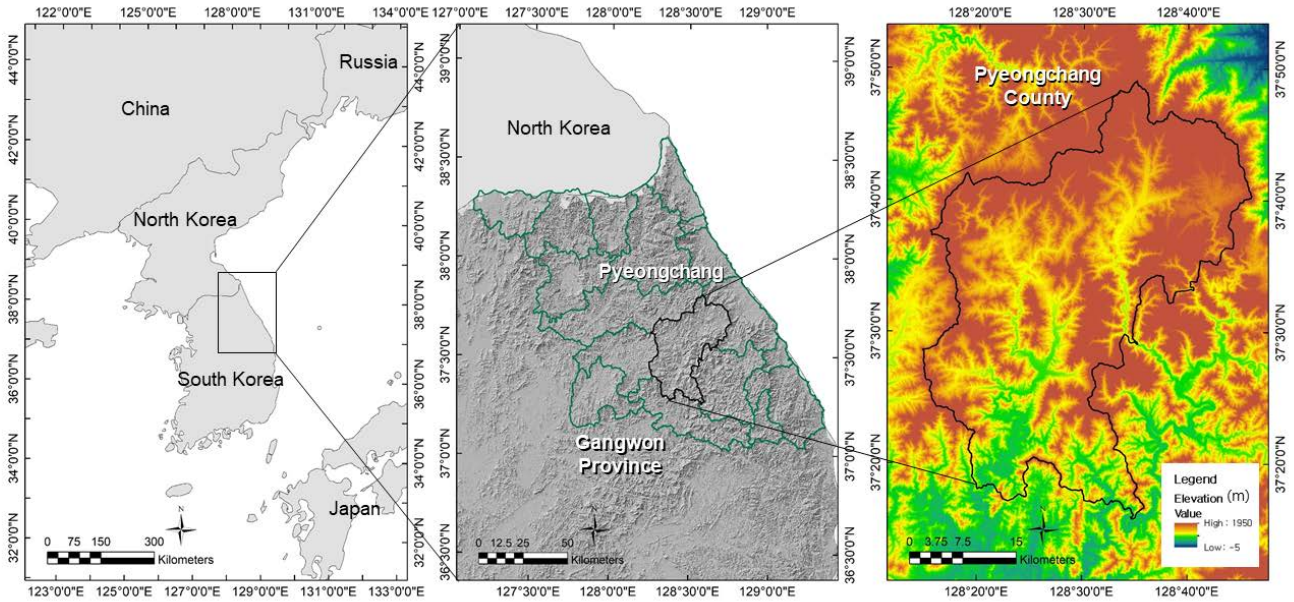

Figure1. The study site of Pyeongchang County in Gangwon Province, South Korea

2.2 Landslide susceptibility data

To obtain the spatial probability data from a landslide susceptibility classification, we used the landslide hazard map prepared in national scope by the Korea Forest Service in 2012 (Korea Forest Service, 2012). The landslide hazard map was made based on a logistic regression analysis of around 2000 landslides caused by multiple weather events (Korea Forest Service, 2013). The map is used as basic data for surveys of areas vulnerable to landslides and for implementing preventive actions.

According to the map, the scope areas are classified into five classes from grade 1 (the highest hazard) to grade 5 (the lowest hazard). The following nine factors reflecting the characteristics of mountainous terrain were analysed to produce the hazard map: slope inclination, slope orientation, slope length, slope curvature, topographic wetness index (TWI), the type of forest, the age of the forest, soil depth, and bedrock. The data from the landslide hazard map were used in 1:25000 scale, with pixel units of 10 m × 10 m. It should be noted that the lowest grade of landslide hazard data, grade 5, was excluded in this study because those pixel data were entered in the data set as null including waterbody and lowland plain.

2.3 Landslide inventory data

The landslide inventory data were provided by the local government of Gangwon Province. The inventory was conducted after devastating damage was reported after Typhoon Ewiniar, which brought intense rainfall to the region in July 2006. Ewiniar had weakened into a tropical depression accompanied by torrential rain when it reached the Korean peninsula on July 10. It caused a total of 62 casualties, and the loss of property was estimated to be approximately 1834.4 billion Korean won (N.E.M.A., 2007; K.M.A.N.T.C., 2011).

The landslide inventory data were part of the first round of data collection after the field survey, and 1751 landslide locations were identified in Pyeongchang County. The survey results were digitized in polygons in the GIS platform, and consist of location data established using GPS devices and area data of damage by landslide scar. The information from this inventory was plotted on a 1:25000 scale map.

Unfortunately, time-series inventory data after Ewiniar were not available. Thus, the frequency of landslide occurrence limited to extreme weather event was estimated with this cross-sectional data by establishing a rainfall threshold for the case study. These inventory data do not include landslide types with hazard descriptors, which can distinguish most landslides and rock falls (Fell et al., 2008). Despite the limitations of the inventory, the data provide a spatial distribution of 1751 landslide locations and indicate the overall variation of the landslide occurrence ratio in relation to landslide susceptibility.

2.4 Probability of landslide occurrence

2.4.1 Probability model by Poisson distribution

Using landslide frequency data obtained from the inventory of past landslides, the temporal probability of landslide occurrence can be estimated through a statistical analysis. There have been studies using the temporal probability of landslide occurrence to generate hazard maps not only considering spatial probability. (Lopez Saez et al., 2012; Tien Bui et al., 2013; Guzzetti et al., 2005). To present the probability of landslide occurrence, Crovelli (2000) used the following Poisson distribution model, which is frequently adopted to estimate random events in continuous time in natural environments. The probability of *n* landslides occurring during time *t* is:

$$P\{N(t) = n\} = e^{-\lambda t} \frac{(-\lambda t)^n}{n!} \qquad (1)$$

where n = 1, 2, 3 …,

λ is the rate of occurrence of landslides,

t is the specified time,

$N(t)$ is the number of landslides that occurred during time t.

The probability of a landslide recurrence in time interval Ti that is greater than time t, which means if λ is much less than one (λ<<1), is:

$$P(Ti > t) = P\{N(t) = 0\} = e^{-\lambda t} = e^{-t/\mu} \qquad (2)$$

where *Ti* is the time between landslide events,

μ is the mean recurrence interval in the future.

Finally, the probability of one or more landslides occurring during time *t*, the so-called exceedance probability, is expressed as:

$$P\{N(t) \geq 1\} = 1 - P\{N(t) = 0\} = 1 - e^{-\lambda t} = 1 - e^{-t/\mu} \tag{3}$$

2.4.2 Probability model by the concept of reliability

This probability of landslide occurrence model presented by the Poisson model can also be expressed using the concept of reliability. One of the definitions of reliability in general terms is the probability that an item will perform a required function without failure under stated conditions for a stated period of time (O'Connor and Kleyner, 2012). According to Kapur and Pecht (2014), the reliability function *R(t)* in mathematical terms is expressed as:

$$R(t) = \frac{Ns(t)}{N} \tag{4}$$

where *Ns(t)* is the number of surviving items in time *t*,

N is the number of total items.

Unreliability, *F(t)* is given as:

$$F(t) = 1 - R(t) = \frac{N - Ns(t)}{N} \tag{5}$$

$$\text{and,}\ \ f(t) = \frac{dF(t)}{dt} = -\frac{1}{N}\frac{dNs(t)}{dt} \tag{6}$$

From the equation for the unreliability rate *f(t)*, we obtain the hazard rate *h(t)* shown below with a more conservative meaning in terms of reliability. The hazard rate *h(t)* is normalized with its surviving items *Ns(t)* instead of the total number of items *N*.

$$h(t) = \frac{f(t)}{R(t)} \tag{7}$$

The integral of the hazard rate *h(t)* over the time from 0 to *t* is:

$$\int_0^t h(\tau)\, d\tau = -\ln R(t) \tag{8}$$

Then, $R(t)$ is:

$$R(t) = e^{-H(t)} \quad (9)$$

where $H(t)$ is the number of hazards in time t, and can be expressed as $H(t) = \lambda t$.

Finally, we have $F(t)$ as:

$$F(t) = 1 - R(t) = 1 - e^{-H(t)} = 1 - e^{-\lambda t} \quad (10)$$

This is the same as Eq. (3) above for the probability of landslide occurrence. When a pixel unit of GIS-based spatial information is considered as a component for identifying the frequency of landside occurrence, the equation for the probability of occurrence can be derived from the definition of reliability.

2.5 Frequency of landslide occurrence

Varnes (1984) expressed landslides risk in an equation that includes the probability of occurrence multiplied by the degree of loss to a given element at risk of a landslide. In the risk equation, the probability of occurrence is considered as one of the variables related to natural hazard. Thus, the level of risk can be reduced by decreasing the probability of occurrence. To calculate the probability of landslide occurrence, the frequency of landslide occurrence should be estimated first (Corominas et al., 2014). However, landslide investigation data are not yet sufficiently accumulated in the study region to estimate landslide occurrence frequency. The lack of information about landslide occurrence and the difficulty of obtaining a complete or systematic landslide record from the past have been discussed in previous research (Jaiswal et al., 2010; van Westen et al., 2006;Cardinali et al., 2002).

Corominas & Moya (2008) discussed two separate approaches to the spatial probability and temporal probability of landslide occurrence and presented terms for reporting the frequency of landslides. The relative frequency of landslides was defined as a ratio of the number of landslides directly recorded in a unit area, and is useful for studying multiple landslide events within a region. In this study, we attempted to identify the relative temporal frequency of landslides limited to an extreme weather event because the available landslide inventory data included multiple landslides in a broad region triggered by an occasional intense rain storm.

Provided that the unit pixel is from the data of a landslide hazard map, the relative temporal frequency of landslides for Pyeongchang County is described quantitatively as below:

$$F_L = \text{landslide event} \times \text{pixel}^{-1} \times \text{year}^{-1} \tag{11}$$

where F_L is the relative temporal frequency of landslides,

the area of a unit pixel corresponds to 100 m^2, that is 10 m ×10 m unit pixel of the landslide hazard map.

This approach is based on the following assumptions. To count the number of landslide events classified by the landslide hazard grade, we found the maximum landslide hazard grade value overlaid on the inventory polygon data using GIS. This was regarded as the representative hazard grade for that landslide occurrence point. Second, when determining the total area corresponding to each landslide hazard grade, we did not include areas where landslides did not occur at all. The reason for this was to approach risk analysis conservatively by selecting a high failure rate. Moreover, the occurrence frequency varies depending on the size of the area. The frequency unit in this study are only representative for the Pyeongchang administrative area. Lastly, to estimate the probabilistic return period of landslide occurrence with an equivalent magnitude, rainfall intensity and duration were considered as factors triggering landslide occurrence. The rainfall threshold for landslide initiation is further explained below.

On the other hand, the relative temporal frequency of landslides can be derived from the concept of reliability as follows:

$$F_L = (N - Ns) / (Ns \times \Delta t) \tag{12}$$

where Δt is the probabilistic return period of landslide occurrence.

Provided that $N - Ns$ is considered as the number of landslide events, rather than the area, because it refers to the point source of landslide initiation, the temporal landslide frequency expressed in Eq. (12) can be interpreted from the definition of unreliability in Eq. (5). In that equation, Ns is considered to be the number of pixel components with no landslide initiation and Δt is the probabilistic return period of landslide occurrence estimated by establishing the rainfall threshold.

2.6 Rainfall thresholds for landslides to be triggered

The mechanism of landslide occurrence triggered by rain storms can be explained by the increase in pore water pressure and rain water seepage forces (Cullen et al., 2016). Since Caine (1980) examined the relationship between the minimum rainfall duration and intensity required to cause a landslide, various methodologies have been examined and proposed to determine the rainfall threshold for triggering a landslide (Crozier, 2005; Guzzetti et al., 2007; Zêzere et al., 2005; Frattini et al., 2009; Crosta and Frattini, 2003). Based on the previous studies, we also estimated the temporal probability of landslide occurrence by applying a rainfall threshold with daily rainfall level and duration that may trigger landslides. In determining the criteria of rainfall duration, different numbers of days have been examined to find the most suitable correlation with landslide initiation (Aleotti, 2004; Polemio and Sdao, 1999; Zêzere et al., 2005).

However, researchers' proposals of different numbers of days only have local validity (Jakob et al., 2006; Martelloni et al., 2012). Therefore, we referred to domestic research results that account for the characteristics of local geology, soil, vegetation, and precipitation patterns. According to the findings of Kim and Chae (2009), landslides in Gyeonggi Province in South Korea tend to occur when there is rainfall of more than 200 mm for 48 h. On this basis, cumulative precipitation of more than 200 mm over 48 h was adopted as one of the criteria to determine the rainfall threshold. To determine the daily rainfall intensity, which is another factor affecting the threshold, the daily precipitation level was reviewed for July 2006 when Typhoon Ewiniar hit. It was assumed that landslide will occur in the future with a similar magnitude as in the past.

Although no continuous landslide inventory data are available from the study area, the rainfall threshold was used to estimate the frequency of landslide occurrence limited to the extreme weather event for this case study. In addition, there must be non-uniformity of rainfall intensity over the study area when the typhoon affected. However, weather data were adopted as a representative sample to estimate landslide frequency. Further studies with accumulated landslide inventory data will allow more accurate estimations of the probability of landslide occurrence.

2.7 Average probability of landslide occurrence

From the model of the probability of landslide occurrence, either derived from the Poisson distribution or the reliability concept, it can be seen that the probability of one or more landslides being initiated will increase over time. However, if landslide risk management is conducted through periodic monitoring with a low temporal resolution method, it can be assumed that the probability of landslide occurrence will be reduced.

In order to quantitatively estimate the monitoring interval, we adopted the concept of time-average probability of failure. With this method, it becomes possible to calculate the monitoring interval needed to reduce the risk of landslide occurrence below the desired level. This concept is commonly used in reliability studies. The average probability of failure on demand (PFDavg) is introduced in the standard IEC 61511 by the International Electro-Technical Commission and ISA-TR84 by the Instrumentation, Systems, and Automation Society. It represents the average probability of a safety-instrumented shutdown system not operating in its desired function in an unwanted emergency situation (I.S.A., 2002; I.E.C, 2003). Those standards are applicable in separate ways to a high demand mode, such as a basic process control system, and a-low demand mode for emergency systems. In this study, we referred to the proposed module for low demand mode, since landslides occur with relatively low frequency. The average probability of failure on demand is expressed by the equation below, as described in ISA-TR84. It is obtained by integrating the probability of the failure function from time 0 to the proof testing time and dividing by the time interval (I.S.A., 2002). The proof test is the test for recovering components of the emergency shutdown system.

$$\mathrm{PFDavg} = \frac{1}{\mathrm{TI}}\int_0^{\mathrm{TI}} 1 - e^{-\lambda t}\, dt \qquad (13)$$

where TI is the time interval between the proof tests, and λ is the failure rate.

In this equation, if we consider the failure rate (λ) as the frequency of landslide occurrence and replace the proof test time interval with the monitoring time interval, the average probability of failure on demand (PFDavg) refers to the time-average probability of landslide occurrence, which is dependent on the monitoring time interval. In other words, the formula shows that the probability of landslide occurrence can be stably managed at a certain level by periodic monitoring in ideal conditions.

Although this is not achievable in reality, due to imperfections in monitoring, the probability of occurrence can be reduced to some extent by periodic monitoring. Different constants will contribute to the probability equation by increasing the probability at each monitoring iteration. The increasing probability depends on features of the monitoring process itself, the characteristics of the person performing it, or the nature of the area. Despite the imperfections of monitoring, it is possible to identify the effectiveness of monitoring with different time intervals, assuming that periodic monitoring will manage the probability of occurrence at a steady state. Investigating techniques to improve the effectiveness of monitoring can be a subject for further research. Investigating the constant value attribute to increase the probability of occurrence with monitoring activities can be a subject for further research.

Notably, in terms of the structural safety of dams, Su et al. (2012) presented the differences in time-average probability of system failure by reinforcement interval in a search for an optimized earth dam reinforcement strategy. This is an example of applying the average probability of failure for the collapse of an earthen structure. In this study, by using the time-average probability of failure, monitoring time intervals were differentiated expecting the same level of risk reduction with discrete grades of landslide hazard to suggest efficient landslide risk management.

2.8 Landslide monitoring with low temporal resolution

Monitoring is one of the key activities for preventing landslides, which can cause losses of life and property. Adequate monitoring to identify the kinematic and hydrological aspects together with a climatic parameter can assist in providing an alert before mass movements occur and suggesting a plan to manage risk (Angeli et al., 2000). Various combinations of monitoring techniques and instruments are employed to acquire complete information regarding landslide triggering factors and mechanisms (Dixon et al., 2015). However, pore water pressure, displacement, and deformation have been identified as crucial parameters for landslide monitoring and early warning in previous studies (Baroň and Supper, 2013; Uhlemann et al., 2016). Among the ground-based monitoring techniques, manually read inclinometers that detect subsurface deformation and piezometers that monitor ground water have low temporal resolution, and they can be effective solution for monitoring areas at risk of landslides (Uhlemann et al., 2016). In this study, we only considered landslide monitoring methods with low temporal resolution in analysis of monitoring time intervals. With these methods, a municipality can conduct effective monitoring at a low cost.

3 Results

3.1 Rainfall threshold for landslides to be triggered

To determine the rainfall threshold for landslides to be triggered, we reviewed the past precipitation data in the Pyeongchang County region. The survey results of daily rainfall and 48-hour cumulative rainfall in the region for the last 11 years, which were acquired from the data of the Automatic Weather Station (AWS) located in Pyeongchang County (K.M.A., 2017), are plotted in Fig. 2a and Fig. 2b below.

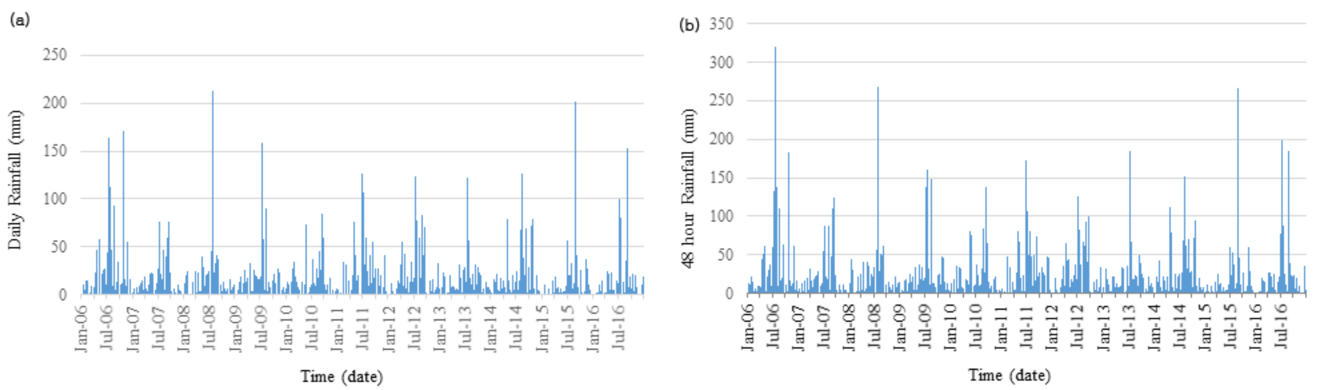

Figure 2. (a) Daily rainfall in Pyeongchang County in 11 year (2006–2016). The graph depicts the pattern of annual rainfall. (b) 48-hour cumulative rainfall in Pyeongchang County. The graph displays 48-hour rainfall in 11 year (2006–2016).

The daily rainfall graph indicates that the precipitation pattern is characterized by a monsoon climate in which rainfall is mainly concentrated in summer, and intense rainfall events occur on multiple occasions (K.M.A., 2017). Additionally, the graph shows that daily precipitation exceeded 150 mm on both July 15 and July 16, 2006, when landslides occurred because of rain storm. Thus, a daily rainfall intensity of more than 150 mm was set as the rainfall threshold. As a result, the average landslide occurrence interval was estimated by counting the dates that met both the 48-hour cumulative precipitation of over 200 mm and daily precipitation of over 150 mm for 11 years starting in 2006. As shown in Fig. 3, three events in the last 11 years (July 16, 2006; July 24, 2008; Aug 25, 2015) exceeded the rainfall threshold of this study. Thus, the probabilistic return period of landslide occurrence limited to extreme weather events was estimated as 3.7 years.

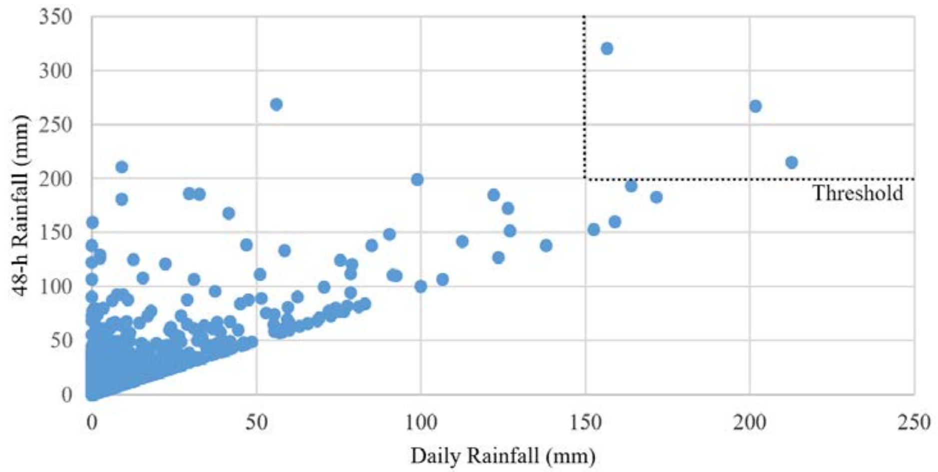

Figure 3. Scatter diagram of daily rainfall and 48-hour cumulative rainfall showing that 3 events exceeded the rainfall threshold in Pyeongchang County in 11 years (2006-2015).

3.2 Landslide occurrence frequency

The landslide hazard map and locations where landslides occurred in the inventory data are presented in Fig. 4. The landslide hazard map of Pyeongchang County shows that grade 3 and grade 2 are generally distributed over the study area and that grade 1, the most hazardous one, is sparsely scattered along the ridges of the mountains. Meanwhile, the landslide locations drawn from the inventory data reveal that landslides occurred primarily in the mountainous areas in the north-eastern part of Pyeongchang County.

To investigate how the frequency of landslide occurrence varied according to the landslide hazard grade, the landslide locations from the inventory data were overlaid on the landslide hazard map, and the number of events in each grade was analysed. As shown in Table 1, the total areas of each grade were calculated, and grade 3 occupied the largest area of 733.4 km^2, followed by grade 2 (431.7 km^2), grade 4 (24.9 km^2), and grade 1 (14.3 km^2). A total of 111 landslides occurred in grade 1 areas, 938 landslides took place in grade 2 areas, 446 in grade 3 areas, and 5 in grade 4 areas. The largest absolute number of landslides occurred in grade 2 areas, due to the total area it occupies; however, the highest number of landslide events per area occurred in grade 1 areas.

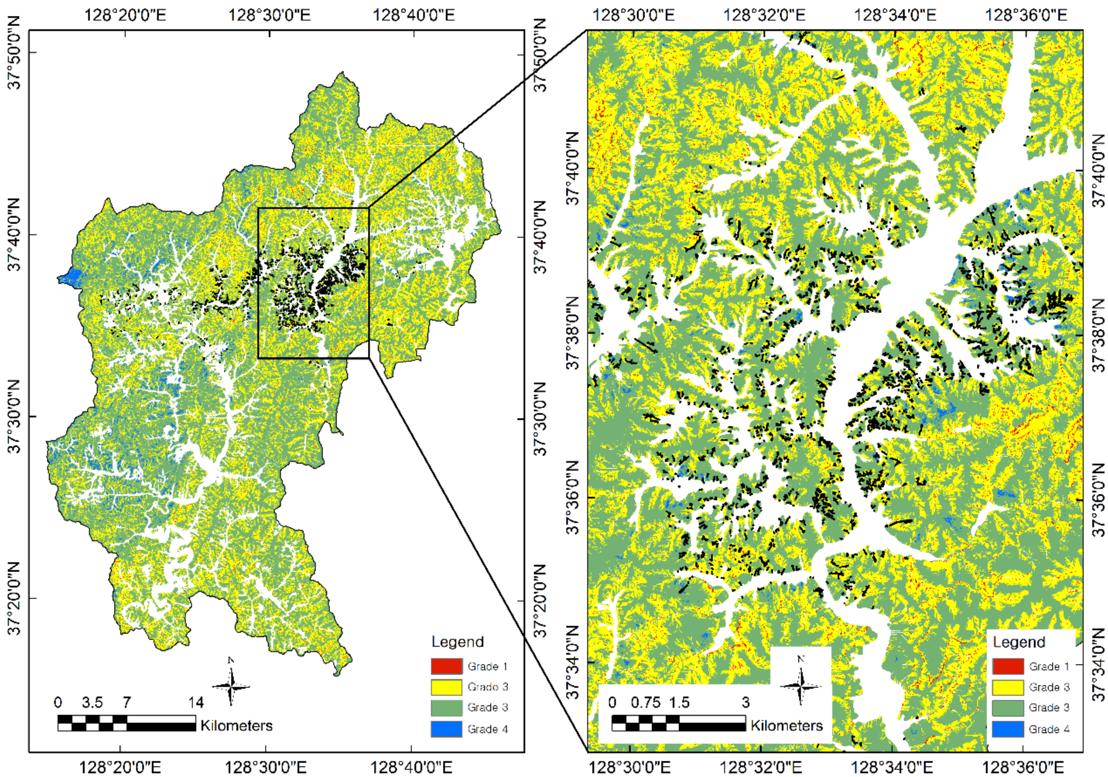

Figure 4. Landslide hazard grade and locations of landslide occurrence in the study area

Next, using the unit of relative temporal frequency of landslides, the resulting landslide occurrence frequency (λ) for Pyeongchang County was calculated, as shown in Table 1. The area of landslide hazard grade 1 had the highest value of landslide occurrence frequency, 2.12E-04 (landslide event × pixel^{-1} × year^{-1}), and the frequency sequentially decreased from grade 2 to grade 4. In particular, the numerical value of landslide occurrence frequency varied depending on the unit area. For instance, the given frequency value (λ) in Table 1 would be higher if we used a larger unit area, such as a unit of km^2 or to the whole county area. This issue will be explored further in the discussion section.

Table 1. The calculated landslide occurrence frequency

Landslide hazard grade	No. of landslides (N)	Total area* (A)	Occurrence ratio (N/A)	Landslide occurrence frequency ** (λ)
1	111	142761	7.78E-04	2.12E-04
2	938	4316864	2.17E-04	5.93E-05
3	446	7334461	6.08E-05	1.66E-05
4	5	248687	2.01E-05	5.48E-06

* The unit of the total area A is one pixel (10 m × 10 m)

** The unit of the landslide occurrence rate (λ) is landslide event × pixel $^{-1}$ × year $^{-1}$

3.3 Determination of landslide monitoring time intervals with average probability

By referring to the results of the landslide occurrence frequency calculated above, the graph in Fig. 5 with a logarithmic scale on the Y-axis delineates the change in the average probability of landslide occurrence as the monitoring interval increases. This graph was calculated based on the formula of average probability of landslide occurrence presented in Eq. (13). The logarithmic plot in Fig. 5 categorizes discrete curves according to the landslide hazard grades, enabling the analysis of differentiated monitoring time intervals for landslide prevention by considering the risk reduction effects. The highest average probability of landslide occurrence was 1.06E-04 for grade 1, gradually lowered to 2.96E-05 for grade 2, 8.29E-06 for grade 3, and 2.74E-06 for grade 4, if we conduct the monitoring in the concerned areas at the same time interval, once per year. Thus, landslide monitoring with the same time interval for the different grades yields higher risk reduction effects for the lower hazard grade areas than for the higher hazard grade areas.

The same level of risk reduction effect can be achieved for grade 2 areas with a monitoring interval of 3.6 years as for grade 1 areas with annual monitoring. The equivalent risk reduction would be achieved by monitoring grade 3 sites and grade 4 sites on a rotational basis, with periods of 12.8 years and 38.7 years, respectively. Table 2 shows the discrete values of the average probability of landslide occurrence yielding the same level of risk reduction as when the monitoring interval for grade 1 is set to one year. Variation in the monitoring time interval is shown according to the landslide hazard grades. The results of setting the monitoring interval for grade 1 to higher frequencies (monthly and weekly) are shown in the Appendix.

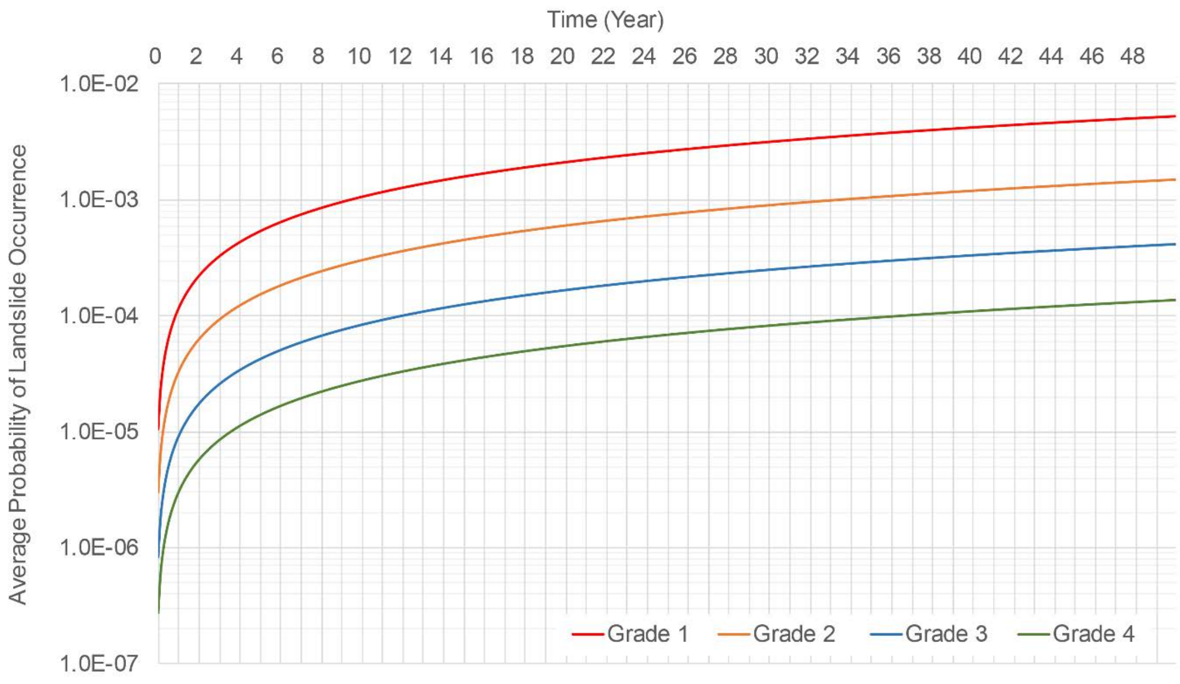

Figure 5. Change in the average probability of landslide occurrence

Table 2. Monitoring time intervals yielding the same average probability of landslide occurrence

Landslide hazard grade	Monitoring time interval (years)			
	1	3.6	12.8	38.7
1	1.06E-04	3.82E-04	1.36E-03	4.11E-03
2	2.96E-05	1.07E-04	3.79E-04	1.15E-03
3	8.29E-06	2.99E-05	1.06E-04	3.21E-04
4	2.74E-06	9.87E-06	3.51E-05	1.06E-04

4 Discussion

4.1 Landslide risk management plan considering risk reduction

Our results show that the same level of risk reduction can be achieved for lower landslide hazard areas with longer monitoring time intervals than are necessary for higher landslide hazard areas. This finding is valid for landslide monitoring methods with a low temporal resolution, such as manually read inclinometer or piezometer. These findings can be utilized to allocate human and financial resources efficiently for preventive landslide management throughout a wide area. Landslides occur in scattered areas, especially in mountainous regions, and municipalities can find it difficult to distribute the manpower and financial budget to manage the risk that arises from landslides. Our results indicate that management for landslide prevention in the study region can be implemented by covering 12 times more grade 3 sites and 38 times more grade 4 sites with rotational site visiting with the same resources that are assigned to grade 1 areas, producing the equivalent risk reduction effect. The enforcement to prevent disasters from unstable slopes (2007) in South Korea requires that official monitoring inspections are conducted at least once a year for all concerned unstable slopes; however, no scientific evidence has been introduced to determine the appropriate monitoring time interval for risk assessment. The graph in Fig. 5 that depicts the average probability of landslide occurrence can be applied, with the inclusion of frequency data suitable for other regions, to develop a logical plan for landslide monitoring with targeted risk reduction. In addition, if we convert the concept introduced in the probability of landslide occurrence into the probability of failure of engineering mitigation system such as a fence, net or retaining wall, the monitoring schedule can be planned to check their functional competence and integrity degradation. Doing so is possible wherever a valid frequency of flaws is recognized. Furthermore, risk analysis can be conducted to maintain the risk below tolerable levels considering societal risk criteria (Dai et al., 2002) by implementing monitoring activities. Such analysis is useful for areas with potential landslide risk that are anticipated to experience losses near townships, infrastructure, or ecologically valuable areas. However, this task requires the consideration of the vulnerability (V) and the element at risk (E) in the risk formula proposed by Varnes (1984) for complete risk analysis. The accumulation of sufficient landslide inventory data is also required for the task. In this study, we performed the risk analysis by limiting to the extreme weather event because of lack of continuous landslide inventory data. This limitation should be improved in future research to reflect a common example of regional weather patterns.

4.2 Characteristics of determining the monitoring interval with average probability

By referring to the average probability of landslide occurrence in Eq. (13), when λ is sufficiently smaller than one ($\lambda \ll 1$), it is possible to use an approximate equation for the probability of occurrence as below (I.S.A., 2002) because the exponential e^x can be simplified:

$$\text{Average probability of landslide occurrence} \approx \lambda \times TI / 2 \qquad (14)$$

Through this simplified equation, it was found that the monitoring time intervals needed to achieve the same risk reduction effect with different landslide hazard grades depend neither on the landslide occurrence period estimated from the rainfall threshold nor on the size of the unit area. This implies that if a municipality maintains inventory data of the number of landslide events according to their own hazard classification, differentiated monitoring intervals can be easily determined through decision-making about the risk reduction level for the highest hazard grade considering their resource pool. After reliable frequency data for landslide occurrence have been established with continuous inventories and the extent of the scope of the area is fixed, meaningful calculation results for risk reduction can be obtained. Then, mitigation measures such as monitoring to prevent loss of life or property can be implemented in a quantitative manner founded on individual risk or societal risk criteria. Regarding the size of the unit area, a municipality needs to decide on the management scope of the area for landslide risk management because the frequency of occurrence is altered by the unit area. If the size of the unit area increases from the pixel unit to the area unit of km^2, or to the entire county, the occurrence frequency will be increased. This means that the probability of disaster occurrence for a larger unit area will increase as the frequency of occurrence increases, and more resources will be required to reduce the risk over the scope area. This is an issue of scale related to resolving effectiveness.

4.3 Importance of the combination of spatial and temporal probabilities

When a landslide management system is established, it is important to combine both spatial probability and temporal probability in the system because landslides will not be initiated on high susceptibility areas with no temporal triggering factor and the distribution of the landslide events cannot be provided without spatial data (Jaiswal et al., 2010; Corominas and Moya, 2008). For landslide risk management, when a spatial unit is classified by landslide hazard grades after the analysis of susceptibility, it is necessary to collect and accumulate sufficient temporal probability data according to the hazard grade. Consequently, it is crucial to build a landslide risk management system that combines spatial and temporal information to estimate the probability accurately and to construct a preventive mitigating action plan. For this goal, it is necessary to distinguish the types of landslides and adopt an appropriate unit of landslide frequency. Importantly, as a dynamic change in land surface morphology, the cause of a landslide is removed once the landslide has occurred, and it changes to a more stable condition (Guzzetti et al., 2005). Thus, landslide occurrence data should be continuously collected and updated using a landslide inventory framework or web-based platform. This will ensure the continued validity of the data on the frequency of occurrence. Due to the lack of an accumulated inventory of landslide data in the study region, the estimation of landslide frequency was limited to an extreme weather event that may have resulted in fast slope movements in our study. Risk treatment is the final resolution for risk management, and a balance between simplicity for convenience and rigor in methodology should be maintained when approaching landslide treatment (Kadry and El Hami, 2015).

4.4 Preventive landslide management by periodic monitoring

Early warning systems for natural hazards can prevent unwanted loss of life or damage to property by timely detection and transmission of the detection signal to an enforcement body that can perform proper mitigation (Sättele et al., 2015). Moreover, reinforcing an earthen structure considering the time-average probability of failure was shown to be the most favourable option for securing its structural safety (Su et al., 2012). The preventive strategy with periodic monitoring to reduce risk is a convincing approach to landslide risk management. This approach reduces the likelihood of landslide occurrence, and it is a cost-efficient model in contrast to approaches aiming to reduce the magnitude of disasters. The implementation of landslide monitoring is a form of preventive maintenance. It can be regarded as a leading indicator for landslide risk management. However, the understanding of the condition by an experienced person at the local level is a pivotal factor for landslide risk management including efficiency of work because the initia3339ting causes of landslides are complex (Nourani et al., 2014). For instance, specific and more frequent landslide monitoring after extreme weather events is also essential considering seasonal factors. An example of this is provided by regions affected by monsoons. In addition to regular pore water pressure monitoring and deformation monitoring, efforts should be made to increase monitoring activities in the rainy season. Installing monitoring equipment capable of continuous logging and transmitting will also be required to protect core vulnerable areas against landslides involving fast slope movements.

5 Conclusion

This paper calculated the probability of landslide occurrence with frequency data estimated by a rainfall threshold, which was used to identify an optimized set of landslide monitoring time intervals for low temporal resolution methods, such as manually read inclinometer or piezometer. The goal of this approach is to obtain the same level of risk reduction effect in different landslide hazard areas. By studying the landslide inventory data reported when Typhoon Ewiniar struck Pyeongchang County together with local weather data, the temporal probability was integrated with spatial probability information based on the landslide hazard map. The concept of reliability can be employed to estimate the frequency of landslide occurrence with appropriate units. This approach can be used to derive the same formula for the probability of landslide occurrence as that derived using the Poisson distribution model.

More landslide events were initiated in grade 2 and 3 areas than grade 1 areas due to their greater total respective areas; however, the highest number of landslide events per area was observed in grade 1. In the study region, areas with a greater landslide hazard had higher frequencies of landslide occurrence. The frequency data limited to an extreme weather event were used to calculate the probability of landslide occurrence. By analysing the average probability of landslide occurrence, we ascertained that implementing monitoring with the same time interval in all areas at risk for landslides will yield greater risk reduction effects in lower landslide hazard grade areas than in higher landslide hazard grade areas. Thus, an equivalent level of risk reduction can be achieved for lower landslide hazard areas with a longer monitoring time interval.

These results prove that a timely landslide monitoring schedule according to the different landslide hazard grades can be planned by calculating the average probability of landslide occurrence considering risk reduction effects. Human and financial resources can then be allocated efficiently for preventive landslide management. The analysis of this study can be used for landslide risk management by municipalities where the areas vulnerable to landslides are scattered throughout a broad region, after establishing the accumulated occurrence frequency. Especially for Pyeongchang, which is not only an upcoming Olympic host city but also a county with a continuously increasing population, we propose that more systematic and quantitative landslide management is required to avoid potential losses due to landslides. This involves a preventive strategy with a detailed plan of periodic monitoring to reduce the likelihood of landslide occurrence.

6 Appendix

Table 3. Monitoring time intervals sets yielding the same average probability of landslide occurrence on a yearly, monthly, or weekly basis.

Landslide hazard grade	Yearly monitoring time interval for grade 1 (days)			
	365	1314	4672	14126
1	1.06E-04	3.82E-04	1.36E-03	4.11E-03
2	2.96E-05	1.07E-04	3.79E-04	1.15E-03
3	8.29E-06	2.99E-05	1.06E-04	3.21E-04
4	2.74E-06	9.87E-06	3.51E-05	1.06E-04
Landslide hazard grade	**Monthly monitoring time interval for grade 1 (days)**			
	30	107	384	1161
1	8.72E-06	3.12E-05	1.12E-04	3.38E-04
2	2.44E-06	8.72E-06	3.12E-05	9.43E-05
3	6.82E-07	2.44E-06	8.72E-06	2.64E-05
4	2.25E-07	8.07E-07	2.88E-06	8.72E-06
Landslide hazard grade	**Weekly monitoring time interval for grade 1 (days)**			
	7	25	90	271
1	2.03E-06	7.29E-06	2.60E-05	7.88E-05
2	5.68E-07	2.03E-06	7.27E-06	2.20E-05
3	1.59E-07	5.69E-07	2.03E-06	6.15E-06
4	5.26E-08	1.88E-07	6.73E-07	2.03E-06

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