ORIGINAL PAPER

Improving flash flood forecasting using a frequentist approach to identify rainfall thresholds for flash flood occurrence

Ziyi Wu[1,2,3,4] · Biswa Bhattacharya[3] · Ping Xie[1] · Chris Zevenbergen[2,3]

Abstract

Flash Flood Guidance (FFG) is a rainfall threshold which initiates flooding in streams. It merely provides a binary output (*yes* or *no*) which has large uncertainties in forecasting. In this paper, we propose a new method by combining FFG with the Frequentist method to present the probability of flash flood occurrence based on historical rainfall events. We first calculated deviation from the log transform rainfall data leading to flash floods. Kernel Density Estimation (KDE) was used to describe the deviation. Normal Distribution Function (NDF) was chosen to fit the KDE output and to calculate probabilities of flooding as per the Frequentist FFG. In order to aid decision making, three probability thresholds (10, 20 and 60%) were used for defining four flood risk classes, namely *very low*, *low*, *significant* and *high*, and were colour coded respectively as green, yellow, orange and red. The proposed Frequentist FFG method was then applied to the Posina River basin in Italy. Comparison of forecasts from the conventional FFG (with probability 0 or 1) and Frequentist FFG for 94 6-hourly rainfall events, including 23 flood events, shows that the Frequentist FFG presented a probability of flooding varying from 0 to 100% and the corresponding risk class can be used to reduce false alarms while still reducing the disaster risk. The application of the developed approach to the Posina basin shows that decision making regarding flash forecasting is easier with the presented approach compared to the traditional FFG approach.

Keywords Flash flood · Flash flood guidance (FFG) · Frequentist · Probability · Posina

Abbreviations

FFG	Flash Flood Guidance
KDE	Kernel Density Estimation
NDF	Normal Distribution Function
AMC	Antecedent Moisture Condition
MISE	Mean Integrated Squared Error
WMO	World Meteorological Organization
FFC	Flood Forecasting Centre
ERA	Extreme Rainfall Alert

✉ Ziyi Wu
wuziyiyou@foxmail.com

[1] State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan 430072, China

[2] Faculty of Civil Engineering and Geosciences, Delft University of Technology, 2628 CN Delft, The Netherlands

[3] IHE Delft Institute for Water Education, 2601 DA Delft, The Netherlands

[4] Pearl River and South China Sea Administration of Ministry of Ecology and Environment, Eco-Environmental Monitoring and Research Centre, Guangzhou 510610, China

1 Introduction

Flash floods are floods with rapid occurrence, likely to occur after short intense rainfall in small catchments. Distinguished from regular floods, flash floods are usually localized disasters hitting basins up to a few hundred square kilometres or less and leaving short time for hazard warnings (Borga et al. 2007). Flash floods are almost a global issue frequently causing both mortality and economic loss during last decades (Creutin et al. 2013; Miao et al. 2016; Ntelekos et al. 2006). Often accompanied with landslides and mudflow, flash floods have huge destructive capabilities. In addition, changing demography (and consequent increased urbanisation) and climate change will result in larger population being prone to more severe flash floods (Hapuarachchi et al. 2011). Therefore, challenges of flash floods, including risk assessment and forecasting, always attract researchers' attention (Ali et al. 2017; Braud et al. 2018).

Flood forecasting is considered to be the main risk mitigation tool for catchments experiencing flash floods. Nowadays, discharge threshold comparison methods and rainfall threshold comparison methods are often used in flash flood forecasting (Hapuarachchi et al. 2011). The core idea of flow threshold comparison approaches is to compare the modelled flow value with the observed flooding threshold. They usually rely upon the understanding of the physical laws in local hydrological processes with high quality data (Hapuarachchi et al. 2011). Using lumped conceptual rainfall-runoff models or physically based distributed hydrological models, runoff is simulated with measured/forecasted rainfall (often together with soil moisture condition) (Reed et al. 2007; Ghadua and Bhattacharya 2019). This runoff is then compared with a pre-determined runoff threshold to determine whether flooding is likely to happen. Global Mapper is used for the river simulation level to produce flooding maps on a large-scale or when a rapid flood risk assessment is required (Shareef and Abdulrazzaq 2021). However, small catchments experiencing flash floods are often poorly gauged or ungauged, which limits the use of such a modelling system in forecasting (Hapuarachchi et al. 2011). Instead of comparing discharge, rainfall comparison methods (e.g. Flash Flood Guidance), which compare the rainfall required to produce flooding with the rainfall forecast, are widely used in different regions (Hapuarachchi et al. 2011). They are easily understood by the general public and allow decision makers to estimate and consider risks in different time frames (e.g.3 h, 6 h, 12 h) (Ntelekos et al. 2006). Therefore, rainfall threshold-based methods may be an option to cope with flash flood alert challenge.

Flash Flood Guidance (FFG) is the numerical estimation of rainfall depth in a given duration that initiates flash floods in small streams of ungagged basins (Norbiato et al. 2008). In computing FFG, rainfall-runoff curves are prepared with rainfall depth on the x-axis and corresponding runoff on the y-axis. For every chosen rainfall duration, a rainfall-runoff curve can be prepared. From the rainfall-runoff curves the rainfall amount for a specific duration that causes flooding in the basin may be determined and is known as FFG. Subsequently, in the operational mode if the forecasted rainfall depth is greater than FFG, then flooding in the basin is likely. FFG is widely used as a part of flash flood warning programmes (Mogil et al. 2002). For example, a real-time flash flood warning system was setup for the basins in Vietnam using FFG to issue an appropriate warning (Chau et al. 2021).

Computation of FFG and its operational usage has some more complexities. Due to varying catchment conditions, typically the antecedent moisture condition (AMC), the required rainfall to cause flooding in streams varies. Accordingly, different FFG values are computed for different AMC, such as AMC1 (dry condition), AMCII (average condition) and AMCIII (wet condition). While using the computed FFG for the operational usage typically a hydrological model for the river basin which contains the flashy catchment is run at daily level. The prevalent soil moisture condition is used in selecting the right FFG (wet/dry/average soil moisture condition).

However, it is worth noting that FFG only forecasts a binary flooding possibility with *yes* or *no*. While there may be rainfall events with rainfall depths lower than FFG resulting in flash floods, some rainfall amounts greater than FFG may not lead to flooding. Considering the fact that FFG is used to issue a flood alert, the likely high rates of false alarms and misses may lead to a lack of trust to the alert (Ntelekos et al. 2006). As a result, uncertainties are inherent in FFG which constrain decision making regarding the issuance of warning.

On the contrary, probability-based methods provide a quantitative assessment of threshold reliability and present a better ground for estimating extreme events using probability distribution of the forecast quantity (Bean 2009; Berti et al. 2012). With the above advantages, probabilistic methods are commonly used to decide the confidence levels of the prediction in quantitative risk assessment (Refice and Capolongo 2002). For example, Bayesian probability, which can be defined as the probability of an event A given the occurrence of another event B, is applied in issuing natural hazard warning and landslides occurrence (Berti et al. 2012; Economou et al. 2016). A Bayesian approach is a conditional probability or a probabilistic construct that allows new information to be combined with existing information. This approach has been explored to compute Bayesian probabilities of flash flood occurrence (Ghadua and Bhattacharya 2019; Martina et al. 2006). By using pressure distribution graphs, the position of maximum dynamic pressure on the bed of flip buckets in large dam reservoirs with high radius can be determined (Yamini et al. 2020).

Another method known as the Frequentist approach is based on a frequency analysis of the empirical conditions (e.g. rainfall) that have resulted in known events (e.g. flooding) (Brunetti et al. 2010). Specifically, for any given event, only one of the two possibilities may hold: it occurs or it does not. The relative frequency of occurrence of an event, observed in a number of repetitions of the experiment, is a measure of the probability of that event. It does not need assumptions similar to the Bayesian method and it may perform better when it is applied to large data sets (Brunetti et al. 2010; Peruccacci et al. 2012). Recently, the Frequentist approach has been used for the possible occurrence of landslides (Brunetti et al. 2015). Although we have not noticed any publication on the use of the Frequentist approach in flash flood forecasting, it seems

that this probabilistic approach may be appropriate to estimate uncertainties in flash flood alert.

The innovation of the paper is in presenting a probabilistic approach for flash flood forecasting and warning to complement the binary alerts issued following the FFG approach. We first illustrate the Frequentist flash flood probability by combining the FFG with the Frequentist method in order to forecast probability of flash floods corresponding to any rainfall amount in a specific duration. Then, we define different risk levels based on the proposed Frequentist FFG. Finally, we apply the proposed method to Posina River basin in Italy and provide flash flood forecasts as well as suggestions on alert to local decision makers.

2 Study area and data

The Posina river basin (Fig. 1) is located in the north-eastern Italian region Veneto, close to Venice and Padua, and has an area of 116 km^2. Most of the catchment (about 75%) is covered by deciduous forests, thereby saturation-excess is the main rainfall-runoff generation mechanism of the basin. The forest area expanded significantly in last decades due to land use changes. Elevation range from

387 m at the outlet to 2232 m at the watershed divides (Ghadua and Bhattacharya 2019).

As a natural watershed situated in one of Veneto's most rainy areas, the annual precipitation accumulation of the Posina basin is estimated to be in the range of 1600–1800 mm. Especially during autumns the region is often hit by severe rainfall that can result in flooding situations (Barbi et al. 2005).

In this study, we used hourly rainfall depth data for the time period 1992–2000. Measured data from five gauges were used to compute basin average hourly rainfall data using Thiessen polygons. Typically, 1, 3, 6, 12 and 24 h are used in FFG as rainfall accumulation time periods; the suitable time window is a characteristic of the catchment under study. For Posina 6-hourly rainfall typically leads to flash floods (Ghadua and Bhattacharya 2019). As in this paper a comparison with FFG is presented so we considered 6-hourly rainfall amounts in all analyses. The historical rainfall data was used to compute 6-hourly rainfall amounts. Hourly discharge data at the outlet of the basin was collected for the time period 1985–2000. The threshold discharge that causes flood in the basin was considered as 24 m^3/s. In total, 94 separate six-hourly rainfall events, including 23 flood events, were selected (Fig. 2). The
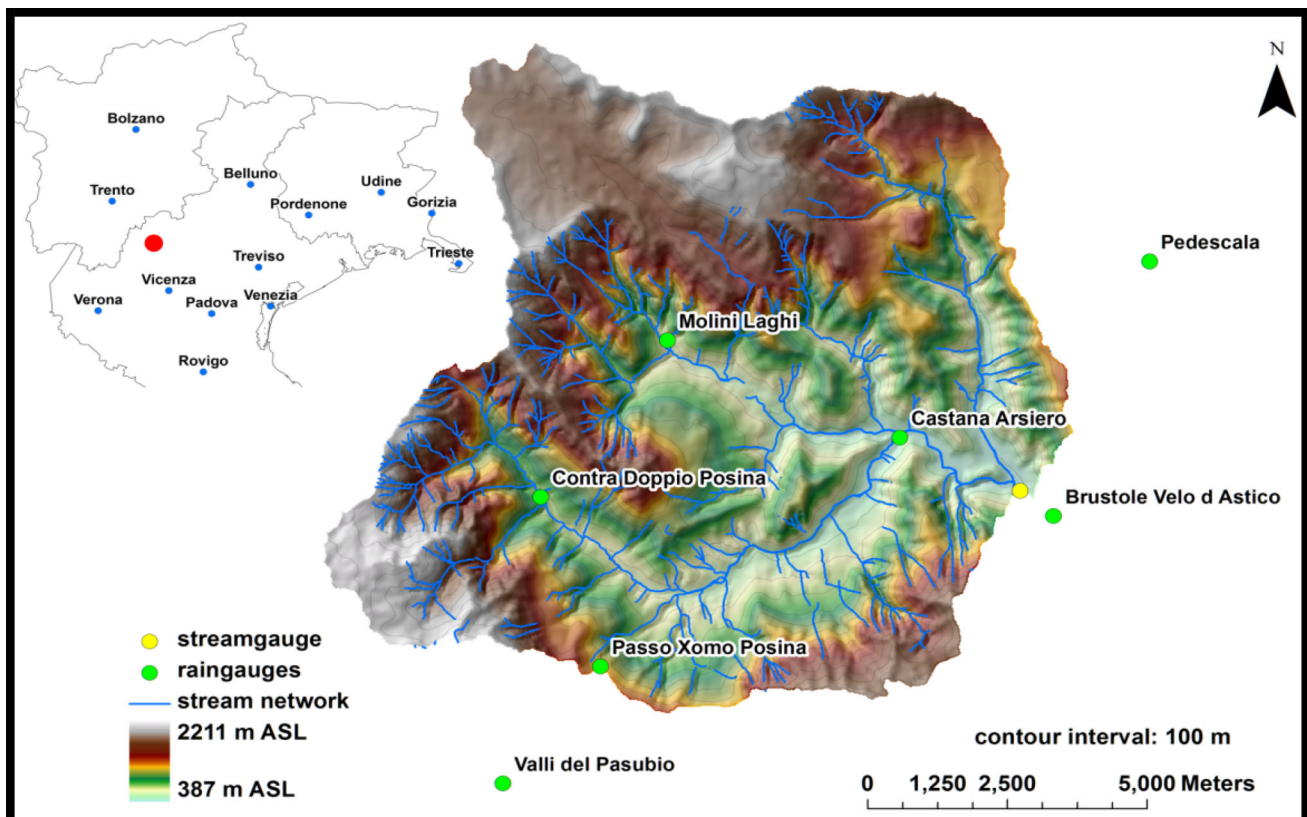

Fig. 1 The Posina river basin with the main river network, the rain gauges and stream gauge (Ghadua and Bhattacharya 2019. Source: the University of Padova, Italy)

considered FFG was 36 mm/6 h. Note that some rainfall events with rainfall depth less than the FFG resulted in flooding.

Soil moisture condition in the drainage basin is an important factor influencing the discharge. Here three types of antecedent moisture condition (AMC) according to seasonal rainfall limits for AMC classes were considered based on 5-day antecedent rainfall amounts (Soil Conservation Service, 1985). There were 8 events with AMCI (dry), 2 with AMCII (average) and 13 with AMCIII (wet) conditions. A HEC-HMS based event simulation model was developed for the Posina basin and all 23 flood events were simulated by varying AMC to find out effect of the same rainfall with different AMC. This resulted in a dataset (simulated and observed) with 23 events with AMCI (dry), 23 with AMCII (average) and 23 with AMCIII (wet) conditions. More details are provided in Ghadua and Bhattacharya (2019).

3 Method

3.1 Frequentist FFG method

In order to introduce the proposed methodology, 200 rainfall events of 6-h duration (measured and simulated) have been used in Fig. 3. The conventional FFG of this dataset was 36 mm/6 h (Fig. 3a). This dataset was not used in the subsequent computation specific to Posina basin.

Suppose for a specific time duration D (which is considered to be 6 h in this study), there are n rainfall data $R_{D,i}$ ($i = 1, 2, …, n$) leading to flood. Following Brunetti et al. (2010) we first log (base 10) transform $R_{D,i}$ into $log(R_{D,i})$ (Fig. 3b). Differences between each rainfall amount
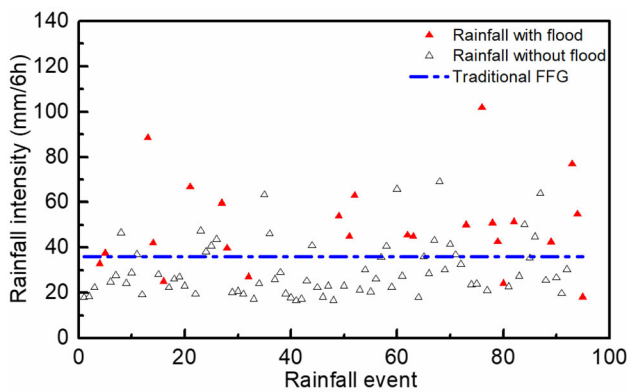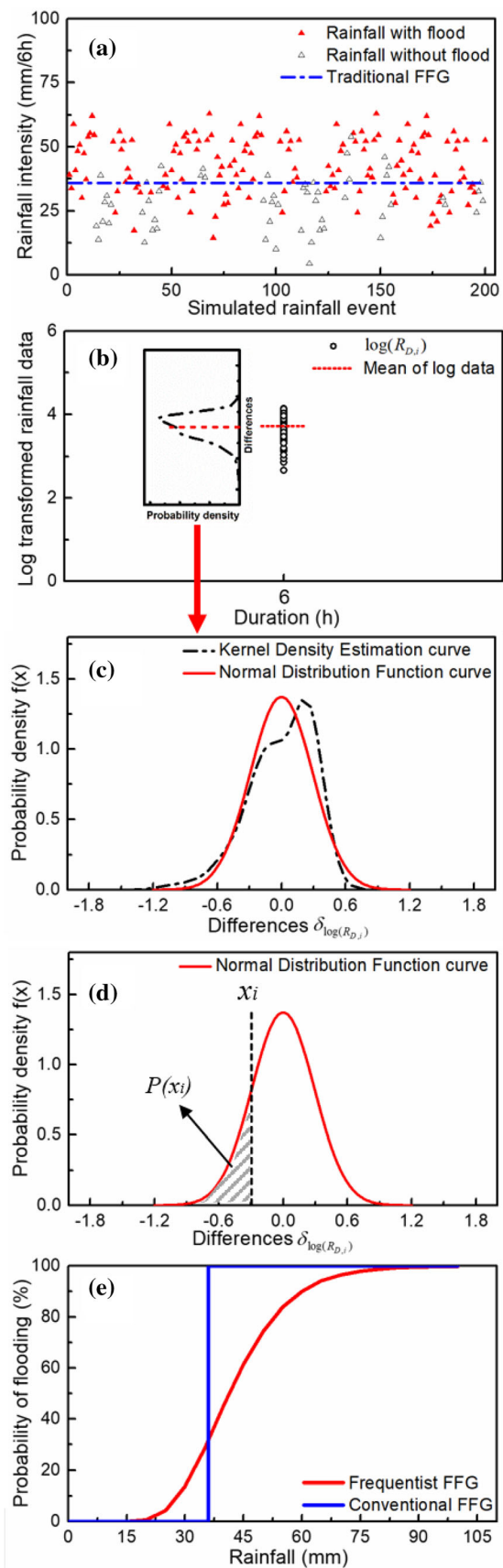

Fig. 2 Measured rainfall data (over 6 h) for the Posina basin. Some of the rainfall events led to flash floods (shown in red triangles) while the other rainfall events did not lead to flash floods (shown in grey triangles)

◀**Fig. 3** Results from each step of the Frequentist FFG method based on simulated data as a conceptual case (duration D is 6 h). **a** 200 simulated 6-hourly rainfall events with conventional flash flood guidance (FFG). **b** Log transformed rainfall data with probability density of the differences $\delta_{\log(R_{D,i})}$ obtained by Kernel Density Estimation (KDE). **c** KDE curve fitted with the Normal Distribution Function curve which shows the probability density $f(x)$. **d** Probability of a particular x_i is obtained by integral calculation which is described by the area under the probability density curve. **e** Comparison between Frequentist FFG and conventional FFG after probability calculated by Eq. (7) using

$(\delta_{\log(R_{D,i})})$ and mean rainfall amount (for the same time duration, i.e., 6 h) are calculated as

$$\delta_{\log(R_{D,i})} = \log(R_{D,i}) - M_{\log(R_D)} \tag{1}$$

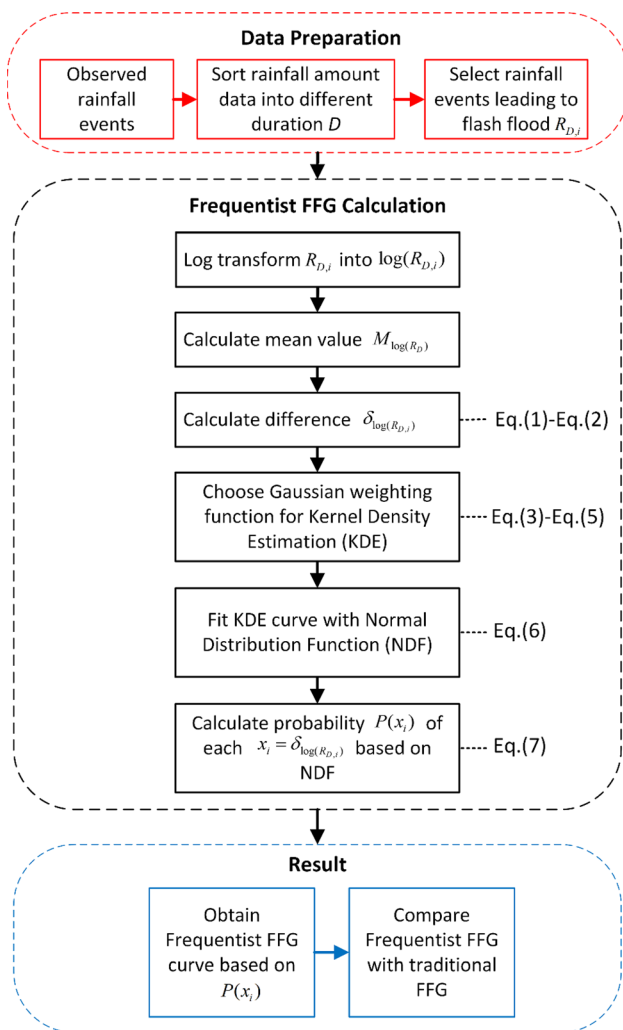The mean value $M_{\log(R_D)}$ (in Fig. 4a) is described by:

Fig. 4 Steps of the proposed Frequentist FFG method to calculate flash flood probabilities based on known rainfall events leading to flash flood

$$M_{\log(R_D)} = \frac{1}{n}\sum_{i=1}^{n}\log(R_{D,i}) \tag{2}$$

Kernel Density Estimation (KDE) is a non-parametric estimation method based on a group of observations and random variables from an unknown distribution function (Silverman 2003; Terrell and Scott 1992). Only using the sample data itself, this method is often used to estimate an unknown probability density function without any prior knowledge or hypothesis of the data distribution (Peng et al. 2016; Wang et al. 2019). Hence, we use KDE to describe the distribution of the difference $\delta_{\log(R_{D,i})}$ first.

Here, we suppose $x_i = \delta_{\log(R_{D,i})}(i = 1, 2, ..., n)$. The KDE function $\widehat{f}(x)$ can be expressed as,

$$\widehat{f}(x) = \frac{1}{n}\sum_{i=1}^{n}w(x - x_i, h) \tag{3}$$

where x is a data series consisting of several points equally spaced within the range of x_i values. The parameter h is called the bandwidth or smoothing constant. It is a free parameter which determines the amount of smoothing applied in estimating $f(x)$ (Zucchini 2003). The most common optimality method used to select this parameter is the Mean Integrated Squared Error (MISE) (Parzen 1962). The MISE of $\widehat{f}(x)$ is given by

$$MISE(\widehat{f}(x)) = E\int(\widehat{f}(x) - f(x))^2 dx \tag{4}$$

E denotes the expected value with respect to that sample. There is an optimal value of h which minimizes $MISE(\widehat{f}(x))$(Zucchini 2003).

The expression $w(x - x_i, h)$ in Eq. (3) is named as the weighting function which can be based on different types of kernels (Zucchini 2003). In this paper we use Gaussian weighting function which is widely used. Suppose $t = x$-x_i, then,

$$w(t, h) = \frac{1}{\sqrt{2\pi}h}e^{-\frac{t^2}{2h^2}}, -\infty < t < +\infty \tag{5}$$

The KDE result further fits with Normal Distribution Function (NDF, also known as Gaussian Distribution Function) according to least square method (Luciani et al. 2010),

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{6}$$

where x represents the residuals $(\delta_{\log(R_{D,i})})$,μ and σ are the mean and standard deviation of the differences $(\delta_{\log(R_{D,i})})$. The fitted KDE and NDF curves are shown in Fig. 3c.

In accordance with Eq. (6), we can calculate the probability of each $x_i = \delta_{\log(R_{D,i})}$ using:

$$P(x_i) = \int_{-\infty}^{x_i} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx \qquad (7)$$

It shows that, we can obtain the probability $P(x_i)$ of each rainfall difference (Eq. 1) to result in a flash flood, which can be used to estimate the probability of each rainfall amount to result in a flash flood. Thus, for any new rainfall amount R of duration D, we can first calculate $\delta_{\log(R_{D,i})}$ as x_i and then obtain its flash flood occurrence probability $P(x_i)$. Note that if Fig. 3 is created with actual data of a basin corresponding to a specific time duration then $P(x_i)$ can be directly estimated from Fig. 3d.

Corresponding to different rainfall amounts the probability of having flash floods with this method will be between 0 and 100% and not just 0 (will not flood) and 100% (will flood) (in Fig. 3e). The methodology described above has been presented as a flowchart in Fig. 4.

3.2 Warning levels of flash flood based on Frequentist FFG curve

We present in this section the assessment of the potential risk of flash floods based on the Frequentist FFG method. The World Meteorological Organization (WMO) suggested the use of colour coded hazards or risk matrix for expressing the extreme weather impact (WMO 2015). The UK Met Office issued Flood Guidance Statements which provide colour-coded risk information based on the confidence of the alert (Met Office 2017). The Flood Forecasting Centre (FFC), based at the Met Office in Exeter, proposed four levels of flood impact based on forecast likelihood of flooding, which were used for surface water flood risk assessment (Perez 2016):

- 0–19%: Very low
- 20–39%: Low
- 40–59%: Medium
- 60–100%: High

   While, Extreme Rainfall Alert (ERA) service provided warnings of extreme rainfall via three types of alert. They were based on the predicted probability of the extreme rainfall event to trigger the issuing of an alert occurring at the county level (Hurford et al. 2012):

- 10%: Advisory alert
- 20%: Early alert
- 40%: Imminent alert

These types of ERA have been revised to the second-generation surface water flood risk assessment, but are still based on the level of flooding probability according to FFC (Hurford et al. 2012).

Inspired by FFC and the ERA services, we propose to use four alert classes for flash floods based on the Frequentist FFG method: *very low*, *low*, *significant* and *high* and adopt the following four colours to express them: green, yellow, orange and red (Table 1).

From Table 1, when the probability of flash flood occurrence is less than 10%, we suppose the flash flood risk is very low. Here the advice could be to keep monitoring but not to issue a public warning. If the flood probability exceeds 10%, but is lower than 20%, the flash flood risk is classified as low and we suggest decision makers to focus on the area and people most likely to be affected first and keep watching the situation. With higher flood probability (20–60%), the flash flood risk is classified as significant and we suggest that all mitigating actions against the probable flash flood should be prepared. Decision makers are suggested to make public announcements about the significant risk from a likely flash flood occurrence. If flooding probability further increases ($> 60\%$), the flash flood risk is classified as high and we suggest decision makers to raise alarm to the local people and to take emergency actions. The probability thresholds adopted are to some extent arbitrary and needs to be re-evaluated based on future research and practical applications. We anticipate that these thresholds will vary with catchments and the users' needs. Users may have to define their suitable thresholds.

4 Results

We first obtained the KDE curves corresponding to different soil moisture conditions (AMCI, AMCII, AMCIII and without considering the influence of AMC) to present the distribution of differences ($\delta_{\log(R_{D,i})}$). Figure 5 shows the KDE results together with the respective NDF fitting curves. Parameters, including expected values of μ and variance σ^2 in NDF are shown in Table 2.

Flash flood probability corresponding to each rainfall amount for the three AMC classes and the case without considering the influence of AMC were calculated based on Eq. (7). The Frequentist FFG as well as conventional FFG are shown in Fig. 6. For AMCI, the FFG was 44 mm. As a result, if the rainfall in 6 h is larger than 44 mm then according to the conventional FFG, a flash flood is imminent and a warning should be issued. However, the proposed FFG shows the flash flood occurrence probability is only about 10%. Flash flood probability increases a lot with the increase of rainfall from 44 to 75 mm. Even when rainfall is larger than 95 mm the probability of flash flood occurrence is still about 95%.

Table 1 Risk levels based on flash flood probabilities associated with different suggested actions for decision makers, inspired by FFC and ERA services.

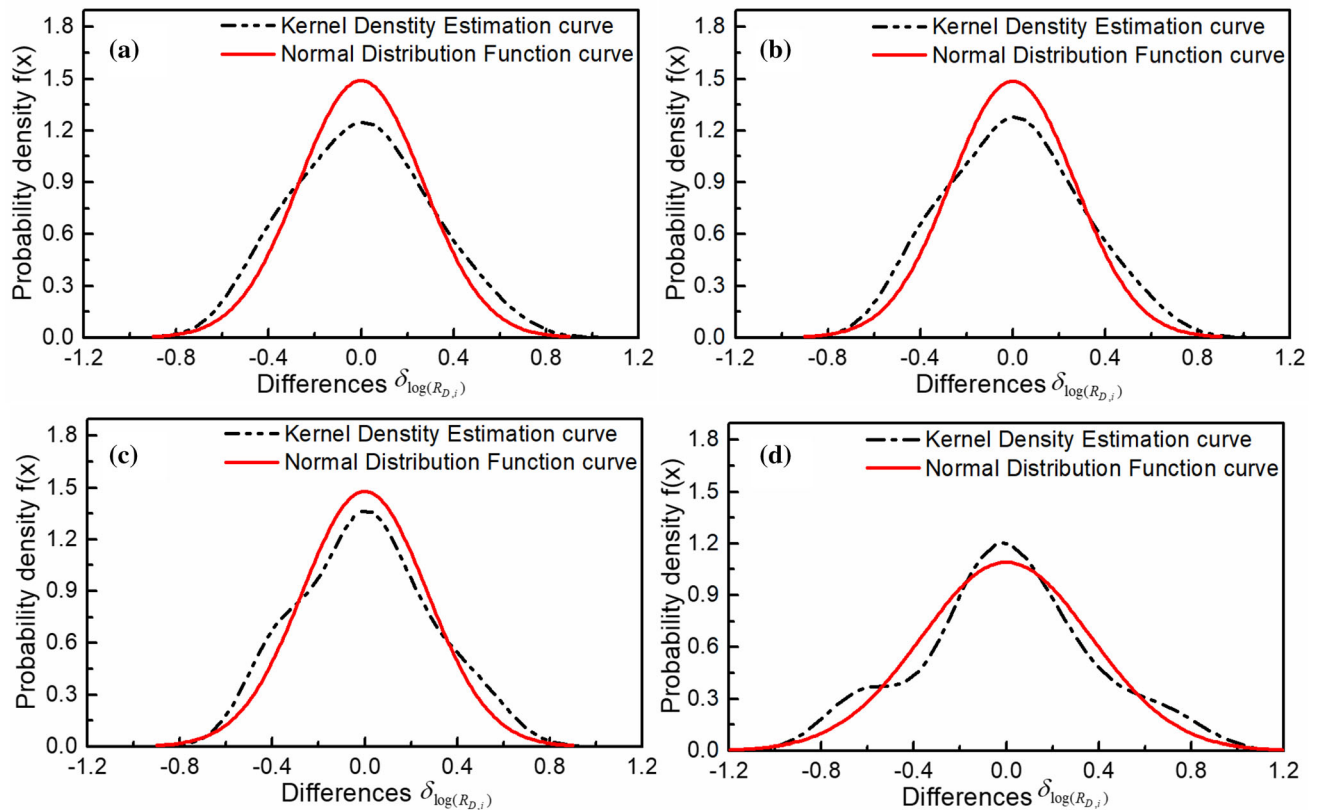|	Very low risk	Low risk	Significant risk	High risk
Probability threshold	< 10%	≥ 10 to < 20%	≥ 20 to < 60%	$\geq 60\%$
Reflect to potential risk	Keep monitoring	Be aware Keep watching	Give announcement Be prepared	Give alarm Take emergency action

Fig. 5 Kernel Density Estimation (KDE) curve of the differences fitted with a Normal Distribution Function curve (duration is 6 h). **a** AMCI (dry); **b** AMCII (average); **c** AMCIII (wet); **d** Without AMC

Table 2 Parameters used to describe NDF fitting curves under different AMC in Posina river basin

AMC	μ	σ^2
AMCI	$-$ 8.69E-16	0.2677
AMCII	$-$ 1.16E-15	0.2681
AMCIII	$-$ 5.99E-16	0.2696
without AMC	4.83E-16	0.3655

In AMCII, the conventional FFG is 36 mm, whereas according to the Frequentist FFG the flash flood occurrence probability with the same rainfall amount is only about 30%. The probability of flash flood occurrence with 60 mm rainfall is much higher ($\sim$ 91%).

In AMCIII, the conventional FFG is 28 mm which means if rainfall is less than 28 mm, there will not be flash floods, but the Frequentist FFG shows a potential flash flood occurrence probability of about 44% even when the rainfall amount is only 25 mm in 6 h.

For the cases without considering the influence of AMC based on Fig. 6d if the rainfall amount is 36 mm the probability of flooding is 100% according to existing FFG whereas it is only about 22% accordingly to the Frequentist FFG.

Comparison of (a), (b) and (c) in Fig. 6 shows that the probability of flooding based on the Frequentist FFG
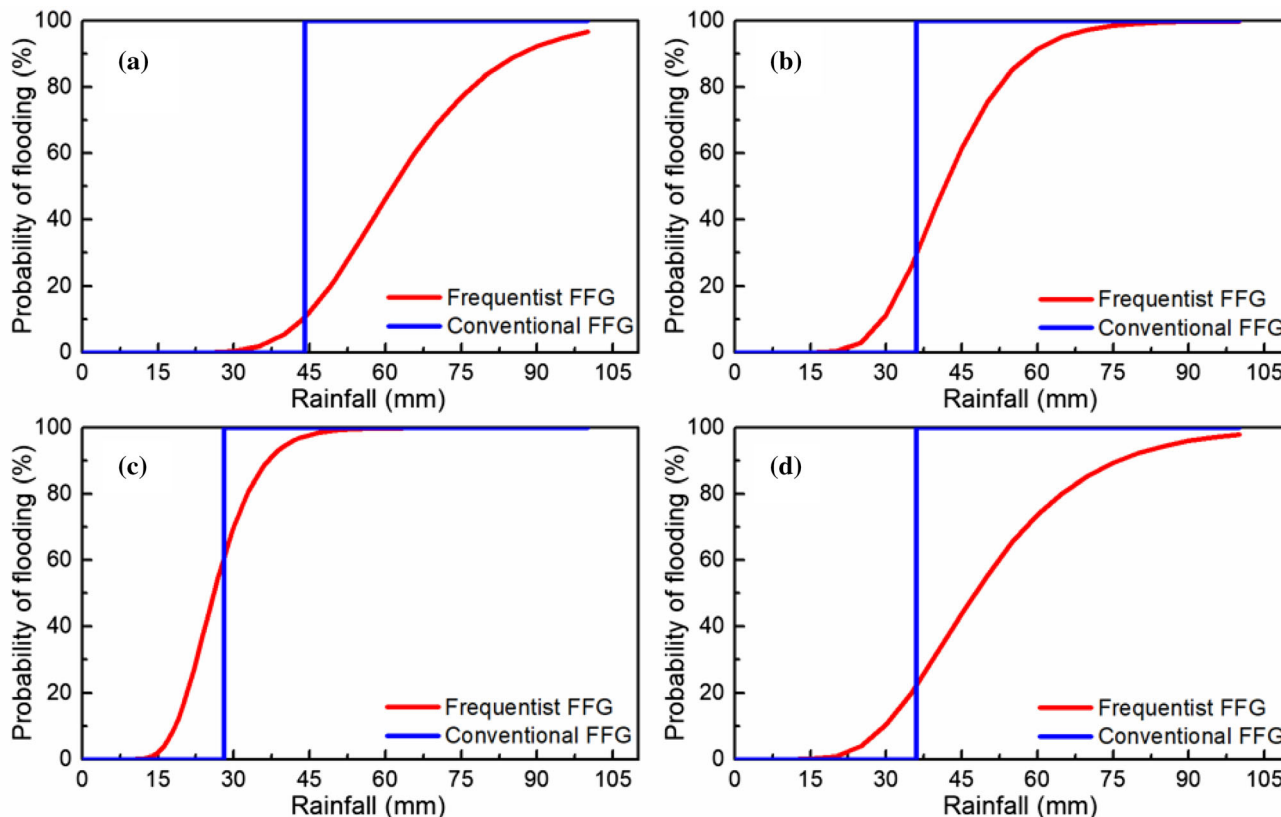
Fig. 6 Comparison between the proposed Frequentist FFG and traditional FFG for different antecedent soil moisture conditions: **a** AMCI (dry); **b** AMCII (average); **c** AMCIII (wet); **d** Without AMC

changes slowly with dry antecedent soil moisture (AMCI) whereas it increases rapidly if the soil is wet before rain comes. With AMCIII (wet) the flooding probability according to the existing FFG and as well as the Frequentist FFG is 100% when the rainfall amount increases to 60 mm. However, with AMCI the Frequentist flooding probability with similar rainfall amount is still not high. Besides, conventional FFG in Fig. 6b and d are the same, while Frequentist FFG are different. In general, Fig. 6 can be used as an aid to decision making.

Based on the procedure described in Sect. 3.2 and using the probability curves (Fig. 6) we further calculated rainfall thresholds according to four risk levels: *very low, low, significant* and *high* corresponding to four AMC classes (Table 3). Then, rainfall thresholds combined with the Frequentist FFG show the four risk levels in different colours (Fig. 7).

Figure 7 shows the relationship between flash flood probability, rainfall amount in 6 h and flood risk levels. As can be seen from Fig. 7 that the width of the green area (= risk class *very low*) is directly related to the AMC class. With higher soil moisture the width of the green area is smaller. For the narrow yellow areas (= risk class *low*) we suggest decision makers to keep monitoring rainfall event since it is easy to increase the flooding risk. Similarly, the orange area (= risk class *significant*) has smaller widths with increased soil moisture and the red area (= risk class *high*) have increased widths with higher soil moisture. The red areas denote high risk, which may be used by the decision makers to raise alarms to residents. Note that the probability thresholds for all four cases are the same (based on the definition presented in Table 1). The rainfall thresholds are different based on AMC (Table 3).

AMC	Very low risk	Low risk	Significant risk	High risk
AMCI	$R < 43.6$	$43.6 \leq R < 49.1$	$49.1 \leq R < 65.8$	$R \geq 65.8$
AMCII	$R < 29.5$	$29.5 \leq R < 33.2$	$33.2 \leq R < 44.5$	$R \geq 44.5$
AMCIII	$R < 18.4$	$18.4 \leq R < 20.8$	$20.8 \leq R < 27.9$	$R \geq 27.9$
without AMC	$R < 29.8$	$29.8 \leq R < 35.0$	$35.0 \leq R < 52.2$	$R \geq 52.2$

Table 3 Rainfall threshold R (in mm) for flash flood risk levels with different AMC in Posina river basin
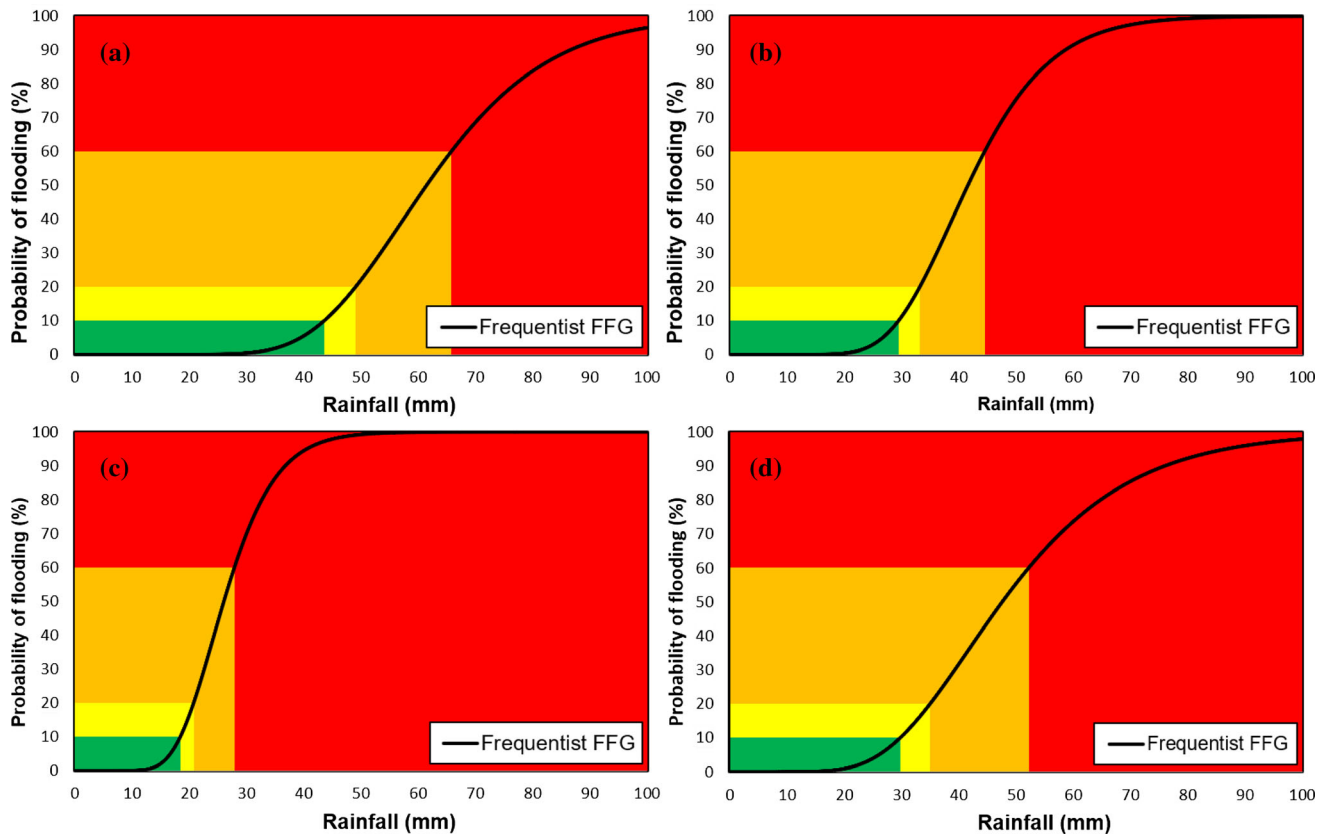
Fig. 7 Flash flood risk levels based on the Frequentist FFG for different antecedent soil moisture conditions (the duration is 6 h). Green represents *very low risk*; yellow means *low risk*; orange is *significant risk*; red alerts *high risk*. **a** AMCI (dry); **b** AMCII (average); **c** AMCIII (wet); **d** Without AMC

To illustrate the application of the Frequentist FFG together with the four risk levels, we chose four rainfall events corresponding to each of the four risk levels defined as per the Frequentist approach. We calculated the probability of flash flooding occurrence based on the Frequentist FFG curves (Fig. 6) and then compared them with the existing FFG. Furthermore, the risk classes were computed for these four rainfall events using Fig. 7. Results are compared in Table 4.

These four rainfall events conceptually depict the presence of inherent uncertainty in the forecasts from conventional FFG and the handling of it in the Frequentist FFG. For the first event, both approaches forecasted zero or close to zero probability (very low risk, colour code green) of flooding and the event did not end up in flooding (Table 4). For the second event, which ended up in flooding, was forecasted as no-flood and as of low risk (colour code yellow) respectively based on the conventional FFG and Frequentist FFG. Based on the conventional FFG no action might be taken whereas the low risk forecast from the Frequentist FFG might be used in monitoring and as a result the disaster risk might be reduced substantially. For the third rainfall event (Table 4), which

did not end up in flooding, the conventional FFG raised a false alarm, too many of which may cause cry wolf syndrome (see also Fig. 2). Compared to that the Frequentist FFG presented a significant risk ($\sim 40\%$ probability of flooding, colour code orange). Although this also was somewhat a false alarm but $\sim 60\%$ chance of not being flooded also helps in realizing that this was still not a highly likely flood. Once again if the emergency team uses similar forecasts in continuing to monitor, likely without issuing public flash flooding warning, then risk can be managed without increasing false alarms. For the last event the conventional FFG and Frequentist FFG forecasted flash flood probability of 100% and 82% (high risk, colour code red) respectively and it ended up in flooding. The probabilistic forecasts and the corresponding risk classes present the uncertainty of forecast, helps in decision making regarding issuance of flood warning and when combined with monitoring can aid in reducing disaster risk.

Figure 8 presents a comparison of forecasts from the conventional FFG and Frequentist FFG for 94 6-hourly rainfall events in Posina, which include 23 flood events. For each event Fig. 8 shows the flooding probability based on the conventional FFG. For the same events Fig. 8 also
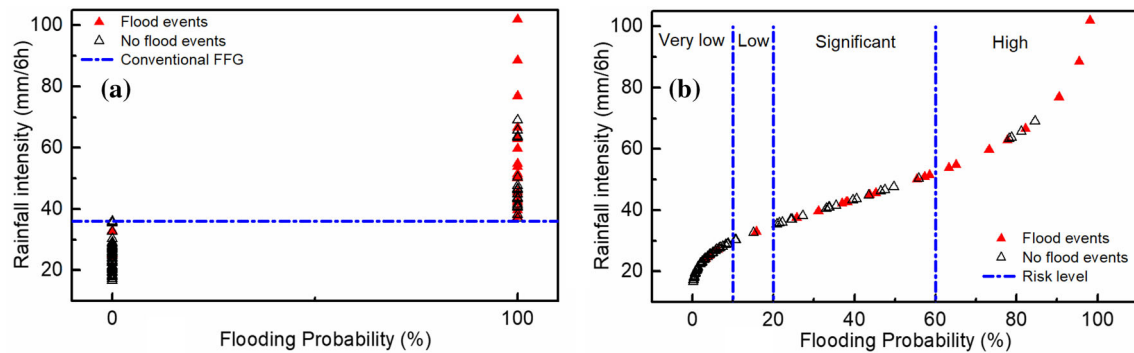
Fig. 8 Flash flood probability of 94 rainfall events with 23 flood events: **a** with the conventional FFG, **b** with the Frequentist FFG

shows the flooding probability and the corresponding risk class based on the Frequentist FFG. This figure should not be read as a comparison of accuracy of the two approaches. It rather presents the uncertainty of forecasts in the conventional FFG and the handling of it to present the probability of flooding and risk class according to the Frequentist approach. As can be seen that for several events, which ended up in flooding, while the conventional FFG forecasted no-flood, the Frequentist FFG presented a probability of flooding. Decision makers can use the probability and the corresponding risk classes to take different actions. Actions can be starting to monitor, alert notification or issuance of forecasts. Similarly, for the events which did not end up in flooding, the probability of flooding and the corresponding risk class can be used in similar decision making and it is likely that this will reduce false alarms while still reducing the disaster risk. The actual number of classes, their description, actions and the associated probability boundaries require more careful study, which in this study was taken up somewhat arbitrarily to present the usefulness of the approach.

5 Discussion

The Frequentist FFG requires historical rainfall records. Availability of sufficient rainfall data will improve the reliability of forecasted probabilities of flooding. This approach, similar to many hydrological approaches, has a limitation. It assumes stationarity in catchment responses to meteorological forcing. However, urbanisation, deforestation and other land-use changes may affect catchment response. In such cases past rainfall-flood data may not be useful. Moreover, as the flash flood prone catchments often have hilly terrain and spatial variation of rainfall in such terrains are high so computing basin wide areal rainfall by using any interpolation technique may introduce errors. These errors also depend upon the gauge density. Additionally, gauges (and weather radars if they are used) may

introduce measurement errors. These errors were not considered in this research and may be taken in future research.

Nevertheless, some ungauged basins lack flow and precipitation data. Regionalization techniques, which can be defined as the transfer of information from one catchment to another (Kokkonen et al. 2003; Li et al. 2019), may help data scarcity issues. Also, for flash flood warning, rainfall forecast data are needed. Remote sensing data can be used to obtain rainfall data (if latency allows) but need to be first evaluated by data from rain gauges (Byteway et al. 2019). Accuracy of rainfall forecast data is critical to reducing errors in computing flood probability and issuance of flood warning. Moreover, Frequentist FFG can be updated in future with new rainfall data. Extending the rainfall database with new rainfall data will help adjusting the flash flood probability ranges to better help the public and decision makers with more reliable forecasts. Land use changes in the basin will call for adjusting the probability ranges associated with the risk classes of the Frequentist FFG.

Hence, a possible future application of the proposed method may consider more factors impacting flash flood. Combining with hydrological modelling, more scenes with various local land and soil characteristics, topography and land use changes can be designed. Also, the Frequentist FFG method will be used in other cases to get more sufficient information for result evaluation and method improvement in order to better support decision makers during the flash flood warning process.

6 Conclusions

In this paper, a new flash flood forecasting method Frequentist FFG, which is developed by combining Flash Flood Guidance (FFG) with the Frequentist method, is presented. The proposed method can be used to compute the probability of flash flood corresponding to a rainfall

Table 4 Comparison results of flooding probability with risk levels for the chosen four rainfall events happened during 1992 to 2000 in the Posina basin

Event	Time	6-h rainfall (mm)	Probability of flooding based on conventional FFG[a] %	Probability of flooding based on Frequentist FFG %	Risk level	Occurrence of flood
1	1995/12/31 9:00	17.29	0	0.3	Very low risk	No
2	1992/12/5 6:00	32.97	0	15.8	Low risk	Yes
3	1998/5/28 16:00	43.23	100	39.6	Significant risk	No
4	1994/5/18 15:00	66.71	100	82.2	High risk	Yes

[a]The conventional FFG is 36 mm/6 h.

amount (or rainfall forecast). Compared to the existing FFG, which presents a binary output flood or no-flood, the Frequentist FFG depicts specific flood probability values for any rainfall amount. Four risk classes, namely, very low, low, significant and high, and the probability ranges corresponding to each class were proposed. For the issuance of warning the four risk classes were colour coded as: green (very low), yellow (low), orange (significant) and red (high). In the Posina river basin, flash flood probabilities for 6-hourly rainfall events were calculated. Based on the Frequentist FFG method the probabilities changed slowly in dry soil condition but rapidly in the wet. The rainfall ranges for very low level of risk (colour code green) was larger in dry soil conditions, which is intuitively understandable. The small rainfall ranges for low level of risk (colour code yellow) showed flooding risk easily increased whether in dry or wet conditions. Rainfall range of significant risk (colour code orange) was smaller in wet soil condition while it of high risk (colour code red) was larger. When rainfall amount increased to these two levels, decision makers would be suggested to give announcement or even alarm to local residents. The application of the proposed method in the four rainfall events (Table 4) illustrated the usefulness of the approach. The applicability of the approach is further elaborated with 94 6-hourly rainfall events (Fig. 8). It showed it was reliable to support decision makers with flooding probability varying from 0 to 100% and appropriate risk level warnings.

Declarations

References

Ali K, Bajracharyar RM, Raut N (2017) Advances and challenges in flash flood risk assessment: a review. J Geogr Nat Disasters. https://doi.org/10.4172/2167-0587.1000195

Barbi A, Bonan A, Millini R, Rossa AM (2005) Charactierization of intense rcipitation events over small scale, southern Alpine river catchments. Hrvatski Eteorološki Časopis 40(40):141–144

Bean MA (2009) Probability: the science of uncertainty with applications to investments, insurance, and engineering. American Mathematical Soc, Washington

Berti M, Martina MLV, Franceschini S, Pignone S, Simoni A, Pizziolo M (2012) Probabilistic rainfall thresholds for landslide occurrence using a Bayesian approach. J Geophys Res Earth Surf 117:1–20. https://doi.org/10.1029/2012JF002367

Borga M, Boscolo P, Zanon F, Sangati M (2007) Hydrometeorological analysis of the 29 August 2003 flash flood in the Eastern Italian Alps. J Hydrometeorol 8:1049–1067. https://doi.org/10.1175/jhm593.1

Braud I, Vincendon B, Anquetin S, Ducrocq V, Creutin J-D (2018) The challenges of flash flood forecasting. Mobilities Facing Hydrometeorol Extrem Events 1:63–88. https://doi.org/10.1016/b978-1-78548-289-2.50003-3

Brunetti MT, Peruccacci S, Rossi M, Luciani S, Valigi D, Guzzetti F (2010) Rainfall thresholds for the possible occurrence of landslides in Italy. Nat Hazards Earth Syst Sci 10:447–458

Brunetti MT, Peruccacci S, Antronico L, Bartolini D, Deganutti AM, Gariano SL, Iovine G, Luciani S, Luino F, Melillo M, Palladino MR, Parise M, Rossi M, Turconi L, Vennari C, Vessia G, Viero A, Guzzetti F (2015) Catalogue of rainfall events with shallow landslides and new rainfall thresholds in Italy. In: Lollino G, Giordan D, Crosta GB, Corominas J, Azzam R, Wasowski J, Sciarra N (eds) Engineering geology for society and territory, vol 2. Springer International Publishing, Cham, pp 1575–1579

Bytheway JL, Hughes M, Mahoney K, Cifelli R (2019) A multiscale evaluation of multisensor quantitative precipitation estimates in the Russian River Basin. J Hydrometeorol 20:447–466. https://doi.org/10.1175/JHM-D-18-0142.1

Chau TK, Thanh NT, Toan NT (2021) Primarily results of a real-time flash flood warning system in Vietnam. Civil Eng J 7(4):747–762

Creutin JD, Borga M, Gruntfest E, Lutoff C, Zoccatelli D, Ruin I (2013) A space and time framework for analyzing human anticipation of flash floods. J Hydrol 482:14–24. https://doi.org/10.1016/j.jhydrol.2012.11.009

Economou T, Stephenson DB, Rougier JC, Neal R, Mylne K (2016) On the use of Bayesian decision theory for issuing natural hazard warnings. Proc Royal Soc A. https://doi.org/10.1098/rspa.2016.0295

Ghadua Z, Bhattacharya B (2019) Improving flash flood forecasting with a Bayesian probabilistic approach: a case study on the

Posina Basin in Italy World Academy of Science, Engineering and Technology. Int. J. Environ. Ecol. Eng. 13(5):331–337

Hapuarachchi HAP, Wang QJ, Pagano TC (2011) A review of advances in flash flood forecasting. Hydrol Process. https://doi.org/10.1002/hyp.8040

Hurford AP, Priest SJ, Parker DJ, Lumbroso DM (2012) Short Communication The effectiveness of extreme rainfall alerts in predicting surface water flooding in England and Wales 1774:1768–1774. https://doi.org/10.1002/joc.2391

Kokkonen TS, Jakeman AJ, Young PC, Koivusalo HJ (2003) Predicting daily flows in ungauged catchments: model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina. Hydrol Process 17:2219–2238. https://doi.org/10.1002/hyp.1329

Li W, Lin K, Zhao T, Lan T, Chen X, Du H, Chen H (2019) Risk assessment and sensitivity analysis of flash floods in ungauged basins using coupled hydrologic and hydrodynamic models. J Hydrol 572:108–120. https://doi.org/10.1016/j.jhydrol.2019.03.002

Luciani S, Brunetti MT, Valigi D, Guzzetti F, Peruccacci S, Rossi M (2010) Rainfall thresholds for the possible occurrence of landslides in Italy. Nat Hazards Earth Syst Sci 10:447–458. https://doi.org/10.5194/nhess-10-447-2010

Martina MLV, Todini E, Libralon A (2006) A Bayesian decision approach to rainfall thresholds based flood warning. Hydrol Earth Syst Sci 10:413–426. https://doi.org/10.5194/hess-10-413-2006

Miao Q, Yang D, Yang H, Li Z (2016) Establishing a rainfall threshold for flash flood warnings in China's mountainous areas based on a distributed hydrological model. J Hydrol 541:371–386. https://doi.org/10.1016/j.jhydrol.2016.04.054

Mogil HM, Monro JC, Groper HS (2002) NWS's flash flood warning and disaster preparedness programs. Bull Am Meteorol Soc 59:690–699. https://doi.org/10.1175/1520-0477(1978)059%3c0690:nffwad%3e2.0.co;2

Norbiato D, Borga M, Degli Esposti S, Anquetin S, Gaume E (2008) Flash flood warning based on rainfall thresholds and soil moisture conditions: an assessment for gauged and ungauged basins. J Hydrol 362:274–290. https://doi.org/10.1016/j.jhydrol.2008.08.023

Ntelekos AA, Georgakakos KP, Krajewski WF (2006) On the uncertainties of flash flood guidance: toward probabilistic forecasting of flash floods. J Hydrometeorol 7:896–915. https://doi.org/10.1175/jhm529.1

Met Office (2017) Processing ECMWF ENS and MOGREPS-Gensemble forecasts to highlight the probability of severe extra-tropical cyclones: Storm Doris. ECMWF, Reading, U.K. https://www.ecmwf.int/sites/default/files/elibrary/2017/17276-processing-ecmwf-ens-and-mogreps-g-ensemble-forecasts-highlight-probability-severe-extra.pdf

Parzen E (1962) On estimation of a probability density function and mode. Ann Math Stat 33:1065–1076

Peng J, Zhao S, Liu Y, Tian L (2016) Identifying the urban-rural fringe using wavelet transform and kernel density estimation: a case study in Beijing City. China Environ Model Softw 83:286–302. https://doi.org/10.1016/j.envsoft.2016.06.007

Perez J (2016) Verification of FFC flood risk forecasts. Flood Forecastin Center. https://www.ecmwf.int/sites/default/files/elibrary/2016/16446-verification-fc-flood-risk-forecasts.pdf

Peruccacci S, Brunetti MT, Luciani S, Vennari C, Guzzetti F (2012) Lithological and seasonal control on rainfall thresholds for the possible initiation of landslides in central Italy. Geomorphology 139–140:79–90. https://doi.org/10.1016/j.geomorph.2011.10.005

Reed S, Schaake J, Zhang Z (2007) A distributed hydrologic model and threshold frequency-based method for flash flood forecasting at ungauged locations 402–420. https://doi.org/10.1016/j.jhydrol.2007.02.015

Refice A, Capolongo D (2002) Probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment. Comput Geosci 28:735–749

Shareef ME, Abdulrazzaq DG (2021) River flood modelling for flooding risk mitigation in Iraq[J]. Civil Eng J 7(10):1702–1715

Silverman BW (2003) Density estimation for statistics and data analysis. http://users.stat.ufl.edu/~rrandles/sta6934/smhandout.pdf.

Terrell GR, Scott DW (1992) Variable kernel density estimation. Ann Stat 20:1236–1265

Wang S, Wang S, Wang D (2019) Combined probability density model for medium term load forecasting based on quantile regression and kernel density estimation. Energy Procedia 158:6446–6451. https://doi.org/10.1016/j.egypro.2019.01.169

World Meteorological Organization (2015) WMO guidelines on multi-hazard impact-based forecast and warning services. https://doi.org/10.1088/0029-5515/52/8/083015

Yamini OA, Kavianpour MR, Movahedi A (2020) Performance of hydrodynamics flow on flip buckets spillway for flood control in large dam reservoirs. J Human Earth Future 1(1):39–47

Zucchini W (2003) Applied smoothing techniques, Part 1: Kernel Density Estimation. http://isc.temple.edu/economics/Econ616/Kernel/ast_part1.pdf.