Antecedent wetness and rainfall information in landslide threshold

Binru Zhao[1,2], Qiang Dai[3], Dawei Han[2], Huichao Dai[1], Jingqiao Mao[1], Lu Zhuo[2]

[1]College of Water Conservancy and Hydropower Engineering, Hohai University, Nanjing, China.
[2]Department of Civil Engineering, University of Bristol, Bristol, UK.
[3]Key Laboratory of VGE of Ministry of Education, Nanjing Normal University, Nanjing, China.

Correspondence to: Qiang Dai (bz17336@bristol.ac.uk)

Abstract. For rainfall-induced landslides, their occurrence is attributed to both the antecedent wetness condition and the recent rainfall condition. However, when defining thresholds for landslide occurrences, these two types of information have been used incompletely or implicitly, which may affect the threshold's predictive capability. This study aims to investigate how to make a better use of these two types of information in the landslide threshold definition. Comparative study is carried out among four types of landslide thresholds. By including different variables that are responsible for landslide occurrences, these thresholds could represent different cases, like whether to include the antecedent wetness information or whether to consider the recent rainfall condition explicitly. The predictive capability of these thresholds is then compared crossly with the help of the receiver operating characteristic (ROC) approach. We carry out this study in a northern Italian region called Emilia-Romagna. Results show that the false positives could be reduced by incorporating the antecedent wetness information in the threshold definition. It is beneficial for the threshold's predictive capability to explicitly consider the antecedent wetness information and the recent rainfall. When including soil moisture information in landslide threshold, the reliability of the soil moisture measurement is a key factor affecting the threshold's prediction performance. These results complement the exploration on hydro-meteorological thresholds for landslide occurrence, benefiting its development in landslide early warnings.

1 Introduction

Landslides are one of the most frequent and widespread natural hazards, posing threat to human lives and local infrastructures. These threats increase with the continuous development in the mountain areas. Landslide alerts or early warnings are able to provide useful information for disaster managers and emergency planners to mitigate the related socio-economic risk (Keefer et al., 1987;Jakob et al., 2006;Mirus et al., 2018b).

The occurrence of landslides is a result of multiple factors, such as rainfall, snowmelt, earthquakes, human activities, etc. Among these factors, rainfall is the most common driving force. Rainfall-induced landslides are typically due to the increase of the negative pore-water pressure which decreases the shear strength of the soil and leads to the slope failures. This type of landslide usually follows a long period of the wet condition and then triggered by intense rainfall. Given rainfall could be seen as a good proxy for both the antecedent wetness condition and the recent rainfall condition, it is widely used to derive the threshold for landslide occurrence based on an empirical approach. Generally, two features of the rainfall event are identified and labelled with landslide occurrence or non-occurrence. Hereafter, a line or zone is derived to separate rainfall events inducing landslides from those without landslide hazards. The separation line or zone can be determined visually (Caine, 1980) or by some statistical methods, like the method based on Bayesian inference (Guzzetti et al., 2007a;Guzzetti et al., 2007b) and the frequentist approach (Brunetti et al., 2010). The most common variables used to characterize rainfall events are rainfall intensity-duration (ID) and cumulated event rainfall-rainfall duration (ED). Various rainfall thresholds for landslide occurrences have been proposed and applied (Peruccacci et al., 2012;Segoni et al., 2014;Gariano et al., 2015;Peruccacci et al., 2017;Guzzetti et al., 2007a;Guzzetti et al., 2007b). Although these thresholds are the main tool in landslide early warning systems, their shortcomings are frequently recognized and discussed. For example, the information of the antecedent wetness or the recent rainfall is not explicitly considered in setting the threshold. When deriving rainfall thresholds, the rainfall events responsible for landslides have a duration ranging from one day to a few months. For rainfall events with short durations, they are likely to neglect the information of the antecedent wetness. As for the rainfall event with long durations, although it implicitly includes the antecedent wetness information, it is not able to reflect the real causal relationship between rainfall events and landslides, because in this case, there may be an intensity peak, which is the real trigger of landslides, preceded by a rainfall period which predisposes the slope to failure (Bogaard and Greco, 2018). However, the intensity calculated based on such a long period flattens the intensity peak, ignoring the role of the rainfall trigger.

To more explicitly take into account the antecedent wetness condition and the recent rainfall, several attempts have been proposed to derive the hydro-meteorological thresholds, which are based on the concept that the landslide occurrence is attributed to both the antecedent wetness condition (hydrological information) and the final rainfall trigger (meteorological information). They incorporate measures of the antecedent wetness condition into the definition of thresholds. In some landslide early warning systems, the antecedent cumulated rainfall over a certain period is calculated to characterize the antecedent wetness condition, which is used together with the recent rainfall amounts to derive the thresholds. For example, Chleborad et al. (2008) and Scheevel et al. (2017) made use of the recent 3-day rainfall and the antecedent 15-day rainfall to define the threshold, while Lee and Park (2015) considered the recent daily rainfall and the antecedent 3-day rainfall information. Besides the antecedent cumulated rainfall, Glade et al. (2000) employed an Antecedent Precipitation Index (API) to describe the antecedent wetness condition, which could take the loss of the antecedent rainfall into consideration. In addition to the use of rainfall information, some direct measures or proxies for the antecedent wetness condition were also explored (Crozier, 1999;Godt et al., 2006;Ponziani et al., 2012;Gabet et al., 2004). Mirus et al. (2018b) and Mirus et al. (2018a) accounted for the antecedent wetness condition with direct subsurface hydrological measurements, which are then combined with the rainfall information to define the threshold for landslides. The derived thresholds show improved performances in landslide alert systems. The catchment storage is also regarded as a source of information on the antecedent wetness condition. Ciavolella et al. (2016) included the catchment storage in the definition of landslide thresholds in a catchment in the northern

Apennines (Italy). The hydro-meteorological threshold based on event rainfall and catchment specific storage performs slightly better than the rainfall intensity-duration threshold. Segoni et al. (2018) substituted the antecedent rainfall accumulated over long periods with the soil moisture thresholds in the rainfall thresholds of the regional-scale landslide early warning system. A back analysis demonstrated this approach is able to reduce false alarms and missed alarms. These examples all explicitly consider the antecedent wetness condition and the recent rainfall when defining the thresholds for rainfall-induced landslides. There are other studies integrating the antecedent wetness condition and the recent rainfall into one variable. Zhuo et al. (2019) used the remotely sensed soil moisture prior to landslides to include these two types of information and proposed the soil moisture thresholds for landslides under different environmental conditions (land cover, soil type and type). The thresholds proposed by the published studies consider the antecedent wetness condition and (or) the recent rainfall condition implicitly or explicitly. However, to the authors' knowledge, such studies lack a more thorough analysis of the role the antecedent wetness condition and the recent rainfall in the landslide occurrence and their usage in the threshold definition, though their importance is stressed in a series of works (Ciavolella et al., 2016;Bogaard and Greco, 2018;Mirus et al., 2018a;Mirus et al., 2018b).

Therefore, this study aims to explore how to make a better use of the antecedent wetness information and the recent rainfall information in the definition of landslide thresholds. The first objective is to investigate the role of the antecedent wetness information in landslide threshold definition, and the second one is to answer whether it is necessary to explicitly consider the antecedent wetness condition and the recent rainfall when defining thresholds for landslides? As for the role of the antecedent wetness information in the landslide threshold, its importance has been widely recognized (Godt et al., 2006;Ponziani et al., 2012;Segoni et al., 2018;Mirus et al., 2018a;Mirus et al., 2018b). In our recent work (Zhao et al., 2019), this issue is also explored by proposing probabilistic thresholds for landslide occurrence, which could integrate soil moisture conditions with rainfall thresholds. The probabilistic thresholds advance the predictive capability of the rainfall threshold, indicating the crucial role of the antecedent soil moisture condition. Despite this, the direct contribution of the antecedent wetness information to the improved predictive capability remains unexplored, which is the focus of this study. In order to address these two issues, four types of thresholds are proposed. Through including different variables that are responsible for landslide occurrences, these thresholds could represent different cases, like whether to include the antecedent wetness information or whether to consider the recent rainfall condition explicitly. The predictive capability of these thresholds is compared crossly with the help of the receiver operating characteristic (ROC) approach. Here the wetness condition is characterized by the Antecedent Precipitation Index (API) due to its simple formulation and low requirement for data. We carry out this study in a northern Italian region called Emilia-Romagna, where the landslide records and hydrometeorological data are abundant and available.

This paper is organized as follows. Section 2 introduces the study area and data sources. Section 3 details the methods used in this study. The results are described in Section 4, followed by further discussions and limitations in Section 5. In the final section, we outlined the conclusions and future works.

2 Study Area and Data Sources

2.1 Study Area

Emilia-Romagna region is located in the north of Italy and is one of the most fertile and productive regions in the country. Bordered to the north by the River Po and to the south by the Apennine Mountains, the area is characterized by mountains in the southern and western portions and wide plains in the northern and eastern parts. The mountainous areas are occupied by the fold and trust belt of the Apennines, with the maximum altitude as 2165m (Figure 1a). This study focuses only on the mountain areas because they are extremely prone to landslides. The studied area has a typical Mediterranean climate: warm and dry summers and cool and wet winters.

The studied area suffers from a wide variety of landslide topologies, with the rainfall-induced landslides most common (Martelloni et al., 2012). Two kinds of rainfall are often associated with landslide events: the short but intense rainfall is likely to trigger shallow landslides, and deep-seated landslides are mainly influenced by the moderate but prolonged periods of rainfall (Ibsen and Casagli, 2004). Although landslides are not usually deadly, they are destructive. When landslides occur, the private and public properties, facilities and infrastructures are always exposed to the hazards, associated with the large cost of the regeneration and remedial works. Berti et al. (2012) mentioned that this kind of cost reached €130 million for 4 years from 2008 to 2012 in the Emilia-Romagna region. The abundance of landslides, as well as the availability of the required data, makes this region a good site to carry out this study.

2.2 Data Sources

The data used for the threshold definition includes daily rainfall, daily average temperature and daily soil moisture data. The daily rainfall is used to calculate the Antecedent Precipitation Index (API_{v1}) and the cumulated rainfall prior to landslide occurrences. The temperature and soil moisture information together with the daily rainfall are for the calculation of a modified Antecedent Precipitation Index (API_{v2}), which will be detailed in the following section. We collected all these data from ARPAE-ER (Regional Agency for the Prevention, Environment and Energy of Emilia Romagna), who maintains a hydro-meteorological network in the Emilia-Romagna region. This hydro-meteorological network could provide various data at different temporal scales, such as rainfall, air temperature, wind speed, relative humidity, etc. All these data can be obtained online (http://www.smr.arpa.emr.it/dext3r/). The rainfall and temperature data used in this study is from 50 weather stations, whose location is marked with the red triangle in Figure 1b. As for the soil moisture data, only the soil water content (m^3/m^3) at 10 cm soil depth of San Pietro Capofiume site is applied, due to its long-term records. The location of this site is marked with the yellow star in Figure 1b.

Our landslide inventory is provided by the Emilia-Romagna Geological Survey, who is responsible for maintaining a catalogue of historical landslides in the Emilia-Romagna region. The basic information recorded in the catalogue includes the landslide occurrence location, date and the date accuracy level, which are complete for all events. More detailed information like landslide characteristics (length, width, type and material), triggering factors, damage and references are only available for part of the landslide events. These records rely on various sources, such as reports to local authorities, national and local press, technical documents, etc. Despite the rich source of information, the landslide inventory probably represents a fraction of the actual landslide events, because some landslides with little damage or influences, especially those occurring in the remote area, are likely to be undetected or unreported. In this study, we only take advantage of the landslides with daily accuracy in terms of the occurrence date. Considering the completeness of all the required data, the study period is from 2006 to 2016, during which there are 168 landslides meeting the demand (Figure 1b). The 137 landslides during the period 2006 to 2014 (calibration period) are used for the threshold definition, and those of the period 2015 to 2016 (validation period) are for the threshold evaluation, with a total of 31.

Figure 2 shows the monthly distribution of average temperature and rainfall for 50 weather stations as well as that of landslide events during the period 2006-2016. It can be seen from Figure 2a and Figure 2b, for months with higher temperature, their rainfall amount is smaller, such as the month from May to September. During this period, the difference of both temperature and rainfall is small among weather stations. As for other months, their temperature is relatively lower, and there is more rainfall. The temperature of these months shows small difference among weather stations, while rainfall varies a lot especially for months with high rainfall amounts. It is interesting to see that the landslide distribution is in line with that of rainfall. The majority of landslides occurred in months with higher amounts of rainfall, indicating the crucial role of rainfall in the landslide occurrence in the study area.

3 Methods

3.1 Antecedent Precipitation Index (API)

Antecedent Precipitation Index (API) is employed in this study to characterize the wetness condition, which is derived from the preceding daily rainfall. It is noted that Antecedent Precipitation Index should be seen as a soil moisture index, allowing us to estimate the relative wetness condition of the soil, which is sufficient for the aim of this study. A general formulation of API is written as (Gray, 1970):

$$API_t = \sum_{i=0}^{N} b_i P_{t-i} \quad (1)$$

where API_t is the API value at time t; N is the number of the preceding days; b_i and P_{t-i} are the weight and the daily rainfall, respectively. Though the index of API is based on a daily scale, it can be extended for time series with other temporal resolutions. Assuming $b_i = k^i$, Equation (1) can be written as:

$$API_t = k\,API_{t-1} + P_t \quad (2)$$

where k is the recession coefficient, less than 1, used to reflect the rate of drainage and evapotranspiration process. As the initial value of API and the number of preceding days need to be estimated, we carried out various experiments which are based on different combinations of the initial value of API and the number of preceding days. It is found that the initial value no longer has an effect on the API value when the equation is run from the preceding 60th day. As a result, $\mathrm{API_t}$ is calculated from $\mathrm{API_{t-60}}$, where $\mathrm{API_{t-60}}$ is assumed to be 30 mm.

Depending on the value of the recession coefficient, there are two versions of API. The first one ($\mathrm{API_{v1}}$ hereafter) assumes the recession coefficient constant throughout the year, and the value of 0.84 is widely used in the previous researches, recommended by Crozier and Eyles (1980). The second version ($\mathrm{API_{v2}}$ hereafter) allows the recession coefficient to vary according to the change of temperature, taking into account the effect of temperature on the evapotranspiration process. The variation of the recession coefficient is assumed to be linear in the work of Crow et al. (2005), which also applies in this study:

$$\mathrm{k} = 0.84 + \delta\,(20 - \mathrm{T_{ave}}) \qquad (3)$$

where $\mathrm{T_{ave}}$ is the daily average temperature (℃) and δ is a sensitivity parameter (℃$^{-1}$). When $\delta = 0$, the recession coefficient is constant as 0.84. We used 20 ℃ as the basis as it is the most common temperature when the value of 0.84 is used. The sensitivity parameter δ is determined by comparing the $\mathrm{API_{v2}}$ time series with the soil moisture data of San Pietro Capofiume site for the period from 2006 to 2014, where Pearson correlation coefficient is used as the evaluation criterion. The optimized parameter is then validated using the data of the period 2015 to 2016. Given the study area has the similar variation pattern in terms of temperature, it is assumed the validated parameter at San Pietro Capofiume site could be extrapolated to the study area. The derived two versions of API are used to establish the threshold for landslide occurrence.

3.2 Thresholds for landslides

In order to explore the role of the antecedent wetness information and the recent rainfall in landslide thresholds, we take advantage of the empirical threshold approach, which is carried out by analyzing the hydrological and meteorological conditions that are responsible for the occurrence of historical landslides. The meteorological condition as the final trigger is characterized by the recent 3-day cumulated rainfall prior to landslides. The hydrological condition (here is the wetness condition) is indexed with the API value. When calculating these variables that are responsible for the landslides, the data from the nearest weather station are used. Based on these variables' distribution, their different percentiles are used as the critical value. Here 12 percentile ranks are considered, including 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20 and 50. Four types of landslide thresholds are designed by consisting of one variable or the combination of variables, where the critical value of the variables is used to determine the threshold level. This threshold definition procedure is illustrated in Figure 3. Four types of landslide thresholds are listed in Table 1 and introduced in detail as follows.

1) 3-day rainfall threshold

The component of the 3-day rainfall threshold is the recent 3-day cumulated rainfall. It disregards the antecedent wetness condition and only focuses on the recent rainfall prior to landslides. When determining this type of threshold, we firstly calculate the 3-day cumulated rainfall prior to the landslide occurrence during the period 2006-2014. With the distribution of the 3-day cumulated rainfall that are responsible for landslide occurrence, this variable's different percentiles are used as the critical value to take into account different levels of the threshold. Taking the 3-day rainfall's 10th percentile (P10) as an example, it means that 10% landslides have a 3-day cumulated rainfall less than P10. The higher the percentile rank, the stricter the threshold. One example of the 3-day rainfall threshold is illustrated with the blue line in Figure 4a, which separates the 3-day cumulated rainfall conditions that are likely to trigger landslides from those unlikely to trigger landslides.

2) Hybrid threshold

The hybrid threhsold consists of two components, one is the 3-day cumulated rainfall, used to characterize the recent rainfall condition; the other is the API value of the day prior to the recent 3 days, which could indicate the antecedent wetness condition. With these two components, the hybrid threshold is able to consider both the antecedent wetness condition and the recent rainfall. This raises a question of how to take advantage of these two components when predicting landslide occurrences. Although the threshold could be determined using a function that constructs a relationship between these two components, like the linear function relationship assumed in the work of Mirus et al. (2018b), we used the bilinear format (the red line in Figure 4a), the same as the work of Mirus et al. (2018a). The reason of using the bilinear format is that the component of the 3-day cumulated rainfall could remain the same as the 3-day rainfall threshold, which could facilitate the direct comparison of these two types of thresholds. In this way, we could investigate the direct impact of adding antecedent wetness information on the prediction performance. The critical value of the two components in the hybrid threshold is determined with their different percentiles based on the landslide data, which are then used together to separate conditions that are likely to trigger landslides from those unlikely to trigger landslides. It is assumed only when the critical value of both components is exceeded, landslides are likely to occur, and landslide occurrence is predicted, otherwise landslide non-occurrence is predicted.

3) API threshold

The component of API threshold is the API value prior to the landslide occurrence. As this variable is derived from the preceding rainfall, the value of the day prior to landslides is considered to include the antecedent wetness information and the recent rainfall information. However, these two types of information are implicitly considered compared with the hybrid threshold. Based on the API values prior to each landslide occurrence, its different percentiles are calculated and used to determine the API thresholds. The blue line in Figure 4b is one example of the API threshold.

4) Updated API threshold

As the antecedent wetness information and the recent rainfall information is implicitly included in the API threshold, in order to explicitly consider the role of the recent rainfall, an updated API threshold is designed, which is based on the API threshold and updated with an added rule. The API critical value is firstly used as the criterion, if it is exceeded, whether there is rainfall in the recent 3 days is then evaluated. From Equation (2), it is clear that as the recession coefficient is less than 1, if there is no rainfall, the API value will decrease. Therefore, if the API value of the recent 3 days shows a decrease trend, it is considered there is no rainfall in the recent 3 days. In this case, even the API critical value is exceeded, it is assumed that landslides are unlikely to occur, and the landslide non-occurrence is predicted. In contrast, if the API critical value is exceeded and there is an increase trend of API value during the recent 3 days, the landslide occurrence is predicted. Examples of these cases are shown with red ellipses in Figure 4b, which could help illustrate the updated API threshold.

With these four types of landslide thresholds, three scenarios are designed to address the concerns of this study. First, what's the effect of incorporating antecedent wetness information to the landslide threshold. The comparison of the hybrid threshold and the 3-day rainfall threshold is carried out to answer this question (referred as Scenario 1), because the only difference between these two types of threshold is the antecedent wetness information incorporated to the hybrid threshold. The second concern is whether it is necessary to explicitly consider the antecedent wetness condition and the recent rainfall when defining thresholds for landslides. To answer this question, Scenario 2 and Scenario 3 are designed. Scenario 2 compares the prediction performance of the hybrid threshold with that of the API threshold. In this scenario, the two components of the hybrid threshold could explicitly consider the antecedent wetness information and the recent rainfall information, while these two types of information are implicitly included in the API threshold. As for Scenario 3, as the updated API threshold could explicitly considering the recent rainfall compared with the API threshold, the prediction performance of the updated API threshold is compared with that of the API threshold, which could help investigate the role of the recent rainfall in the threshold definition.

3.3 Threshold evaluation

The prediction performance of different thresholds is evaluated using the data of the period 2015 to 2016, on the basis of the procedure illustrated in Figure 3. When evaluating the threshold performance, we only select the weather stations whose vicinities have landslide events. The contingency matrix and Receiver Operating Characteristic (ROC) curves are applied for the purpose, which are the most common tools used for the threshold evaluation (Gariano et al., 2015;Mirus et al., 2018b;Staley et al., 2013).

The contingency matrix consists of four components: Ture Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN), which are the four possible outcomes of the thresholds' prediction results. These prediction results are based on a fixed daily interval from 0:00 A.M.-11:59 P.M. local time. TP events are when the threshold is exceeded and one or more landslides occur. FN events are when the threshold is not exceeded, but there are one or more landslides; FP events are when the threshold is exceeded, but on landslides occur. TN events are when the threshold is not exceeded and there are no landslides.

Receiver Operating Characteristic (ROC) curve is plotted with True Positive Rate against False Positive Rate. True Positive Rate (TPR) is also known as the hit rate, which is used to measure the proportion of landslides that are correctly predicted. It can be calculated as:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{4}$$

False Positive Rate (FPR) is also known as the false alarm rate, which is used to measure the proportion of false positives over the events when no landslide occurs. It can be calculated as:

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{5}$$

The variation range of TPR and FPR is both from 0 to 1. The optimal value of TPR and FPR is 1 and 0, respectively. Therefore, the optimal prediction performance is achieved when TPR equals 1 and FPR equals 0 (perfect point). In reality, it is difficult for a threshold to reach the perfect point, as a result, the Euclidean distance (d) to the perfect point is used as a criterion to evaluate the prediction performance (Gariano et al., 2015). The smaller the distance, the better the performance. Sometimes owing to the danger of the missed alarms, the optimal one is chosen among thresholds with TPR as 1. In this case, the smaller the FAR value, the better the prediction performance.

$$\mathrm{d} = \sqrt{(\mathrm{FPR})^2 + (\mathrm{TPR} - 1)^2} \tag{6}$$

For each threshold approach, we explored various values or combinations. In order to evaluate the predictive capability of one certain threshold approach, the area under the ROC curve (AUC) of the threshold approach is calculated. The larger the area, the better the predictive capability.

4 Results

4.1 Thresholds for landslides

Before analyzing the hydrological and meteorological conditions responsible for the occurrence of historical landslides, we firstly test the reliability of API in indexing the wetness condition. The sensitivity parameter δ of API_{v2} is calibrated as 0.006 $℃^{-1}$. In order to validate the parameter, its performance is evaluated using the data of the independent period 2015 to 2016. Figure 5 shows the scatter plot of API against the soil moisture data at San Pietro Capofiume site, with Figure 5a for API_{v1} and Figure 5b for API_{v2}. The Pearson correlation coefficient (r_p) is 0.71 for the API_{v2}. Although it can't be considered significant, it shows a great improvement compared with API_{v1}, whose Pearson correlation coefficient (r_p) is 0.51. From the data distribution in Figure 5b, it is seen that the poor linear relationship is mostly attributed to the high values of API_{v2}. The soil water content is limited by the maximum water capacity of the soil layer; however, there is no restriction for the API_{v2} value.

Therefore, if the points with high API_{v2} values are restricted by a maximum value, the linear relationship between the API_{v2} value and soil water content will become more significant. As the API value is employed to index the relative soil wetness state, we also calculated the Spearman's rank correlation coefficient, which could measure the statistical dependence between the rankings of two variables. It is found that the Spearman's rank correlation coefficient is high (0.82), indicating that there is a similar rank between the API_{v2} value and soil water content. Therefore, the parameter of API_{v2} could be regarded as acceptable, and we use it to calculate API_{v2} value of all landslides. As for the API_{v1}, both Pearson and Spearman correlation coefficient are low, implying the poor relationship between API_{v1} and soil water content. Despite this, we also calculated API_{v1} for the comparison purpose.

With landslide records and time series of rainfall and API during the period 2006-2014, the variables that are responsible for landslide occurrences are calculated, such as the 3-day cumulated rainfall and the API values. The distribution of these variables as well as their critical values is shown in Figure 6. Figure 6a is for the antecedent API that are related with landslide occurrences, and Figure 6b for landslides' recent 3-day cumulated rainfall. These two variables are the component of the 3-day rainfall threshold and the hybrid threshold. As for the component of the API threshold and the updated API threshold, the distribution of the API value prior to landslide occurrences is shown in Figure 6c. The critical value of the variables is determined with different percentiles at 12 percentile ranks (including 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20 and 50), which are marked with triangles in Figure 6 and listed in Table 2. The variables' critical values are then used to define different landslide thresholds. Taking the 3-day rainfall threshold as an example, as its component is the 3-day cumulated rainfall, the threshold value is determined using this variable's critical value, such as 5.14 mm at the 10th percentile rank. As for the hybrid threshold which has two components, the critical value of the API prior to the 3 days are combined with the critical value of the 3-day cumulated rainfall to determine various threshold levels.

From Figure 6a, the API value of the day prior to the recent 3 days is higher for API_{v2} than API_{v1}. This is due to the variation of the recession coefficient in API_{v2}. The Emilia-Romagna region is characterized by the Mediterranean climate, with warm and dry summers and cool and wet winters. As shown in Figure 2c, the majority of landslides occurred in the wet season, during which the temperature is low. According to Equation (3), the recession coefficient in wet season is likely to be higher than 0.84, and the lower loss rate of the preceding rainfall leads to a higher API value. The similar result can be found in Figure 6c. It is found all these three variables have a wide variation range. Taking the 3-day cumulated rainfall as an example, as is shown in Figure 6b, the 3-day cumulated rainfall that are related with landslide occurrences ranges from the minimum value of 0.4 mm to the maximum value of 231.2 mm. This indicates in several cases with small rainfall amounts, the occurrence of landslides is not only attributed to the recent rainfall prior to landslides, but the antecedent wetness condition also plays a key role. The variables' wide variation range implies that the conditions responsible for landslides vary a lot, which is also the reason why different threshold levels are explored for each threshold approach.

4.2 Threshold comparison

To compare the thresholds in the three scenarios, their prediction performance is evaluated by calculating contingencies and preforming the ROC analysis. In the ROC plot, the line represents the performance of one certain threshold approach, and the area under the ROC curve (AUC) could measure its predictive capability. The points on each line from right to left represent threshold levels from low to high, which are defined with the variables' critical values listed in Table 2. For the hybrid threshold that has two components, the points on the line represent the variation of the 3-day cumulated rainfall's critical value, where the API's critical value is fixed with its 10th percentile, with 11.01 mm for API_{v1} and 33.87 mm for API_{v2}. The reason of using this case as the representative of the hybrid threshold is that the optimal performance is achieved when API's critical value is determined at the 10th percentile rank, compared with API's other critical values.

For this procedure, the data of the period from 2015 to 2016 are used. There are 12 weather stations whose vicinities have landslide events. The landslides occurring in the same day and belonging to the same weather station are regarded as one landslide event, which is the reason why the 31 landslides are only counted as 22 events with landslides in the validation procedure. As we performed the landslide prediction at a daily interval, there should be 8772 events in total for the 12 weather stations. However, due to the missing data of a few days, only 8745 events are obtained for each threshold. The results of each scenario are introduced as follows.

a) Scenario 1

The prediction results of the 3-day rainfall threshold and the hybrid threshold are compared in Figure 7, with Figure 7a for API_{v1}, and Figure 7b for API_{v2}. It is clear that with the increment of the threshold level, the false positive rate is reduced sometimes at the expense of decreasing the true positive rate. For the hybrid threshold based on API_{v1} (Figure 7a), its AUC value is a little smaller than that of the 3-day rainfall threshold, which is unexpected given the important role of the antecedent soil moisture condition in the initiation of landslides. It is clear that this is mainly due to the missed alarms caused by the lower hybrid threshold levels. However, as for the false positive rate, the hybrid threshold presents a great improvement compared with the 3-day rainfall threshold when the 3-day cumulated rainfall's critical value remains the same. As the only difference between these two types of threshold is the incorporation of the antecedent API in the hybrid threshold, the improvement in false positive rate is attributed to this factor. In order to illustrate this improvement more clearly, the bar plot in Figure 7a shows the false positive rate of these two types of thresholds when their common component (3-day cumulated rainfall) remains the same level. The proportion of the reduced false positives which is attributed to the added antecedent wetness information is also presented in the right plot of Figure 7a. It is clear that the lower the critical value of the 3-day cumulated rainfall is, the higher the proportion of reduced false positives is. This indicates the false positives predicted by the lower 3-day rainfall threshold have a higher proportion of the dry antecedent wetness condition. The false positives with dry antecedent wetness condition are excluded by adding the API information, and thus has a higher proportion of reduced false positives. In contrast, the false positives predicted by the higher 3-day rainfall threshold level have a lower proportion of the dry antecedent soil wetness condition. Therefore, it is implied that considering the antecedent wetness condition is more crucial when using the lower critical value of the 3-day cumulated rainfall. The above results also apply to the case of API_{v2} in Figure 7b except that the AUC value of the hybrid threshold is a littler smaller than that of the 3-day rainfall threshold. From Figure 7b, it is expected that the hybrid threshold based on API_{v2} has a higher AUC value than the 3-day rainfall threshold. Based on the opposite result from the case of API_{v1}, it is implied that API_{v2} has better representativeness of the soil wetness condition than API_{v1}, which is in line with the results in Figure 5. By comparing the hybrid threshold based on API_{v2} with that based on API_{v1}, it is found the hybrid threshold based on API_{v2} not only increases the true positive rate, but also improves the performance by reducing false positives.

b) Scenario 2

Figure 8 shows the prediction results of the hybrid threshold and the API threshold, with Figure 8a for the thresholds based on API_{v1}, and Figure 8b for the thresholds based API_{v2}. By analyzing the AUC value, it is found that for both API_{v1} and API_{v2}, the AUC value of the hybrid threshold is greater than that of the API threshold, and the improvement is more distinct for API_{v2} than API_{v1}. From Figure 8a, although the hybrid threshold is more capable of reducing the false positive rate, its true positive rate of the lower threshold level is smaller, which influences the AUC value. As for the thresholds based on API_{v2}, the hybrid threshold not only reduces the false positive rate, its performance of true positive rate is also superior to API threshold.

c) Scenario 3

The comparison results of the API threshold and the updated API threshold are shown in Figure 9. Figure 9a is for the thresholds based on API_{v1}, and Figure 9b is for the thresholds based on API_{v2}. From Figure 9a, these two threshold approaches have the same AUC value, while for API_{v2} in Figure 9b, the updated API threshold has a larger AUC value than the API threshold. It is found that for both API_{v1} and API_{v2}, the updated API threshold has a superior performance in reducing the false positive rate, which is clear in the right bar plot. With the increase of the API's critical value, the proportion of reduced false positives which are caused by the updated API threshold decreases. This indicates that among the false positives predicted by the lower API threshold, there is a higher proportion of the cases without rainfall during the recent 3 days. In contrast, for the false positives predicted by the higher API threshold, there is a lower proportion of the cases without rainfall during the recent 3 days. Therefore, highlighting the role of the recent 3-day rainfall is more important when the lower API's critical value is used. By comparing Figure 9b with Figure 9a, it is clear that the updated API threshold's ability to reduce false positives is superior for the API_{v2} version to API_{v1} version.

4.3 The optimal threshold

To determine the optimal threshold level for each threshold approach, the Euclidean distance (d) is used as the criterion to measure the balance between the correct predictions and incorrect predictions. The optimal prediction results determined by the smallest Euclidean distance are listed in Table 3. Among the seven optimal thresholds, the hybrid threshold based on API_{v2} has the smallest distance to the perfect point, with the true positive rate as 0.95 and false positive rate as 0.11. The updated API threshold based on API_{v2} could also provide a better prediction result, where the true positive rate is 0.91 and the false positive rate is 0.10. It is interesting to find that these two threshold definition approaches could explicitly consider the antecedent wetness condition and the recent rainfall. The superiority of these two threshold approaches is mainly reflected in reducing the false positive rate, though the improvement in terms of the true positive rate value is more distinct. This is because the landslide events used for the validation procedure are very limited, even a small variation in true positives will lead to an obvious variation in the value of true positive rate. Taking the two versions of the hybrid threshold as an example, although the true positive rate increases from 0.91 to 0.95, this is caused only by the difference of one true positive. However, for the false positive rate, the decease from 0.15 to 0.11 needs a difference of 266 false positives. It is also found the optimal thresholds determined using the API_{v2} data could provide better performance than those based on API_{v1} data.

In practice, in order to avoid the risk of missed alarms, the optimal threshold is determined among thresholds with the true positive rate of 1. In this case, the smaller the false positive rate, the better the threshold's prediction performance. Table 4 lists the optimal results determined in this way. The hybrid threshold based on API_{v1} fails to have the optimal result when the true positive rate is restricted to 1, since all its cases have a true positive rate less than 1. Among the rest five threshold versions, the hybrid threshold and the updated API threshold determined using API_{v2} also provide the best results. Their false positive rate is improved obviously compared with other threshold approaches, with 0.16 for the updated API threshold and 0.17 for the hybrid threshold. It is also found that using API_{v2} data in the definition of threshold could benefit its prediction performance, compared with API_{v1}.

5 Discussion

The hydro-meteorological landslide thresholds are gaining more and more attention in incorporating the antecedent wetness information into the thresholds, owing the increased recognition of the crucial role of the hydrological process in landslides initiation. The hydro-meteorological thresholds are guided by the cause-trigger concept proposed by Bogaard and Greco (2018). They advocate the landslide thresholds should combine the antecedent factors that predispose hillslope to failure (causes) and the recent rainfall events associated with the landslide initiation (triggers). Although the hydro-meteorological landslide thresholds are established in a number of published works (Chleborad et al., 2008;Scheevel et al., 2017;Mirus et al., 2018a;Mirus et al., 2018b), the role of the antecedent wetness and recent rainfall information in the landslide threshold is rarely understood. The results of our proposed framework provide useful information for this topic and complement the prior exploration on the hydro-meteorological landslide thresholds.

First, the comparison of the 3-day rainfall threshold and the hybrid threshold shows that including wetness information in the hybrid threshold could improve the false positive rate, compared with the 3-day rainfall threshold which only considers the recent rainfall information. As the only difference between these two types of thresholds is the incorporation of the wetness information, the improvement in the false positive rate is due to this factor. The work of Zhao et al. (2019) also demonstrates that integrating antecedent soil moisture conditions could improve the predictive capability of the cumulated event rainfall-rainfall duration (ED) thresholds, especially in terms of reducing false positives. However, the improvement directly contributed by the added soil wetness information is unexplored. This study is the first time to investigate this issue. The right plot in Figure 7 shows the proportion of the reduced false positives that is caused by the added antecedent wetness information, which could reach 35% for API_{v1} and 52% for API_{v2}. Such high proportion of reduced false positives further illustrates the crucial role of the antecedent wetness information in affecting the landslide threshold's predictive capability. We also explored the extent to which the false positive rate is improved under different critical values of the 3-day cumulated rainfall. It is found that the false positive rate is improved more distinctly when a lower critical value of the 3-day cumulated rainfall is used. By including the antecedent wetness condition, events whose antecedent wetness condition is dry could be excluded from false positives, and thus reduce false positive rate. Given the dry wetness condition is more frequent in the dry season compared with the wet season, it is implied that incorporating the antecedent wetness condition to the landslide threshold is more advantageous in reducing false positives for the dry season.

Second, as for how to make use of the antecedent wetness information and recent rainfall information in landslide thresholds, two caparisons are carried out. Among the four types of the thresholds proposed in this study, the hybrid threshold and the updated API threshold could be regarded as the case that could explicitly consider the antecedent wetness information and the recent rainfall, while these two types of information are implicitly included in the API threshold. Therefore, by comparing the API threshold with the hybrid threshold and the updated API threshold, respectively, we could answer this question. The comparison of the hybrid threshold and the API threshold shows the hybrid threshold could provide a better prediction performance in terms of increasing true positive rate and reducing false positive rate. By explicitly considering the recent rainfall, the updated API threshold presents a distinct improvement in reducing false positives compared with the API threshold. Based on these results, it is concluded that explicitly considering the antecedent wetness condition and the recent rainfall in the threshold definition could benefit the threshold's prediction performance. Considering the better predictive capability of the updated API threshold, it is considered its format provides a new perspective for the landslide threshold definition. When defining the updated API threshold, only one variable (API) is used, which could avoid the construction of the function relationship between two variables of the rainfall threshold, like the power law of the rainfall intensity-duration threshold. Besides, the updated API threshold could take into consideration both the antecedent wetness condition and the recent rainfall, which proves to be beneficial for the threshold's predictive capability. Though we employed API to index the soil moisture condition, this threshold definition approach could apply to other measures of the soil moisture, like the in-situ measured soil moisture and the remote sensed soil moisture.

In addition to the exploration on the role of the antecedent wetness and recent rainfall information in landslide thresholds, it is also found that the reliability of the soil moisture measurement is also a key factor affecting the threshold's predictive capability. In this study, two versions of API are used to index the soil wetness state when defining the threshold. The recession coefficient remains constant for API_{v1}, while the recession coefficient of API_{v2} is allowed to vary according to the change of the temperature. By comparing API_{v1} and API_{v2} with the measured soil water content at San Pietro Capofiume site, respectively, it is found that API_{v2} is more correlated with the soil water content. The API_{v2}'s better representativeness of the soil moisture is also reflected in the threshold performance, where the thresholds based on API_{v2} present better prediction results than those based on API_{v1}. Therefore, it is implied that the better representation of the soil moisture could also benefit the threshold's prediction performance. The representation of the soil moisture could be improved by using the measured soil moisture (Mirus et al., 2018a;Mirus et al., 2018b) or other indexes estimated with a better model, like the water balance model proposed by Godt et al. (2006), which could account for the monthly variations in evapotranspiration and an exponential decline to reflect faster drainage during wetter conditions.

Although the above results could provide useful information for the landslide threshold definition, it is noted the method we employed in this study is based on the statistical approach. Therefore, the proposed results probably be influenced by the data used for the threshold evaluation, which is also highlighted in the work of Gariano et al. (2015). They stated that the lack of landslide information has a great impact on the contingencies and the skill scores used to evaluate the threshold forecasting performance. In our study, the considered landslides are likely to be incomplete, which will cause the uncertainties to the contingencies and the ROC analysis. However, given the large proportion of the days without landslides (the sum of false positives and true negatives), according to Equation (5) the variation in the landslide events has little impact on the false positive rate. From the results of the thresholds, the improvement caused by adding antecedent soil wetness information (or explicitly including two types of information) mainly reflects in reducing false positives. As a result, it is regarded the proposed results are robust. Despite this, explorations with more complete data are encouraged to test the proposed results. To better understand the role of the antecedent wetness condition and the recent rainfall in the occurrence of rainfall-induced landslides, a physics-based approach is expected. The understanding of the physic process could help construct the threshold which is more in line with the practice. For instance, Napolitano et al. (2015) explored the effect of seasonal variations of antecedent-hydrological conditions on rainfall triggering of debris flows by carrying out a hydrological and slope stability model. The results show the opposing winter and summer antecedent hydrological conditions exert a significant control on intensity and duration of rainfall triggering events. Thomas et al. (2018) designed thousands of storm patterns and coupled them with a physics-based hydrological and slope stability model for various antecedent wetness conditions, the pore water pressure and factor of safety metrics were then analyzed. The proposed physics-based approach facilitates the exploration of the relative impact of plausible variations in soil hydraulic and mechanical properties on thresholds.

There are other points worth noting. First, when separating the antecedent wetness condition from the recent rainfall, 3 days are selected as the boundary. Although there may be many other selections for this separation, the initial exploration we present here is intended as a proof-of-concept. We start by using 3 days as the separation to explore the role of the antecedent wetness condition and the recent rainfall in landslide thresholds. Mirus et al. (2018a) explored a wide range of timescales when developing hydro-meteorological thresholds for landslide initiation. They found that using 3 days as the separation works well for two sites in the Pacific Northwest of the United States. Besides, 3 days are widely used to separate the antecedent condition from the recent condition in the previous studies (Chleborad et al., 2008;Scheevel et al., 2017;Mirus et al., 2018b). Despite this, different regions should expect different durations of recent rainfall to correlate with shallow landslide occurrences. Second, Antecedent Precipitation Index (API) is used as a proxy of soil moisture in this study, owing to its simple formulation and less data input. Although we try to improve the API's representativeness of the soil moisture by allowing the recession coefficient to vary, it can only be regarded as an indicator of the soil moisture, which is a limitation of our study. Therefore, to make the proposed results more reliable, explorations based on more accurate measures of soil moisture are encouraged.

6 Conclusion

We presented a framework to explore the role of the antecedent wetness and recent rainfall information in the thresholds for landslides. The comparative study is carried out among four types of landslide thresholds. By including different variables that are responsible for landslide occurrences, these thresholds could represent different cases, like whether to include the antecedent wetness condition or whether to consider the recent rainfall explicitly. The important role of the antecedent wetness information in landslide thresholds is further reinforced. The false positives could be reduced by incorporating the antecedent wetness information in the threshold definition, where the proportion of reduced false positives could reach as high as 50%. It is beneficial for the threshold's predictive capability to include the antecedent wetness information and the recent rainfall condition more explicitly. It is also found the reliability of the soil moisture measurement is a key factor affecting the threshold's predictive capability. The proposed results provide a timely complement to the exploration on hydro-meteorological landslide thresholds. It is the empirical approach that we used to investigate the relative impact of different information in landslide thresholds, a physics-based approach is also expected to explore this issue, which would benefit the development of the hydro-meteorological thresholds in landslide early warnings.

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Tables

Table 1. Four types of the threshold definition approach

No.	Threshold Type	Component
1	3-day rainfall threshold	the recent 3-day cumulative rainfall prior to landslide occurrences
2	Hybrid threshold	the recent 3-day cumulative rainfall prior to landslide occurrences the API value of the day preceding the recent 3 days
3	API threshold	the API value prior to the landslide occurrences
4	Updated API threshold	the API value prior to the landslide occurrences an increase trend of API value during the recent 3 days

Table 2. The critical values of landslides' three variables

Label	Percentile Rank	API prior to the 3 days (mm)		3-day cumulated rainfall (mm)	API prior to landslides (mm)	
		API_{v1}	API_{v2}		API_{v1}	API_{v2}
P1	1	3.11	10.64	0.58	7.75	15.03
P2	2	3.56	18.16	1.03	10.70	24.22
P3	3	4.61	18.69	1.72	12.97	43.83
P4	4	6.01	19.61	2.45	14.66	46.32
P5	5	6.57	22.81	2.60	15.90	49.70
P6	6	6.90	24.58	2.74	16.03	50.65
P7	7	7.55	27.96	3.63	17.07	51.71
P8	8	8.72	30.00	4.01	18.51	52.79
P9	9	9.90	32.06	4.58	19.27	54.84
P10	10	11.01	33.87	5.14	19.58	57.11
P20	20	15.66	55.00	12.60	28.16	72.48
P50	50	36.72	91.13	36.00	59.52	117.70

Table 3. The prediction results of the optimal thresholds determined by the smallest Euclidean distance

Optimal Threshold		Equation	True Positive	False Negative	False Positive	True Negative	Ture Positive Rate	False Positive Rate	Euclidean distance
Hybrid threshold	API_{v1}	API > 11.01 (P10), R > 12.60 (P20)	20	2	1266	7457	0.91	0.15	0.17
	API_{v2}	API > 33.87 (P10), R > 12.60 (P20)	21	1	1000	7723	0.95	0.11	0.12
3-day rainfall threshold		R > 12.60 (P20)	21	1	1815	6908	0.95	0.21	0.21
API threshold	API_{v1}	API > 28.16 (P20)	20	2	1910	6813	0.91	0.22	0.24
	API_{v2}	API > 72.48 (P20)	20	2	1482	7241	0.91	0.17	0.19
Updated API threshold	API_{v1}	API > 28.16 (P20)	19	3	1364	7359	0.86	0.16	0.21
	API_{v2}	API > 72.48 (P20)	20	2	860	7863	0.91	0.10	0.13

* R is the 3-day cumulated rainfall

Table 4. The prediction results of the optimal thresholds determined among threshold with the true positive rate of 1

Optimal Threshold		Equation	True Positive	False Negative	False Positive	True Negative	Ture Positive Rate	False Positive Rate	Euclidean distance
Hybrid threshold	API_{v1}	NULL	-	-	-	-	-	-	-
	API_{v2}	API > 33.87 (P10), R > 5.14 (P10)	22	0	1465	7258	1	0.17	0.17
3-day rainfall threshold		R > 5.14 (P10)	22	0	2939	5784	1	0.34	0.34
API threshold	API_{v1}	API > 16.30 (P6)	22	0	3582	5141	1	0.41	0.41
	API_{v2}	API > 46.32 (P4)	22	0	2530	6193	1	0.29	0.29
Updated API threshold	API_{v1}	NULL	-	-	-	-	-	-	-
	API_{v2}	API > 46.32 (P4)	22	0	1389	7334	1	0.16	0.16

* R is the 3-day cumulated rainfall

Figures

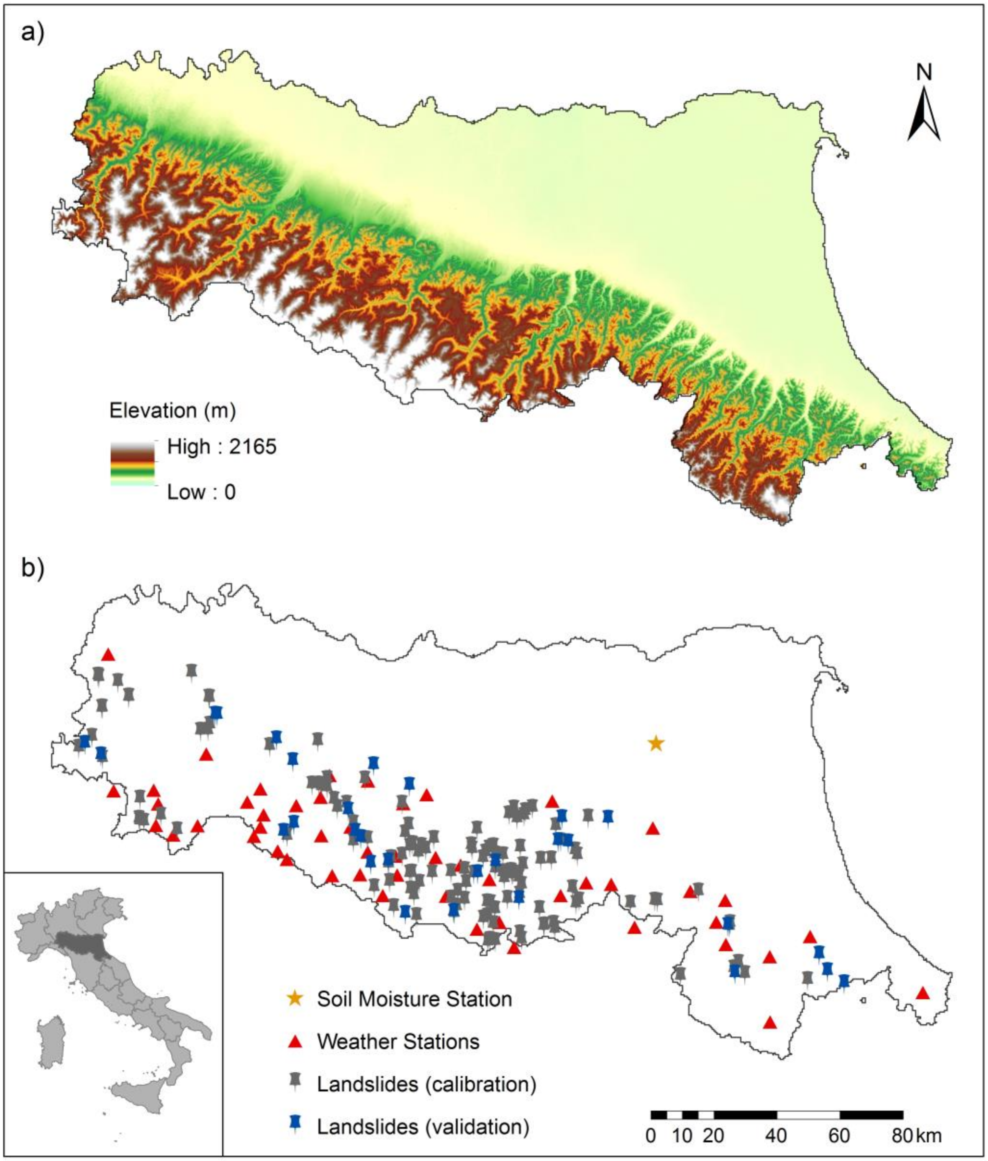

Figure 1. a) Location of Emilia-Romagna region with its DEM map and b) distribution of studied landslides and in-situ measurement stations

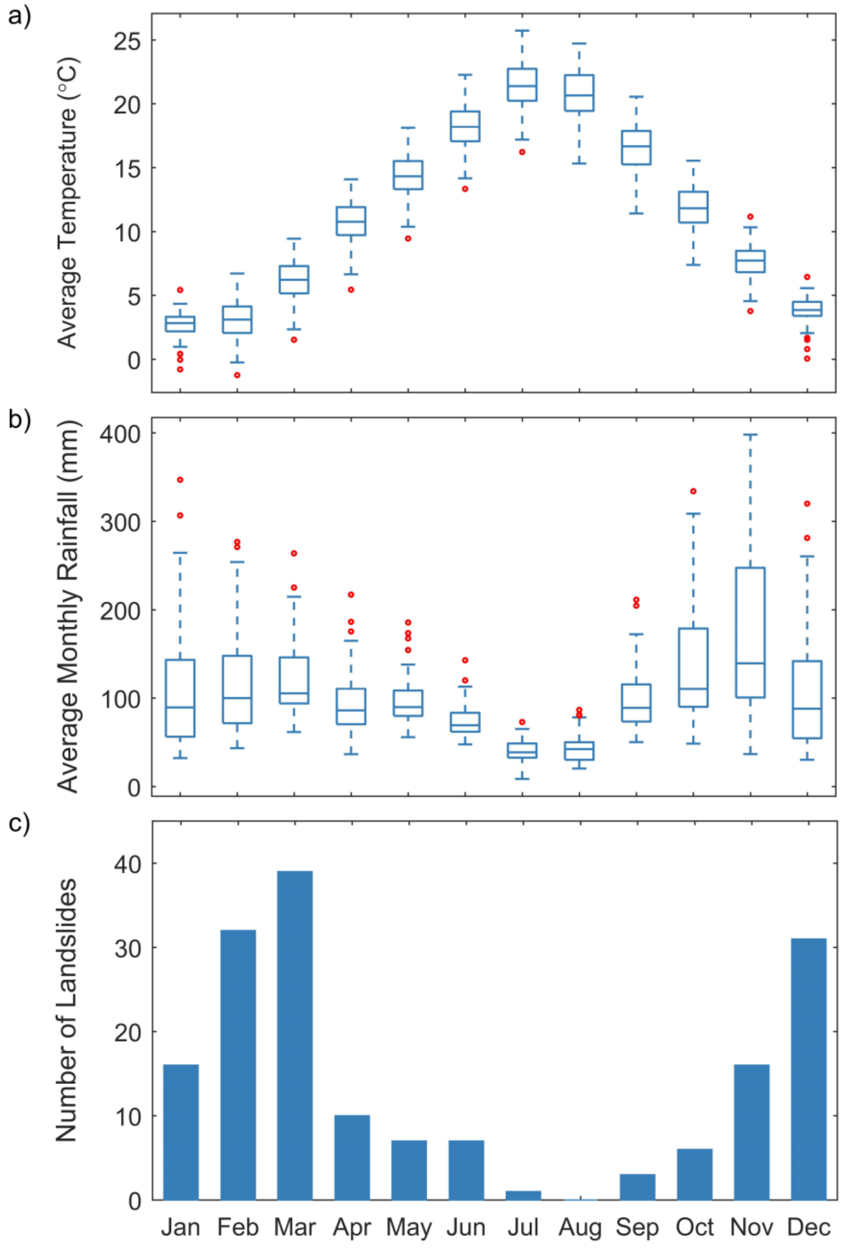

Figure 2. The monthly distribution of average temperature (a) and rainfall (b) for 50 weather stations as well as that of landslide events (c) during the period 2006-2016

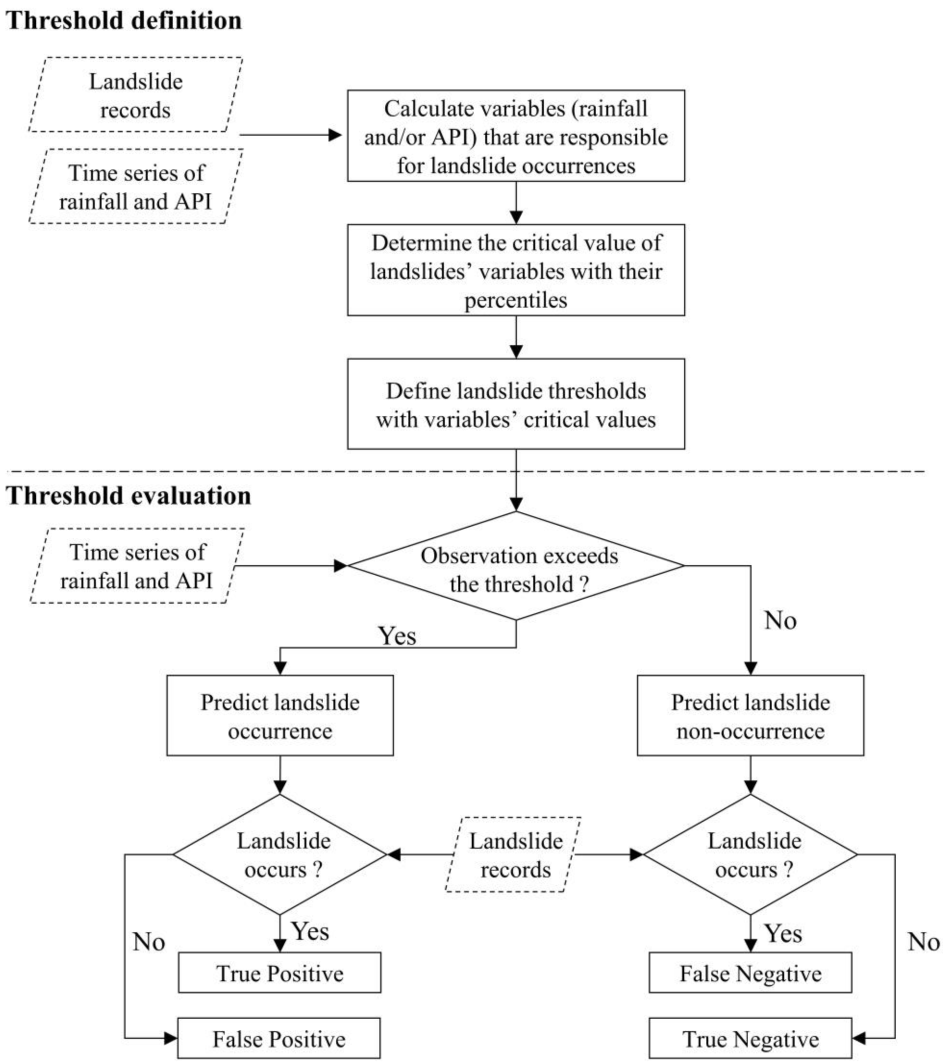

Figure 3. The procedure of threshold definition and threshold evaluation

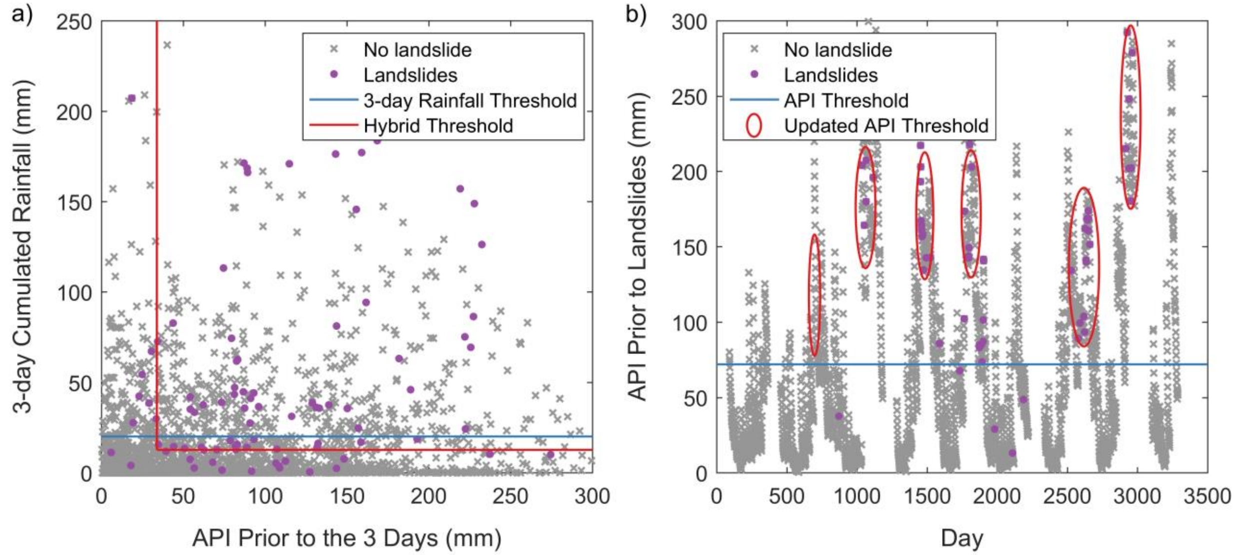

Figure 4. The example of landslide thresholds as well as the events with landslides and without landslide, a) for 3-day rainfall threshold and hybrid threshold, b) for API threshold and the updated API threshold

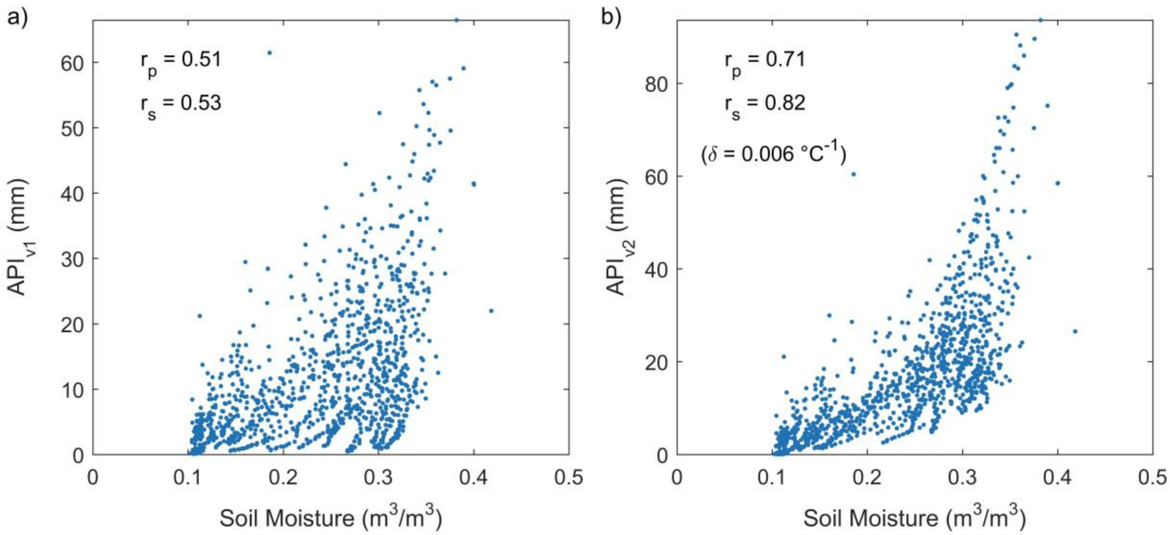

Figure 5. The scatter plot of API against the soil moisture at San Pietro Capofiume site, a) for API$_{v1}$, b) for API$_{v2}$

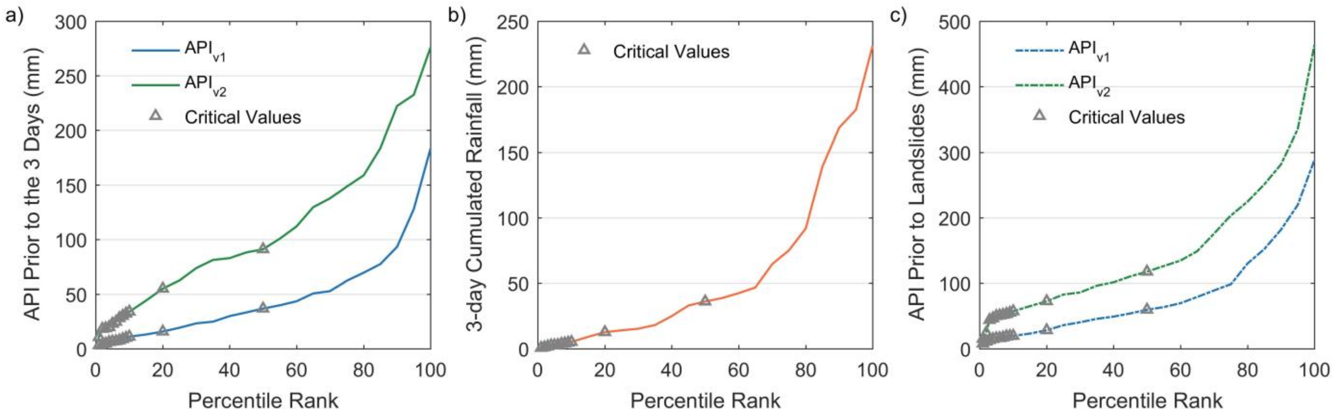

Figure 6. The distribution of landslides' variables as well as their different critical values (determined at the percentile rank of 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20 and 50), a) for the API value of the day prior to the recent 3 days, b) for the recent 3-day cumulated rainfall prior to landslide occurrences, c) for the API value prior to landslide occurrences

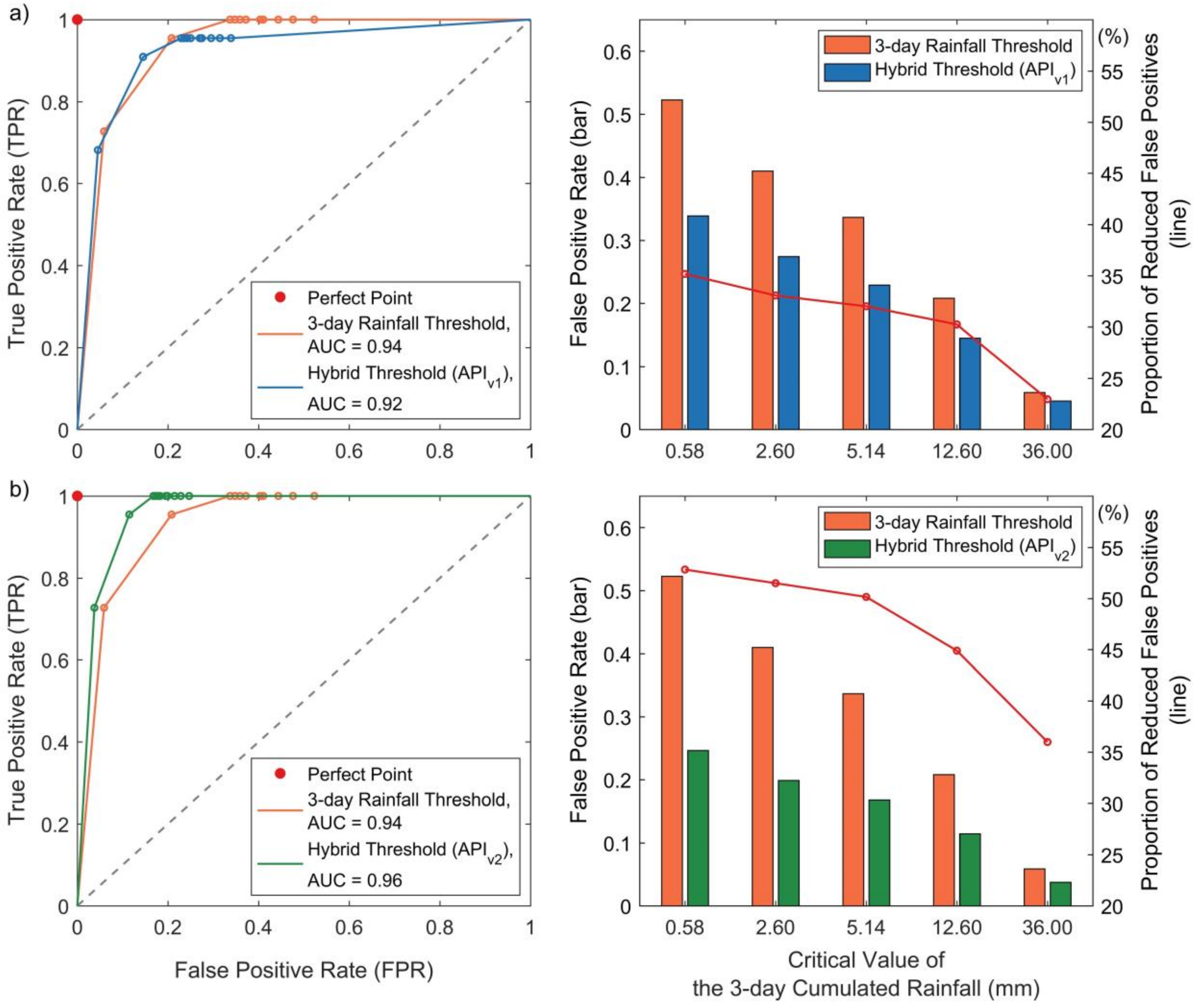

Figure 7. The prediction results of the hybrid threshold and 3-day rainfall threshold, a) for the hybrid threshold based on API$_{v1}$, b) for the hybrid threshold based on API$_{v2}$

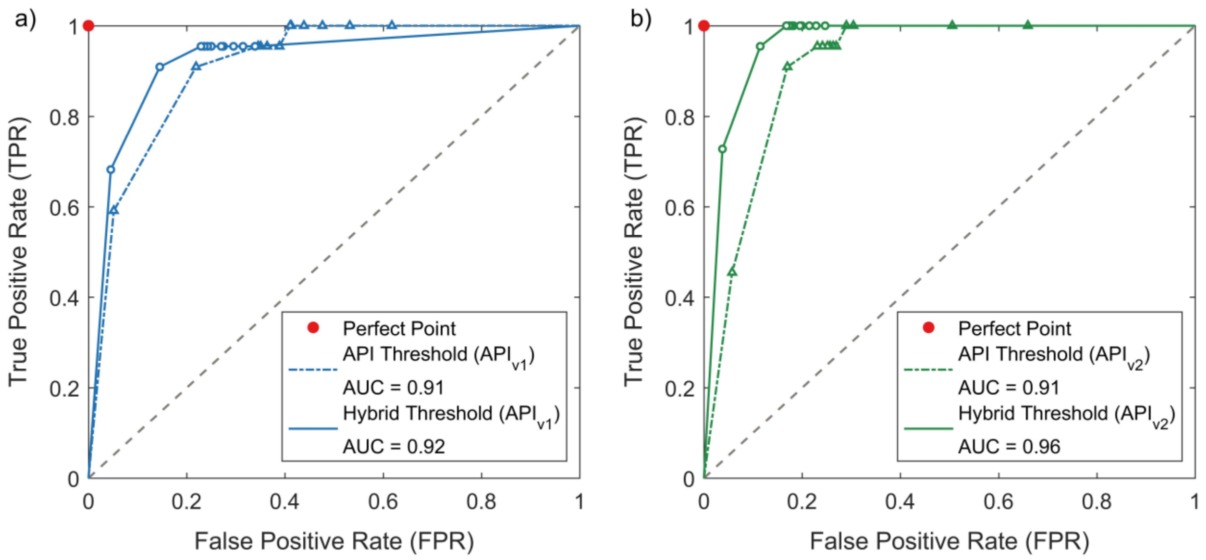

Figure 8. The prediction results of the hybrid threshold and API threshold, a) for the thresholds based on API$_{v1}$, b) for the thresholds based on API$_{v2}$

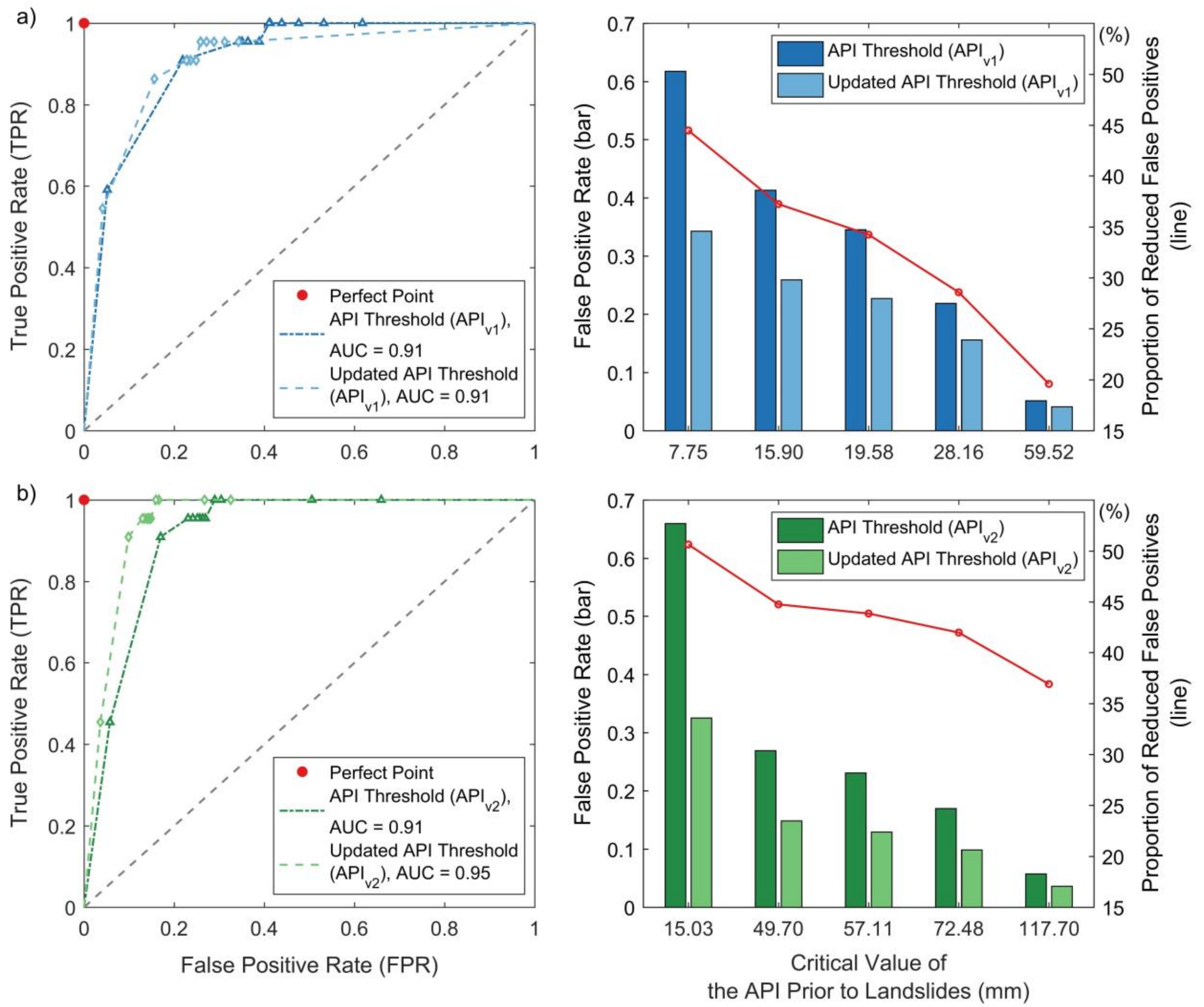

Figure 9. The prediction results of the API threshold and the updated API threshold, a) for the thresholds based on API_{v1}, b) for the thresholds based on API_{v2}