

Article

A Flood Forecasting Method in the Francolí River Basin (Spain) Using a Distributed Hydrological Model and an Analog-Based Precipitation Forecast

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Abstract

Recent flooding events in Spain have highlighted the need to develop real-time flood forecasts to estimate streamflows over the next few hours and days. Therefore, a meteorological forecast that provides possible precipitation for the upcoming hours combined with a hydrological model to simulate the rainfall-runoff processes in the basin and its flood response are needed. In this paper, a probabilistic flood forecasting tool is proposed for the Francolí river basin, located in Catalonia (Spain). For this purpose, the Real-time Interactive Basin Simulator (RIBS) distributed hydrological model was calibrated in this basin for a set of flood events. Then, a series of rainfall field forecasts based on the analog method have been used as input data in the hydrological model, obtaining a set of hydrographs for given flood events as output. Finally, a probabilistic forecast that supplies the probability distribution of the possible response flows of the Francolí river is provided for a set of episodes.

Keywords: distributed hydrological model; analog method; precipitation forecasting; flash floods; flood forecasting



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1. Introduction

Anthropogenic climate change has led to an increase in extreme weather and climate events around the world, causing irreversible damage to societies and economies [1]. Moreover, climate change has altered the global hydrological cycle, causing an increase in extreme water-related events such as floods and droughts. These circumstances, combined with rapid growth in high-risk areas, will increase exposure to climate change damage in the future [2].

In recent years, the frequency and intensity of precipitation events have increased in several regions across the globe, including some European regions, with human action being the main driver attributed to such changes [3,4]. Moreover, in some Mediterranean areas, an increase in convective precipitations and precipitation intensities in both sub-daily and sub-hourly scales have been detected [5,6]. In addition, such a situation will be intensified by atmospheric global warming, leading to an increased risk of rain-induced river flooding [4].

In the future, with climate change, it is expected that extreme precipitation and pluvial flooding will increase all over the world, affecting many sectors of human activities [3,7]. Particularly, in some regions of the Mediterranean area, heavy precipitation is projected to become more frequent at a daily scale, as reported in the northern basins of the Mediterranean area [8] and the eastern area of Spain that includes the Valencia and Catalonia regions [9].

Additionally, rising sea levels and increased precipitation will increase the hazard of compound flooding in some areas [3,10]. However, regional changes in river flooding are more uncertain [3]. Therefore, the intensification of climate change and socio-economic development is projected to increase vulnerability in flood areas and exacerbate flood-related damage in the coming years [2,11].

Some studies have identified changes in flood hazards and increasing trends in the number of floods with major magnitude [4,12]. For example, in areas where snowmelt is not the main flood driver and the effect of drier antecedent soil moisture conditions have a weaker impact, the flood magnitudes can increase significantly for rare events associated with higher return periods, elevating infrastructure risks [13]. Hence, there is an observed shift towards shorter storms with more intense rainfall, exacerbating severe flooding and leading to an increased risk of damage. In contrast, there can be a decrease in minor floods, which adversely impacts to water recharge. Thus, although climate change is increasing the intensity and magnitude of extreme precipitation events, it is simultaneously reducing the magnitude of frequent flood events in many regions of the world. This is the case in regions where floods are not usually generated by snowmelt, where this reduction occurs due to the drying of antecedent soil moisture conditions [12]. Furthermore, in some European regions where snowmelt is the principal cause of floods, global warming will contribute to reduce the flood magnitude [4]. However, these studies determinate that such trends in Europe cannot be linked exclusively to climate change, as they can also be strongly influenced by human action and natural fluctuation processes, making it difficult to isolate their individual impacts.

Additionally, according to IPCC (2022), the magnitude and frequency of flooding is also expected to increase in many areas of the world, like Western Europe, the central part of Africa, Asia, the central and southern part of America and Eastern North America [14]. Furthermore, other studies demonstrate the increase in West Africa [15]. However, it is projected to decrease in other areas such as Eastern Europe and some areas of the Mediterranean Sea, the southern part of South America, and the northern part of North America. Such an increase in predicted flooding in the future will lead to an increase in economic risk and damage, if no action is taken to mitigate climate change. However, there are also great differences in risk depending on the region under consideration [14].

Focusing on studies conducted in Europe, for the 50-year period prior to 2010, existing evidence of climate change has been detected by following distinct regional patterns in observed river floods [16]. Flooding in Europe has shown either increasing or decreasing river flood discharges depending on the studied region. Thus, in north-western Europe, flooding has risen in response to increased rainfall in both autumn and winter periods. Southern Europe has experienced a decline in flood occurrences due to a reduction in rainfall and enhanced evaporation. In Eastern Europe, flooding has been reduced due to higher temperatures, which has resulted in less snowmelt volumes and reduced snow cover area.

In Spain, an overall trend of decreasing flood magnitude and frequency has been documented in the main rivers [17,18]. According to Mediero et al. (2014), precipitation was not the main driver, as increasing evapotranspiration trends and changes in land uses

had a significant influence [17]. Nevertheless, in some regions like Catalonia, flash floods have increased [19,20].

As explained above, in Europe, flood patterns reveal regional variability, indicating distinct flood trends across the continent [12,21,22]. In recent decades, major floods have occurred in Europe, raising the alarm about their increasing frequency and intensity [22], while some studies have not been able to establish a conclusive relationship between variations in flood patterns and climate change, as there are several factors that can affect changes in floods, such as natural climate variability, changes in land uses and river training, and flood control by hydraulic infrastructure [22]. Other studies have identified notable shifts in the seasonal timing of floods events across Europe, providing evidence of a perceptible climate change signal [16,23]. In these new trends analyzed, while Northeastern and Western Europe are shifting towards earlier flooding, areas around the North Sea and parts of the Mediterranean coast, which include Eastern Spain and Catalonia, are shifting towards later flooding. In the Mediterranean area, changes in the seasonality of floods are expected, with some areas such as Southern France, Northwestern Italy and Eastern Greece experiencing earlier flooding, and other areas such as Southern Italy and Greece, and Eastern Spain experiencing later flooding [23,24].

Therefore, aside from global trends, local-scale studies must be analyzed, as outcomes may be different. For instance, in the Mediterranean region, certain climate change-driven phenomena and impacts are intensifying, exceeding global growth expectations. This is the case of warming and droughts, which are expected to be more severe in the Mediterranean than global trends indicate. These changes will lead to reduced precipitation in several areas, though heavy rainfall events will be more intense [24]. Moreover, the frequency of flash floods is increasing, raising the flood risk in coastal regions, due to the combination of different factors like climate change, urban growth in areas subject to fluvial flood risk, and mismanagement [25–27]. In addition, flood risk is expected to increase in most parts of the Mediterranean basins and will also be influenced by urban growth in most areas vulnerable to flooding, with flash floods becoming more frequent and dangerous in the future [23–25].

However, a great variability in the magnitude and impact of extreme floods exists in Mediterranean regions, where the Northwestern Mediterranean area is highly susceptible to devastating flash floods due to intense rainfall events and catchments with short concentration times, which are coupled with the mountainous coastal topography [28]. In particular, areas like Catalonia are highly exposed to such extreme events because of their extraordinary climate conditions [20,28]. In Catalonia, floods are mostly concentrated in autumn and summer, with flash floods being most common between August and October. An increasing trend of exceptional flash floods has been detected, which may be aggravated by either changes in land uses or rising population vulnerability, as communities are more exposed due to high urban growth and density [20]. Convective rainfall events play a significant role, having increased alongside total rainfall in more intense and concentrated events. However, this trend is not the same across Catalonia, as a decreasing trend was found in the northeastern area of the region with a higher frequency of convective rainfall events but with lower intensity and duration [5,20].

These studies should be taken into account considering recent flooding events, such as the 29 October 2024 flood in Valencia (Spain) driven by a cut-off low that generated highly intense rainfall, which was combined with some hydrological factors that caused major floods, resulting in severe human and economic losses [29]. Such an extreme event has highlighted the importance of real-time flood forecasts for the rapid detection of potential flood events, early warning systems, and response strategies to such catastrophic events.

Real-time flood forecasts are based on meteorological forecasts that supply the feasible precipitation in the coming hours combined with hydrological models that simulate the rainfall-runoff processes in the catchment. Therefore, it is important to enhance hydrometeorological predictions for improving flood forecasts and optimizing early warning systems.

The classical meteorological forecasting chain involves mesoscale numerical models driven by global numerical weather prediction (NWP) models at lower resolutions. However, such an approach demands substantial computational resources and it still presents substantial uncertainties and biases in the final forecasts [30]. An established alternative extensively explored in the literature consists in forecasting through meteorological analogs [31–34], particularly for precipitation prediction [35–38]. Analog methods (AMs) define analogs as pairs of atmospheric states that closely resemble each other, assuming similar atmospheric conditions evolve similarly [31]. This technique avoids simplifying atmospheric physic processes, though it is limited by its inability to handle situations absent from the historical analog pool [34,39]. Various AM variants have been tested. They usually parameterized atmospheric variables, such as geopotential heights at 500 hPa and 1000 hPa to assess circulation analogies, sometimes integrating moisture variables for enhanced predictions [40,41]. AMs have also been successfully applied to both the Catalonia region and the broader Mediterranean region [42,43].

While earlier studies established the methodological foundations of AMs, recent work has focused on expanding their predictive capabilities and operational applicability. Modern implementations exploit analog ensembles for the simultaneous prediction of multiple surface meteorological variables at local scales [44], extend the approach to subseasonal-to-seasonal precipitation forecasting for water resources management [45], improve short-to medium-range ensemble precipitation forecasts in diverse climatic contexts [46], and adapt AMs for specialized hazards, including tropical cyclone rainfall prediction [47]. These advances highlight the versatility of AMs and their growing relevance for integrating high-resolution, impact-oriented forecasting into flood risk management and climate adaptation strategies.

Thus, risk management strategies must be adapted to future climate conditions by developing real-time flood forecasts, improving early warning systems, optimizing hydrological models to incorporate evolving climate dynamics, and enhancing infrastructure resilience.

The aim of this study is to provide a probabilistic flood forecast in the Francolí River catchment, located in Catalonia in northeastern Spain, by using a meteorological analog-based methodology to generate a set of rainfall field forecasts that will feed a distributed hydrological model. Such a probabilistic flood forecast can improve the knowledge about the hydrological catchment response of the Francolí catchment in flood events.

In this study, the Real-time Interactive Basin Simulator (RIBS) distributed hydrological model is used to simulate catchment rainfall-runoff processes, considering rainfall field forecasts generated by AMs. However, such a hydrological model requires several parameters to simulate hydrological response processes in the basin, which constitute a challenge. In addition, one single set of parameters cannot represent accurately all flood response types in the basin. Consequently, several flood events must be considered to enhance model efficiency and achieve robust and accurate calibration results [48]. In addition, hydrological model outputs usually have an inherent uncertainty, as a model is a simplification of the real processes, the observed data can have errors, and initial condition estimates contain uncertainty, among other reasons [48,49].

Therefore, the primary objective of the study is to enhance the understanding of the hydrological response of the Francolí catchment and to improve early warning systems through flood forecasting, where priority is given to short-term responding rather than

calculating the probability of exceedance over long return periods or designing flood protection measures against future floods [50,51].

The structure of the paper is as follows: The case study is presented in Section 2. In Section 3, the methodology is explained. The results are shown in Section 4 and discussed in Section 5. Finally, the conclusions are drawn in Section 6.

2. Case Study

The study is carried out in the Francolí river basin, located in Catalonia, in northeastern Spain. The drainage basin of the case study has been delineated considering that its outlet is located at the Montblanc streamflow gauging station (EA028), as seen in Figure 1, situated downstream from the confluence of the Francolí and Anguera rivers. The catchment area is 342 km². This catchment has a short response time and is subject to flash floods. Therefore, flood forecasts in this catchment cannot be generated by using observed precipitation, as not enough time to deliver early warnings would be available. Consequently, in this catchment, a flood forecast based on precipitation forecasts generated some hours or days before the beginning of the flood event is required.

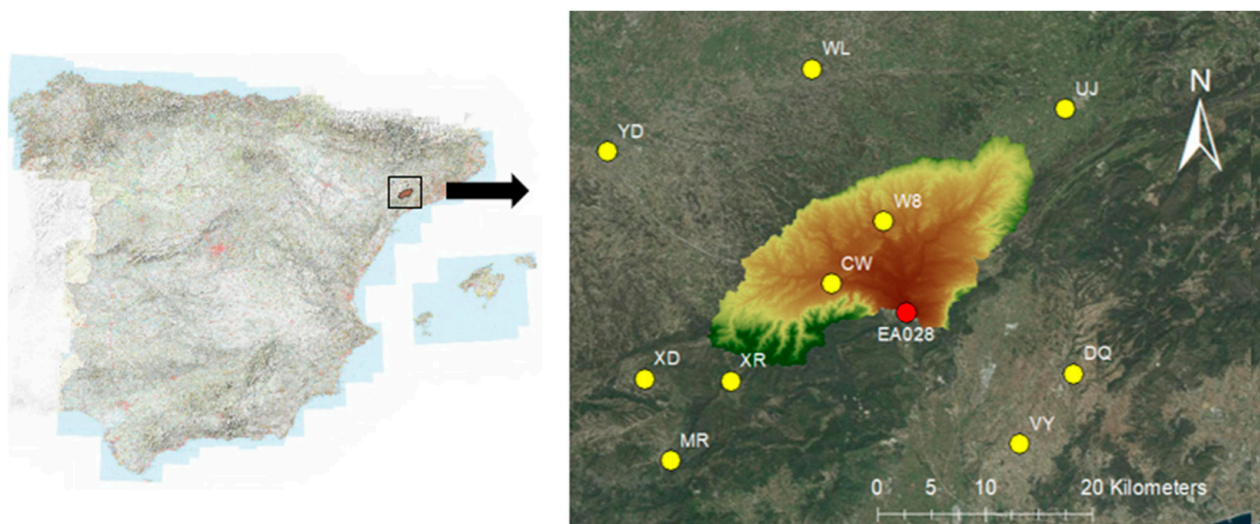


Figure 1. Location of the Francolí river basin and situation of the 10 rainfall gauging stations (yellow circles) and the streamflow gauging station (red circle) considered in the study.

The study basin is located in a Mediterranean climate zone, characterized by highly variable precipitation patterns, where flash floods are predominantly driven by short-duration, high-intensity convective storms [52,53]. Despite their potential for severe impacts, flash floods usually remain underrepresented in hydrometeorological records in this region due to their rarity and localized nature [54]. This poses a significant challenge to both observational studies and predictive modeling efforts, as traditional monitoring networks often fail to capture the spatial and temporal signatures of these extreme events.

Therefore, a key limitation in the hydrological analysis of Mediterranean flash floods is the fragmented nature of available hydrometric data, especially in ephemeral or intermittent rivers [55]. Streamflow records are often short, discontinuous, or entirely absent in many catchments, further complicating model calibration and validation. Consequently, most calibration datasets rely on a limited number of well-documented flood events [56], which may not fully represent the hydrometeorological variability in the region. This lack of representativeness can introduce significant uncertainties into model predictions, particularly in ungauged or poorly gauged watersheds.

The study has considered the observed data at 10 rainfall gauging stations and one streamflow gauging station. Hourly precipitation time series recorded at 10 rainfall gauging stations of the Meteorological Service of Catalonia (Servei Meteorològic de Catalunya, SMC, in Catalan) for the period 1996–2023 were used. The streamflow data were recorded at the Montblanc streamflow gauging station (EA028) that belongs to the Automatic Hydrological Information System (Sistema Automático de Información Hidrológica, SAIH, in Spanish) of the Catalan Water Agency (Agencia Catalana del Agua, ACA, in Spanish) during the same period (1996–2023).

Additionally, the flood events that affected the municipalities of the Francolí River Basin in the period 1981–2020 were identified, based on the updated INUNGAMA database [20,57]

3. Materials and Methods

This section is divided into four parts: (i) a description of the RIBS distributed hydrological model; (ii) the calibration methodology of the RIBS model; (iii) the meteorological analog-based methodology to generate rainfall field forecasts; and (iv) hydrological simulations performed using precipitation field forecasts to develop probabilistic flood forecasts.

Figure 2 presents a summary diagram of the methodology.

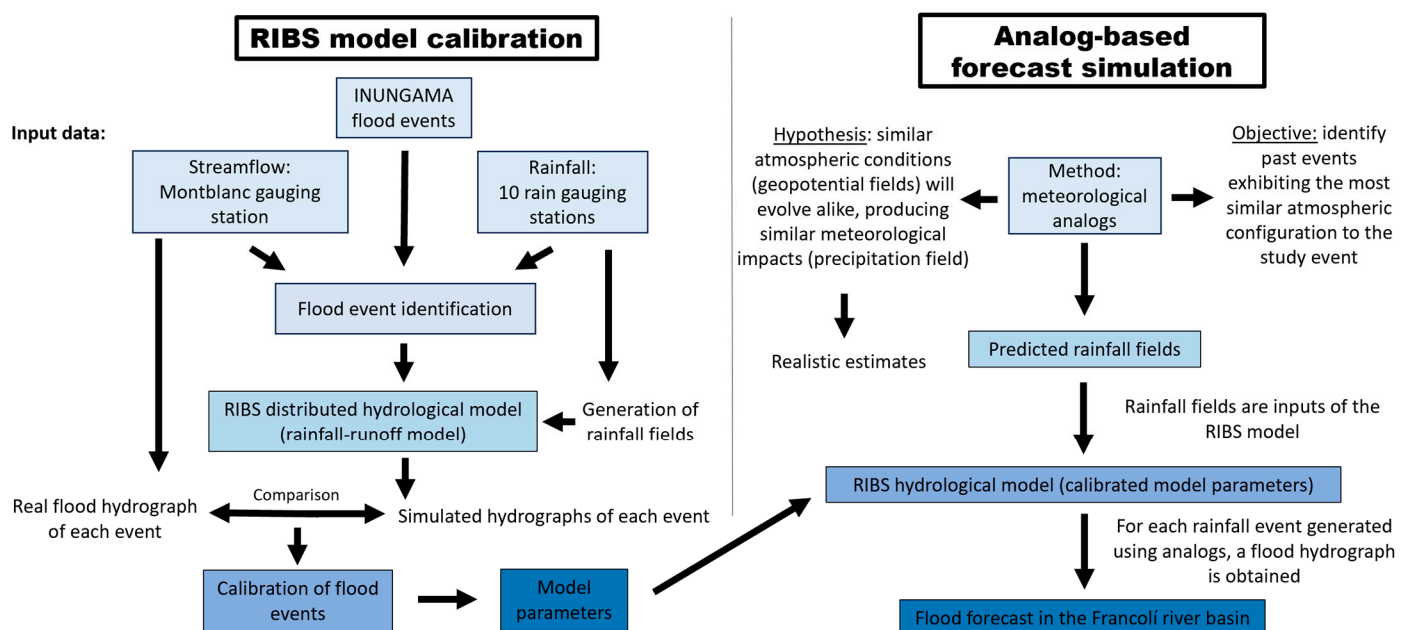


Figure 2. Methodology diagram.

3.1. RIBS Hydrological Model

The event-based RIBS distributed hydrological model is used to simulate the rainfall-runoff processes in the catchment, which allows for an accurate characterization of the catchment response during flood events [58,59]. The RIBS model can be used for real-time applications in medium-sized basins and needs to first be calibrated to effectively simulate rainfall-runoff processes [48]. The RIBS model relies on a digital terrain model (DTM), obtained from the National Geographic Institute (Instituto Geográfico Nacional, IGN in Spanish) in the case study of the Francolí basin, to determine the flow direction and accumulation in each cell. The spatial resolution of the RIBS model is 25 m.

The RIBS model represents the progression in time of the saturated soil surface, simulating the spatial variability in the infiltration process in each cell. The soil conditions are characterized with the Brooks–Corey parametrization (1).

$$K_s(y) = K_0 e^{-f y} \left(\frac{\theta - \theta_r}{\theta_s - \theta_r} \right)^\varepsilon \quad (1)$$

where $K_s(y)$ is the hydraulic conductivity under saturated conditions, i.e., the maximum conductivity value of the soil when its pores are completely filled with water (mm/h); K_0 is the saturated hydraulic conductivity at the surface (mm/h); f is a variable which controls the decay in saturated hydraulic conductivity in depth (mm^{-1}); y represents the depth of the soil (mm); θ is the soil moisture content; θ_s is the saturated soil moisture content; θ_r is the residual soil moisture content; and ε is the porosity index [60].

When either soil is fully saturated or precipitation exceeds the infiltration capacity, surface runoff appears. The RIBS model aims to replicate the runoff dynamics in the catchment. Therefore, it is necessary to obtain the total travel time of the flow. RIBS characterizes the relationship between flow velocities on the riverbed (v_s) and on the hillslope (v_h), as seen in (2), which are the locations where runoff is routed.

$$v_s(t) = C_v \left(\frac{Q(t)}{Q_{ref}} \right)^r \quad (2)$$

where $v_s(t)$ is the flow velocity on the channel at a given time step t (m/s); C_v is a coefficient that represents the channel flow velocity for a reference discharge (m/s); $Q(t)$ is the discharge in the catchment outlet (m^3/s); Q_{ref} is a flow reference discharge (m^3/s); and r is a constant.

At a given time step, both the riverbed and hillslope velocities are considered constant across the catchment. Their relationship is expressed by the dimensionless parameter K_v (3).

$$K_v = \frac{v_s(t)}{v_h(t)} \quad (3)$$

where K_v is a parameter that represents the ratio between channel and hillslope flow velocities (-); $v_s(t)$ is the flow velocity on the channel at a given time step t (m/s); and $v_h(t)$ is the flow velocity on the hillslope at a given time step t (m/s).

For a more detailed explanation, please refer to [48,58,59].

3.2. RIBS Model Calibration

The calibration process is performed to identify the model parameter values that best reproduce the hydrological response in the catchment [48,61]. The calibration process consists of comparing the observed flood hydrograph for a given flood event, obtained from the recorded data at the Montblanc gauging station (EA028), with the simulated hydrographs generated by the RIBS model, using the rainfall time series recorded at the rainfall gauging stations as input data. The spatial distribution of rainfall in each time interval for each flood event is estimated from the point rainfall recorded at the ten rainfall gauging stations considered in the study.

In this study, hourly rainfall data and 5 min streamflow data are complemented with the flood episodes identified previously with the INUNGAMA database to extract the most important flood events in the Francolí catchment, which will be used to calibrate the RIBS model [48,58]. Five flood events were identified (Table 1).

Additionally, the soil types identified and used in the basin for the RIBS model are represented in Figure 3 and the soil conditions characterized with the Brooks–Corey

parametrization are represented in Table 2, in which K_s saturated hydraulic conductivity, θ_s is the saturated moisture content, θ_r is the residual soil moisture content, and ε is the index of soil porosity.

Table 1. Flood events used in the calibration process. Information obtained by the SAIH system of ACA and the INUNGAMA database.

Date	Peak Flow (m ³ /s)	Category ¹	Streamflow Resolution (min)	Rainfall Resolution (h)	DTM Cell Resolution (m ²)
12 August 2010	29.2	0	5	1	25 × 25
6 March 2013	20.2	1	5	1	25 × 25
29 November 2014	24.6	2	5	1	25 × 25
3 November 2015	42.7	2	5	1	25 × 25
15 October 2018	24.2	2	5	1	25 × 25

¹ Category: 0. Ordinary; 1. Extraordinary; 2. Catastrophic; and 3. Major catastrophic.

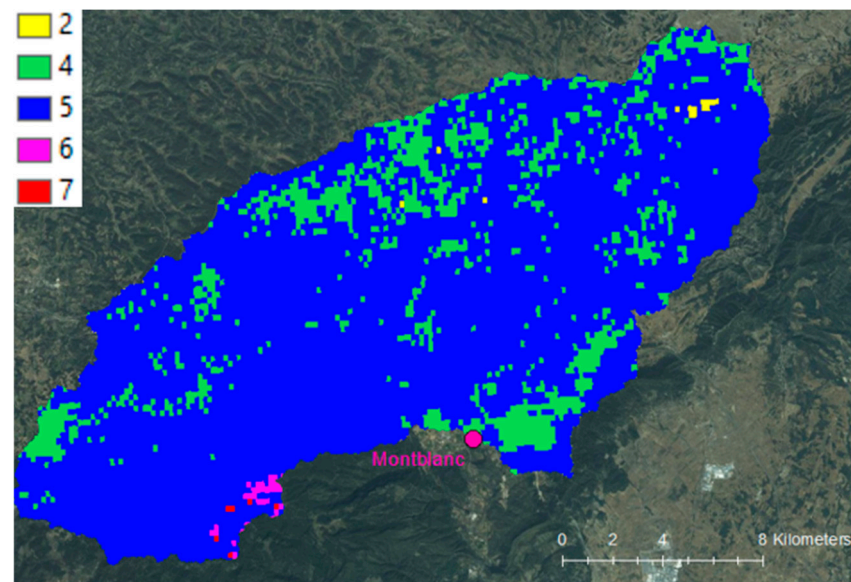


Figure 3. Soil types for RIBS hydrological model. 2. Silt-loam; 4. Clay loam; 5. Loam; 6. Sandy loam; and 7. Sandy clay loam.

Table 2. Soil conditions characterized with the Brooks–Corey parametrization.

Soil Type	Saturated Hydraulic Conductivity K_s (mm/h)	Saturated Moisture Content θ_s (-)	Residual Moisture Content θ_r (-)	Soil Porosity Index ε (-)
2. Silt-loam	4.500	0.450	0.067	1.800
4. Clay loam	10.000	0.410	0.095	2.300
5. Loam	40.000	0.430	0.078	2.000
6. Sandy loam	44.200	0.410	0.065	3.500
7. Sandy clay loam	13.100	0.390	0.100	3.500

The soil data were supplied by National Geographic Institute (Instituto Geográfico Nacional, IGN in Spanish), in a shapefile format with a cell size of 25 m.

The limitations imposed by episodic, highly localized flash flood events; variable and often broken discharge records; and the intrinsic intermittency of Mediterranean rivers

are well documented in hydrological literature [54–56]. Consequently, our selection of five calibration floods, spanning the range of available data and event types, reflects established best practices for these kinds of events and watershed configurations. In Table 3, the valid range for the input parameters of the RIBS model is described.

Table 3. Valid parameter ranges for RIBS model.

Parameter	Minimum Value	Maximum Value
f (mm^{-1})	0.0001	0.1
K_v (-)	0.5	12
C_v (m/h)	2000	10,000

In this research, the following RIBS model parameters are considered in the calibration process: initial soil moisture condition and the parameters f , K_v , and C_v . As mentioned in the introduction section, both hydrological models and parameter estimates have an inherent uncertainty. Hence, in the calibration process, the total error generated by a given model simulation can be expressed by Equation (4) [62]

$$Q(X, t) = M(\theta, X, t) + \varepsilon(X, t) \quad (4)$$

where $Q(x, t)$ is the discharge at position X and time interval t ; $M(\theta, X, t)$ is the discharge obtained under the model parameter configuration θ at position X and time interval t ; and $\varepsilon(X, t)$ is the resulting error with the configuration selected at position X and time t .

The model error is quantified using objective functions. Each objective function assesses the similarity between the observed and simulated flood hydrographs according to a given hydrograph feature, such as its shape, the time at which the peak flow occurs, or the value of the peak flow, among others. In this paper, the objective functions used in the calibration process are the root mean square error (RMSE) and the Nash–Sutcliffe efficiency coefficient (NSE), given by (5) and (6).

$$RMSE(\theta) = \sqrt{\frac{\sum_{i=1}^N \left(Q_{obs(i)} - Q_{sim(i)}(\theta) \right)^2}{N}} \quad (5)$$

$$NSE(\theta) = 1 - \frac{\sum_{i=1}^N \left(Q_{obs(i)} - Q_{sim(i)}(\theta) \right)^2}{\sum_{i=1}^N \left(Q_{obs(i)} - \overline{Q_{obs}} \right)^2} \quad (6)$$

where $Q_{obs(i)}$ is the observed discharge at the time interval i ; $Q_{sim(i)}(\theta)$ is the discharge obtained in the simulation under the parameter configuration θ at the time interval i ; $\overline{Q_{obs}}$ is the mean of the recorded discharge values; and N is the number of time intervals in the episode under study.

The RMSE objective function indicates that the results are better when its value is closer to 0. However, in the case of the NSE objective function, it indicates better results when its values are closer to 1.

Additionally, for the hydrological simulations, two additional objective functions are used to complement the study: the mean absolute error (MAE) (7) and the mean bias error (MBE) (8).

$$MAE(\theta) = \frac{\sum_{i=1}^N \left| Q_{obs(i)} - Q_{sim(i)}(\theta) \right|}{N} \quad (7)$$

$$MBE(\theta) = \frac{\sum_{i=1}^N \left(Q_{sim(i)}(\theta) - Q_{obs(i)} \right)}{N} \quad (8)$$

The MAE objective function demonstrates better model performance when its value is close to 0, providing a measure of the central tendency of the errors without indicating whether they are overestimated or underestimated. The MBE objective function serves as a metric for measuring the systematic mean bias present in predictions, indicating their tendency to underestimate or overestimate. However, the main drawback of MBE is that large errors may cancel each other out. The best MBE values are close to 0.

3.3. Meteorological Analogs Methodology

An analog-based methodology was applied to identify past events with the most similar atmospheric configuration to the event under study, thereby enabling estimates of the associated precipitation field. The analog method (AM) used in this study considers both 500 hPa and 1000 hPa geopotential height fields from GFS analysis (00 UTC, 0.25° resolution) as predictors, as evidenced by [41] to be the most reliable. Additionally, this allows the capture of atmospheric conditions both at the surface layer and in the mid-troposphere.

The search for analogs for each flood event was conducted within a subset of days that share the same weather type with the target flood event, to improve the precision and computational efficiency of the procedure. The weather types were defined using the Beck method [63]. It follows a classification scheme that also is explained in other studies [64,65], where different atmospheric circulation types are analyzed and a weather type is assigned to each atmospheric situation.

The analogs used in this work are of the type WT-PP-S [66] since they yielded the best overall results. Please refer to said reference for a more detailed explanation on the procedure.

To evaluate, among all of the available analog events, which one better predicts the target event, and subsequently select the best analogs, the geopotential height fields are compared. Therefore, for each analog identified in the search process, the degree of similarity between the 500 hPa and 1000 hPa geopotential height fields in the past event and the target day was calculated using a combined metric that integrates the Euclidean distance (Ed) and the spatial Pearson correlation coefficient (r). Thus, the two metrics were normalized, and the arithmetic mean was calculated for both the 500 hPa and 1000 hPa geopotential height fields. Consequently, analog events with a lower value of this composite metric exhibit a geopotential field more closely resembling the target event.

Figure 4 shows an example of the comparison between the target date of 15 October 2018 and its best analog, in terms of the 1000 hPa and 500 hPa geopotential height fields.

Based on this analysis, the 10 most similar analogs were selected, minimizing the value of such a metric, from which 24 h precipitation fields were extracted using the ERA5 reanalysis data [67]. The spatial resolution of the ERA5 analysis is 0.25°. The temporal resolution of the ERA5 analysis is one hour. This spatial resolution is not sufficient for the rainfall maps of previous storms used in this analog method to accurately represent the variability in highly localized storms in the study region, where the catchment has an area of 342 km².

Additionally, it was examined whether any of the 10 past dates, associated with the 10 analogs identified, corresponded to recorded flood events in the study region, using the INUNGAMA flood database. The analogs with a date that corresponded to important flood events included in the INUNGAMA flood database were identified as extreme analogs.

For the RIBS model simulations with such analogs as input data, a computation time interval of 15 min was used. Therefore, the hourly rainfall data extracted from the ERA5 reanalysis data were uniformly distributed over four 15 min time intervals.

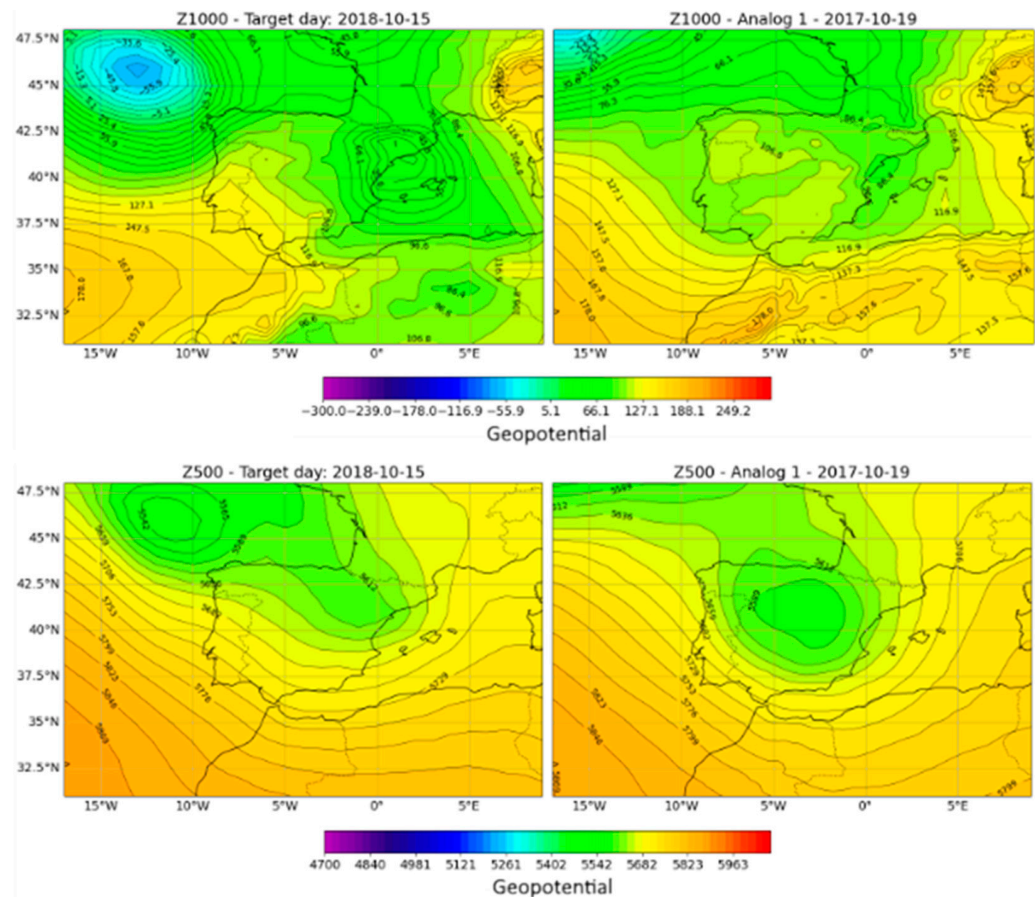


Figure 4. Comparison of geopotential fields between the target date of 15 October 2018 and its best analog found. The upper row shows the results for 1000 hPa and the lower row for 500 hPa. The first column shows the results for the target day and the second column for the analog identified.

3.4. Probabilistic Forecasts Based on the Meteorological Analog Methodology

Hydrological simulations were performed with the precipitation forecast fields generated using the meteorological analog methodology as input data, using the RIBS model with the parameter values obtained in the calibration process. Both analog and extreme analog forecasts are considered for the five flood events identified in the Francolí catchment.

The simulation process consists of introducing the 10 analog rainfall forecasts and 10 extreme analog rainfall forecasts for each flood episode considered in the study, as input data into the calibrated RIBS hydrological model. A simulated hydrograph is obtained for each analog and extreme analog forecast, as output data. Finally, the hydrographs simulated with both the analog and extreme analog rainfall forecasts are compared with both the observed hydrograph at the streamflow gauging station and the simulated hydrograph with the RIBS model using the real rainfall time series recorded at the rainfall gauging stations as input data.

For each flood event, three options were considered to identify the best method to estimate the catchment initial soil moisture content in the hydrological simulations with the RIBS model: (i) without prior warming, i.e., without considering the antecedent precipitation; (ii) with a warming period using the real rainfall time series for the preceding 12, 24, 36, and 48 h (depending on the flood event); and (iii) with a warming period using the ERA5-simulated rainfall for the preceding 12, 24, 36, or 48 h (depending on the flood event).

First, the antecedent precipitation type and length that leads to the best simulation results is identified and considered as the best method to estimate the initial moisture

content in the catchment. Such a method identified to consider the antecedent precipitation is used to perform an ensemble of hydrograph simulations for each event.

Second, for each time interval and flood episode, the percentiles of 10%, 33%, 50%, 67%, and 90% are obtained from the ensemble of simulated flood hydrographs. The percentile curves are graphically represented and compared with the observed hydrograph. Therefore, the probabilistic forecast generated provides a probability distribution of possible response discharges of the Francolí river basin in advance for a given flood event. The probabilistic forecasts have been generated for both analogs and extreme analogs.

4. Results

In this section, first, the results of the calibration of the RIBS hydrological model with the five flood events considered in the study will be exhibited. Second, the results of the generation of rainfall field forecasts by using the analog methodology are presented. Third, the best method to estimate the initial moisture content in the catchment at the beginning of a flood event is identified. Fourth, the probabilistic flood forecasts are obtained.

4.1. Calibration of the RIBS Model

As explained in Sections 2 and 3, the calibration methodology has been applied to the RIBS model for the five flood episodes that have been identified in the Francolí catchment. For each flood episode, either the best single combination or set of combinations of model parameter values are identified. In addition, the results of the objective functions considered in the study (RMSE and NSE) obtained for each parameter value combination identified in the calibration process are also presented. Finally, the comparison between the observed hydrograph and the simulated hydrographs obtained with the best combinations of model parameters values are displayed.

First, the best model parameter values identified for each flood event in the RIBS model calibration were identified. The RMSE and NSE values obtained for each parameter value combination identified in the calibration process are presented (Table 4).

Table 4. RIBS model parameter values and results of the objective functions considered in the study for the best simulations identified for each flood episode in the calibration process.

Flood Event	Simulation	Parameter Values			Obj. Function Values	
		f (mm ^{−1})	K _v	C _v (m/h)	RMSE	NSE
12 August 2010	Simulation 1	0.01	3	5000	8.882	−0.974
6 March 2013	Simulation 1	0.05	7	2000	3.332	0.689
	Simulation 2	0.02	7	2000	2.856	0.783
	Simulation 3	0.02	7.4	2250	3.117	0.736
	Simulation 4	0.0055	7	2100	4.238	0.554
29 November 2014	Simulation 1	0.045	3.5	6000	4.620	0.288
	Simulation 2	0.035	2.07	2000	2.682	0.751
	Simulation 3	0.035	2.6	3200	3.283	0.640
	Simulation 4	0.008	6	4600	5.164	0.086
	Simulation 5	0.0097	5.9	5000	4.937	0.165
3 November 2015	Simulation 1	0.1	2	12,000	17.787	−2.006
	Simulation 2	0.001	2	12,000	18.348	−2.198
15 October 2018	Simulation 1	0.045	3.85	4500	1.377	0.931
	Simulation 2	0.003	4	3600	2.017	0.848
	Simulation 3	0.047	3	3600	1.237	0.943
	Simulation 4	0.0047	3	3600	1.623	0.902

Second, an example of the comparison between the observed hydrograph and the simulated hydrographs that best approximate the real one for the flood event of 15 October 2018 are shown in Figure 5. The figures that show the calibration results for the rest of the flood events are included in the Supplementary Material (Figures S1–S4).

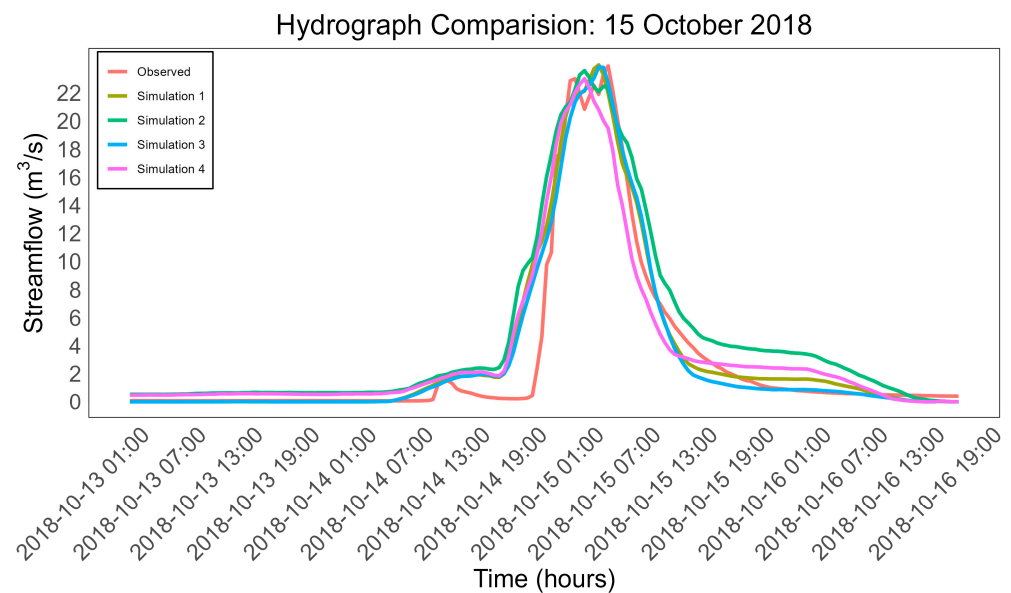


Figure 5. Comparison between the observed flood hydrograph at the gauged station (red line) and the simulated hydrographs identified in the calibration process for the flood event of 15 October 2018.

For the 2018 event (Figure 5), in simulations 1–4, there is minimal spread, backed by the graphics and RMSE and NSE values. It supposes a reduction in the uncertainty for the calibration of such event. There are similar cases, such as the 2013 (simulations 1–4) and 2014 (simulations 1–5) events (Figures S2 and S3), where the simulation of each event shows a little more spread, although they are still small differences and are good calibrated simulations. This is not the case for the events of 2010 and 2015 (Figures S1 and S4), where due to the poor calibration options, it is not possible to limit the dispersion.

In this context, the presence of negative NSE values reflects cases where the simulated hydrographs fail to replicate both the timing and magnitude of peak flows. This behavior is characteristic of NSE's sensitivity to peak errors, especially when the observed hydrograph is highly skewed or dominated by a sharp, narrow peak.

However, these negative values should not be interpreted as a general failure of the modeling framework. Instead, they highlight the localized limitations in capturing rapid-response dynamics, often driven by uncertainties in rainfall intensity, spatial variability, or antecedent soil moisture, factors that can disproportionately affect peak representation in event-based simulations [68].

It is important to note that across the broader dataset, most simulations yield positive and acceptable NSE values, with many exceeding 0.75 and RMSE values falling within a reasonable range. This demonstrates that the model is consistently robust for the majority of events and parameter combinations. Furthermore, simulations with high NSE (e.g., 15 October 2018) show that the model is fully capable of achieving both temporal and volumetric accuracy when boundary conditions are well-represented.

In conclusion, visually, there are examples where better calibration results are obtained, as in the case of the flood events of 2013, 2014, and 2018 (Figures S2–S4). This is supported by better RMSE and NSE values achieved in such events (Table 4).

4.1.1. Calibration Results

Six combinations of the RIBS parameter values have been identified based on the results obtained in the calibration process for each flood event individually (Table 1). Such combinations were identified based on both the RMSE and NSE values obtained considering all of the time steps of the flood event and the RMSE and NSE values in the time steps in which the observed streamflow value is above the mean flow of the event ($\overline{Q_{obs}}$). The different combinations considered are displayed in Table 5.

Table 5. RIBS model calibration test cases.

Combination Number	Description	Events Considered	Comments
1	Average of best calibration results	2013, 2014, 2018	Best calibrations result from the three best calibrations of the five events were used.
2	Average of best calibration results	2010, 2013, 2014, 2015, 2018	Best calibration results of all five events were used.
3	Average of best calibration results	2010, 2013, 2014, 2018	Excludes 2015 (worst calibration).
4	Average of all calibration results	2013, 2014, 2018	All calibration results used of the three best events.
5	Average of all calibration results	2010, 2013, 2014, 2018	Excludes 2015 (worst calibration).
6	Average of all calibration results	2010, 2013, 2014, 2015, 2018	All events and all calibration results included.

For each combination of the RIBS model parameter values, Table 6 shows the model parameter values, as well as their RMSE and NSE results for each flood event (both for all of the time steps of the flood event and for the time steps in which the observed streamflow is above the mean flow of the flood event). Additionally, Figure 6 shows an example of the simulated flood hydrographs for the 15 October 2018 flood event. The figures for the rest of the flood events are shown in the Supplementary Material (Figures S5–S8).

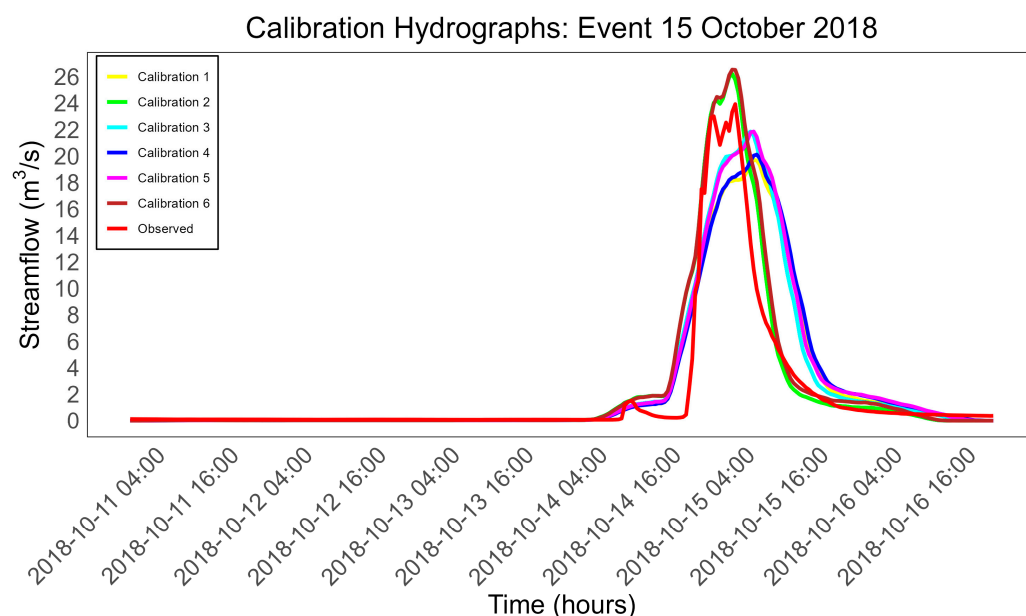


Figure 6. Simulated flood hydrographs obtained with the six model parameter value combinations for the flood event of 15 October 2018. The observed hydrograph is presented with a red line and the simulated hydrograph with the model parameters obtained in the calibration process is presented in green (calibration 2).

Table 6. RIBS model parameter value combinations and results of the RMSE and NSE objective functions.

Calibration	Flood Event	Parameter Values			Objective Functions			
					All Values		Values Above Qmean	
		f (mm ^{−1})	K _v	C _v (m/h)	RMSE	NSE	RMSE	NSE
1	12 August 2010	0.032	5.031	3581	9.171	−1.712	12.317	−1.686
	6 March 2013				5.638	0.37	6.612	−1.633
	29 November 2014				3.914	0.475	5.960	−0.324
	3 November 2015				9.821	−0.37	14.545	−0.316
	15 October 2018				2.725	0.709	6.801	−0.183
2	12 August 2010	0.034	4.174	4544	7.064	−0.444	11.061	−1.166
	06 March 2013				7.331	0.056	9.416	−4.339
	29 November 2014				3.409	0.611	4.743	0.161
	3 November 2015				12.392	−0.968	12.328	0.055
	15 October 2018				1.649	0.898	3.424	0.700
3	12 August 2010	0.030	4.806	3738	9.697	−1.962	13.889	−2.415
	6 March 2013				6.029	0.320	7.409	−2.306
	29 November 2014				2.926	0.706	2.659	0.736
	3 November 2015				10.427	−0.545	15.152	−0.428
	15 October 2018				2.634	0.732	6.828	−0.192
4	12 August 2010	0.031	4.794	3419	9.393	−1.780	12.359	−1.705
	6 March 2013				5.569	0.402	6.689	−1.694
	29 November 2014				4.055	0.434	6.354	−0.505
	3 November 2015				10.062	−0.439	14.978	−0.396
	15 October 2018				2.920	0.670	7.132	−0.301
5	12 August 2010	0.029	4.666	3532	9.737	−1.987	13.484	−2.219
	6 March 2013				6.098	0.296	7.432	−2.327
	29 November 2014				2.924	0.706	2.727	0.723
	3 November 2015				10.557	−0.584	15.691	−0.531
	15 October 2018				2.861	0.684	7.204	−0.327
6	12 August 2010	0.032	4.333	4590	7.039	−0.439	11.031	−1.154
	6 March 2013				7.48	0.020	9.607	−4.559
	29 November 2014				3.478	0.596	4.669	0.187
	3 November 2015				12.421	−0.997	12.772	−0.015
	15 October 2018				1.83	0.875	4.218	0.545

Finally, the RIBS model parameter values associated with calibration 2 are selected because they lead to the best results in general for the five flood events considered in the study, attending to the visual shape of simulated flood hydrographs and to the RMSE and NSE values obtained. Consequently, Table 7 shows the RIBS model parameter values obtained as result of the calibration process.

Table 7. RIBS model parameter values identified as result of the calibration process that correspond to calibration 2.

	f (mm ^{−1})	K _v	C _v (m/h)
Model parameters	0.034	4.174	4544

The results of the RMSE and NSE objective functions, considering all of the time steps of the flood event, obtained with the best model parameter values of Table 7 in each flood event are shown in Table 8.

Additionally, despite some events having poor calibrations, calibration 2 provided a more consistent performance in all events considered. The overall model performance across flood episodes demonstrates a high degree of reliability, with NSE values exceeding 0.6 in the majority of cases and a peak NSE of 0.898 for the 15 October 2018 event, indicating

excellent agreement between observed and simulated discharges. This is further supported by relatively low RMSE values in those cases, highlighting consistent volumetric accuracy.

Table 8. RMSE and NSE values with the RIBS model parameter values identified in the calibration process for the five flood events considered in the study.

Episode	RMSE	NSE
12 August 2010	7.064	−0.444
6 March 2013	7.331	0.056
29 November 2014	3.409	0.611
3 November 2015	12.392	−0.968
15 October 2018	1.649	0.898

The two episodes with negative NSE values, 12 August 2010 and 3 November 2015, correspond to events where the model shows difficulty capturing the precise timing and magnitude of the flood peak, due to high temporal variability in rainfall or unrepresented watershed processes such as urban runoff or channel routing delays. Importantly, while NSE is a valuable efficiency metric, it is highly sensitive to peak flow misalignment, which can disproportionately penalize model performance even when overall hydrograph shape or volume is reasonably well-represented.

Given that three out of five episodes yield positive NSE values with RMSEs consistently under $8 \text{ m}^3/\text{s}$, the model demonstrates robust behavior for a range of hydrological conditions. The few negative NSE values serve as indicators for targeted calibration improvements or enhanced input data resolution, rather than as a reflection of general model deficiency [68].

4.1.2. Sensitivity Analysis

Previous studies by Mediero et al. [48] conducted in-depth analyses of the RIBS model sensitivity. To illustrate the sensitivity of the flood forecast to changes in the model parameters in the Francolí River basin, a sensitivity analysis was conducted for the 2005 event, considering as an example the analog case with a real antecedent precipitation of 36 h.

Table 9 presents the 13 simulations performed along with the model parameters used in each one. Table 10 shows the RMSE results of each simulation for the 10 analogs (A.1–A.10) and for the hydrograph resulting from entering the real rainfall of the event into RIBS (Rainfall). In Figure 7, three examples of how the parameter variation affects the resulting hydrographs are displayed.

Table 9. Selection of parameters for the sensitivity analysis simulation.

Simulation	$f \text{ (mm}^{-1}\text{)}$	K_v	$C_v \text{ (m/h)}$
1	0.034	4.174	4544
2	0.0001	4.174	4544
3	0.001	4.174	4544
4	0.01	4.174	4544
5	0.1	4.174	4544
6	0.034	0.5	4544
7	0.034	2.3	4544
8	0.034	8.1	4544
9	0.034	12	4544
10	0.034	4.174	2000
11	0.034	4.174	6000
12	0.034	4.174	8000
13	0.034	4.174	10,000

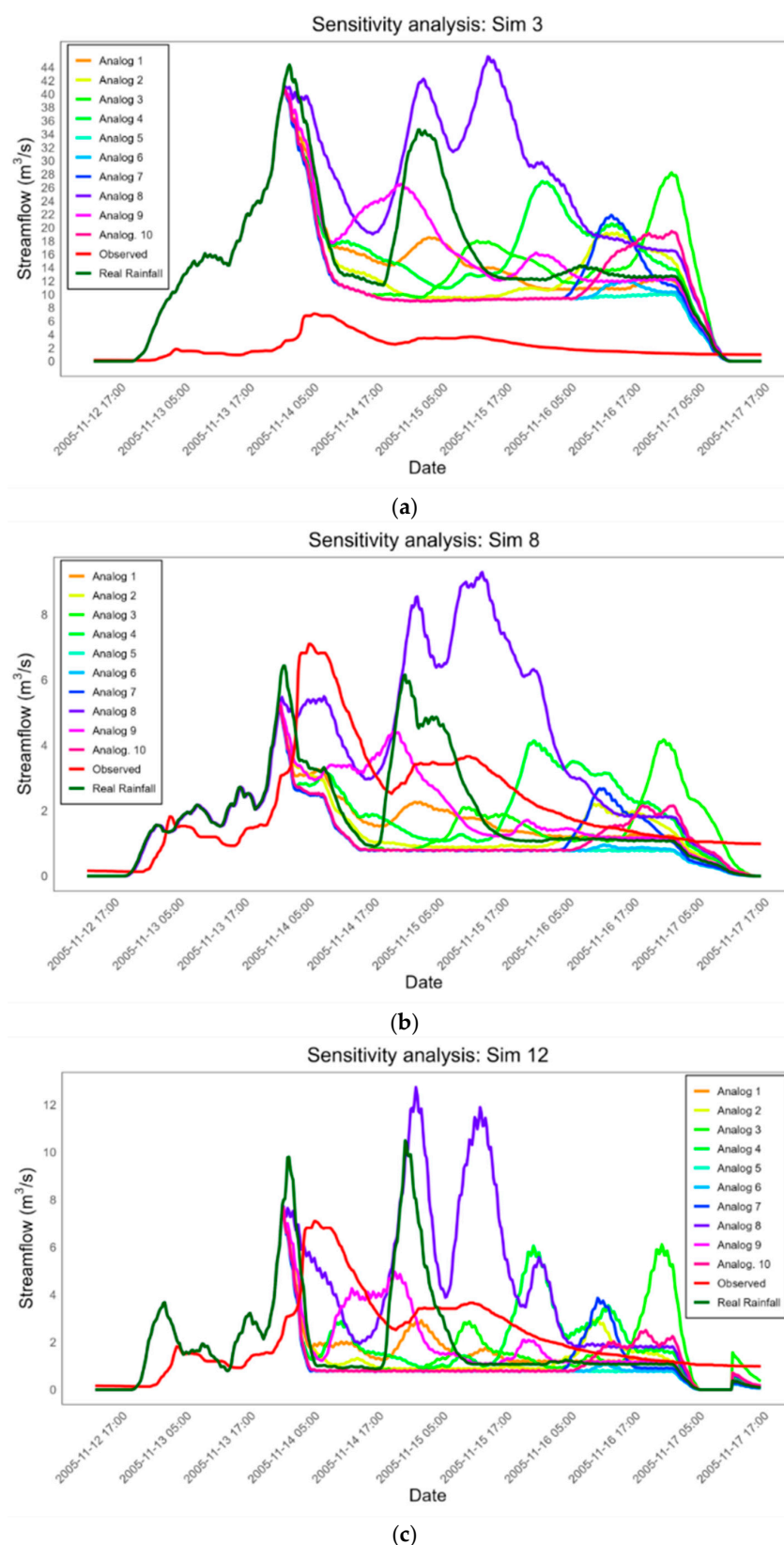


Figure 7. Three examples of simulated hydrographs for analog rainfall field forecasts for the 14 November 2005 flood event in the sensitivity analysis. (a) Simulation 3; (b) simulation 8; and (c) simulation 12. The red line represents the observed hydrograph. The green line is the simulated hydrograph obtained with the real precipitation as input in the RIBS model. The remaining colored lines represent the results with the analog rainfall field forecasts.

Table 10. RMSE values for the ten analogs and real rainfall for each simulation of the sensitivity analysis.

Simulation	RMSE										
	A.1	A.2	A.3	A.4	A.5	A.6	A.7	A.8	A.9	A.10	Rainfall
1	1.63	1.97	2.15	1.89	2.16	2.16	2.17	2.59	1.55	2.14	2.02
2	47.92	45.31	47.28	52.74	38.49	38.89	41.05	76.91	52.94	41.83	53.38
3	14.05	14.06	14.98	15.94	12.12	12.25	13.22	23.59	15.78	13.42	16.53
4	3.22	3.41	3.80	3.85	3.07	3.08	3.39	6.20	3.66	3.39	4.21
5	2.05	2.55	2.64	2.34	2.71	2.70	2.67	2.50	1.91	2.67	2.05
6	2.00	2.32	2.53	2.24	2.48	2.48	2.51	3.06	1.96	2.48	2.67
7	1.81	2.14	2.35	2.06	2.32	2.31	2.33	2.83	1.76	2.31	2.36
8	1.48	1.81	1.94	1.74	2.01	2.00	2.00	2.38	1.36	1.99	1.62
9	1.44	1.75	1.85	1.69	1.94	1.94	1.93	2.38	1.30	1.92	1.46
10	1.31	1.64	1.75	1.62	1.83	1.83	1.82	2.33	1.17	1.81	1.18
11	1.77	2.11	2.30	2.02	2.29	2.28	2.30	2.78	1.71	2.27	2.29
12	1.91	2.24	2.44	2.14	2.40	2.40	2.42	2.96	1.86	2.40	2.53
13	2.00	2.32	2.52	2.22	2.48	2.47	2.50	3.07	1.95	2.47	2.68

Among the 13 simulations selected for this analysis, simulation 1 corresponds to the model parameters selected in the previous section (Table 7). For the remaining simulations, only one parameter was changed at a time in each run to assess the model's sensitivity to changes in that parameter. It can be observed that the parameter f is more sensitive to changes, as the resulting hydrographs reach extremely high flow values and high RMSE values for specific f settings (simulations 2 and 3). In turn, parameters C_v and K_v show less pronounced variations. In fact, the RMSE values calculated for these simulations (6–13) are limited to a small range for the different configurations of the parameters (including the extreme possible values of the C_v and K_v parameters).

4.2. Rainfall Forecast Fields Obtained with the Meteorological Analogs Methodology

The corresponding precipitation fields were extracted using hourly ERA5 reanalysis data for each of the 10 analogs identified for each analyzed flood event. The precipitation fields were retrieved over a spatial domain centered on the Iberian Peninsula and defined following the guidelines of COST Action 733: Harmonization and Application of Weather Type Classification for European Regions [64]. The domain spans from 17° W to 9° E in longitude and from 31° N to 48° N in latitude. The data have a spatial resolution of 0.25° in both latitude and longitude and an hourly temporal resolution. For each analog, a 72 h precipitation field was extracted, starting from 00:00 UTC on the analog date.

From this Western Europe-wide field, the precipitation data were further subset to the domain of interest for this study, specifically the Francolí river basin. The mean areal precipitation in the catchment for each analog and extreme analog rainfall field forecast were obtained. Figure 8 shows an example for the 14 November 2005 flood event. The figures that show the mean areal precipitation for the rest of the flood events are presented in the Supplementary Material (Figures S9–S12).

In each of these four events, both the analog and extreme analog rainfall forecasts present smaller precipitation than the real rainfall. Nevertheless, in the 2005 flood event (Figure 8), a greater variability in the predicted precipitation can be observed, with analogs exhibiting magnitudes closer to the real rainfall, although precipitation is underestimated in most analogs.

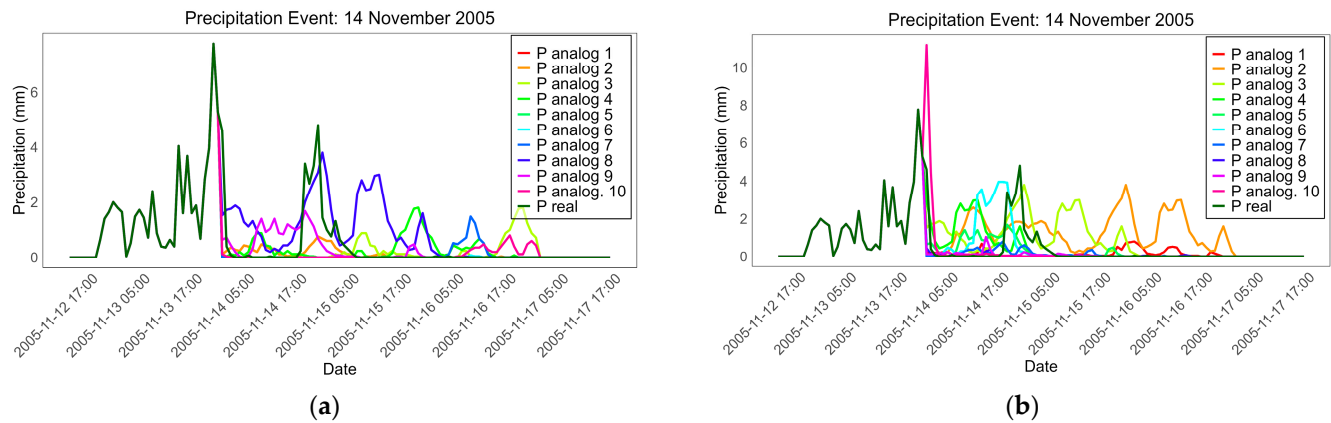


Figure 8. Mean areal precipitation in the Francoli catchment obtained from the rainfall field forecasts: (a) analog rainfall forecasts; (b) extreme analog rainfall forecasts. The mean areal precipitation obtained with the real rainfall in the catchment is presented with a dark green line.

4.3. Identification of the Best Method to Estimate the Catchment Initial Soil Moisture Content at the Beginning of the Flood Event

Hydrological simulations were performed using the precipitation field forecasts derived from analog and extreme analog methods that were obtained in the previous subsection. The simulations for the five flood events considered in the study are conducted considering the three approaches explained in Section 3.4 to identify the best method to estimate the catchment initial soil moisture content at the beginning of the flood event: (i) without prior warming, i.e., without considering the antecedent precipitation; (ii) with a warming period using real rainfall data from the preceding 12, 24, 36, and 48 h; and (iii) with a warming period using ERA5-simulated rainfall for the preceding 12, 24, 36, or 48 h.

An output hydrograph is obtained for each analog and extreme analog rainfall field forecast introduced in the RIBS model as precipitation input. In Figure 9, the option with the longest warming precipitation time series has been selected as an example. In this case, the comparison between simulated hydrographs for 36 h real antecedent precipitation and both the simulated hydrograph obtained with the real precipitation and the observed hydrograph at the gauging station is shown. The figures for the rest of the events are represented in the Supplementary Material (Figures S13–S16).

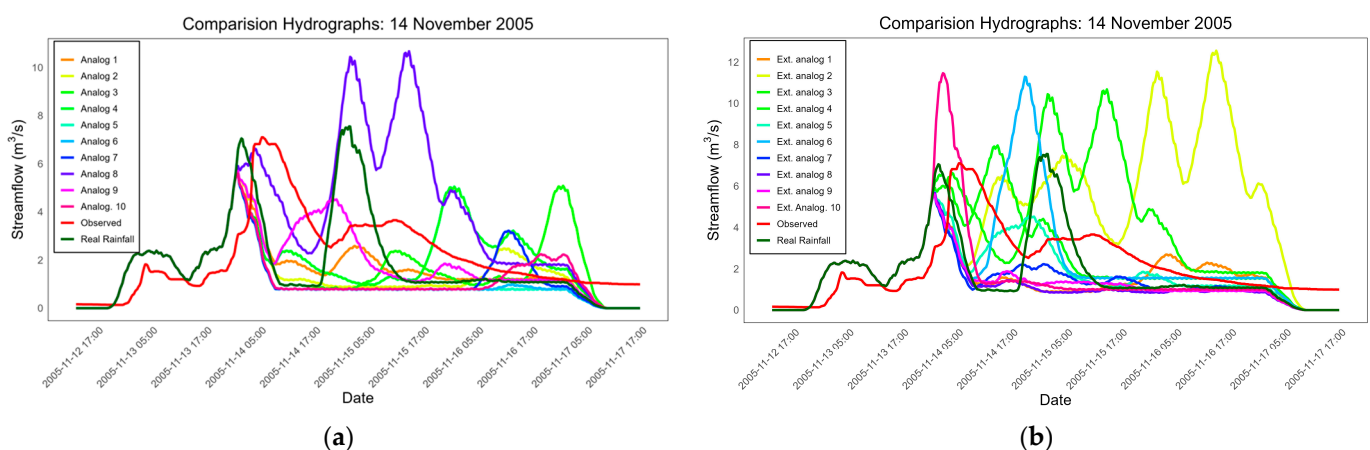


Figure 9. Simulated hydrographs for analog and extreme analog rainfall field forecasts for the 14 November 2005 flood event. (a) Analog rainfall field forecasts; (b) extreme analog rainfall field forecasts. The red line represents the observed hydrograph. The green line is the simulated hydrograph obtained with the real precipitation as input in the RIBS model. The remaining colors represent the results with the analog and extreme analog rainfall field forecasts.

In each of these four events included in the Supplementary Material, the analog and extreme analog simulated hydrographs tend to underestimate the observed flood hydrograph. Such an underestimation can be caused by the small precipitation associated with such predicted events compared with the real precipitation recorded at the gauging stations. However, the 2005 flood event (Figure 9) shows more variability on the predicted flood hydrographs, where some analogs, such as analog 8 and extreme analogs 2, 4, 6, and 10, lead to simulated hydrographs that even exceed the discharges of the observed hydrograph.

In addition, the RMSE objective function is used to evaluate the accuracy of the simulated hydrographs obtained with the analog and extreme analog rainfall field forecasts compared with the observed hydrograph (Figures 10–14).

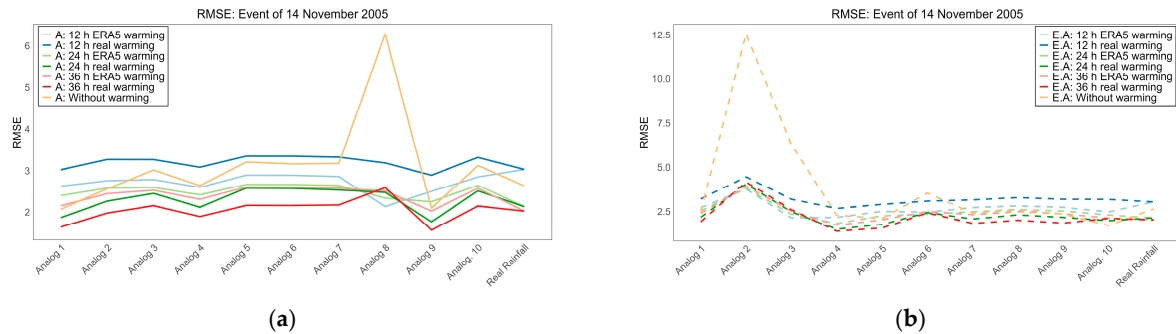


Figure 10. RMSE values for analog and extreme analog rainfall field forecasts for the 14 November 2005 flood event: (a) analog rainfall field forecasts (solid lines); (b) extreme analog rainfall field forecasts (dashed lines).

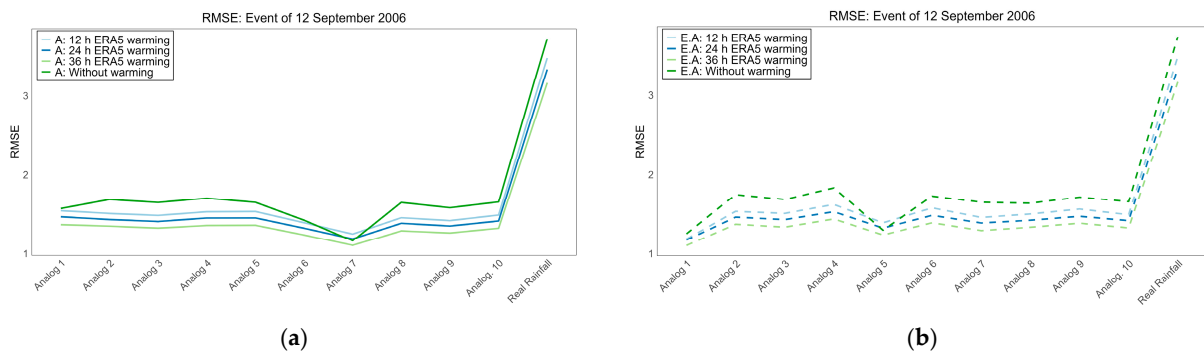


Figure 11. RMSE values for analog and extreme analog rainfall field forecasts for the 12 September 2006 flood event: (a) analog rainfall field forecasts (solid lines); (b) extreme analog rainfall field forecasts (dashed lines).

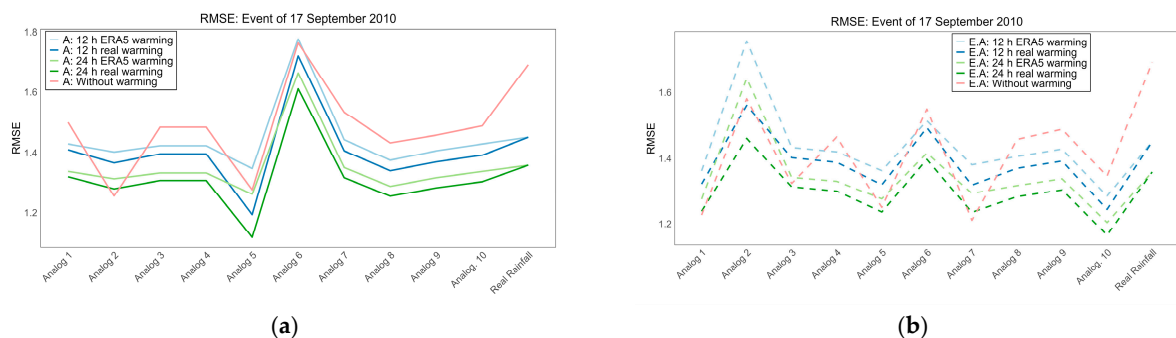


Figure 12. RMSE values for analog and extreme analog rainfall field forecasts for the 17 September 2010 flood event: (a) analog rainfall field forecasts (solid lines); (b) extreme analog rainfall field forecasts (dashed lines).

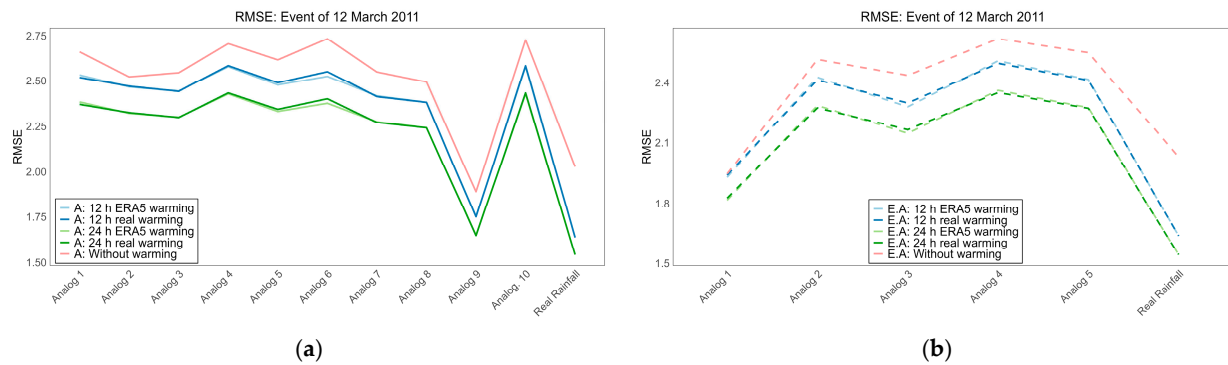


Figure 13. RMSE values for analog and extreme analog rainfall field forecasts for the 12 March 2011 flood event: (a) analog rainfall field forecasts (solid lines); (b) extreme analog rainfall field forecasts (dashed lines).

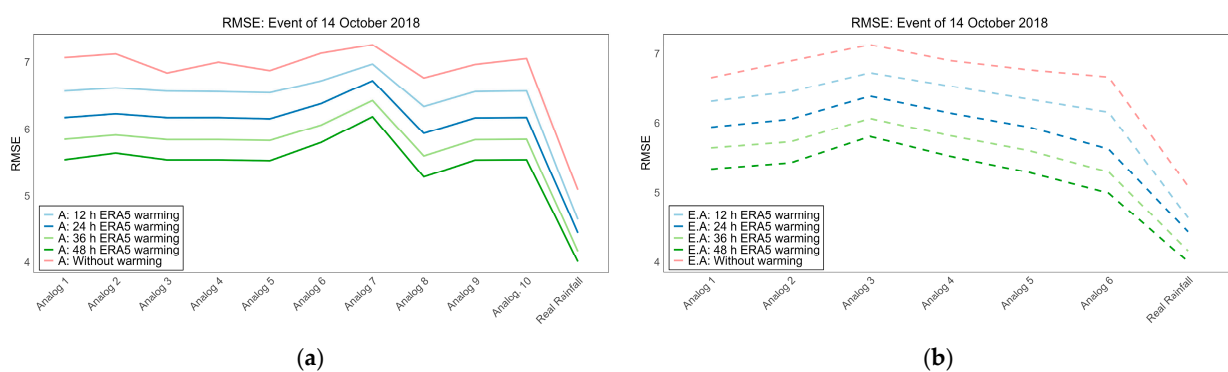


Figure 14. RMSE values for analog and extreme analog rainfall field forecasts for the 14 October 2018 flood event: (a) analog rainfall field forecasts (solid lines); (b) extreme analog rainfall field forecasts (dashed lines).

In the 2005 flood event (Figure 10), better results are obtained with the real antecedent precipitation in 36 h before the beginning of the flood event, as it achieves smaller RMSE values for the analog and extreme analog events in most of the cases.

In the 2006 flood event (Figure 11), only ERA-5 warming precipitation is considered, as the real antecedent precipitation for the period before the beginning of the flood event is zero in all time steps. In this case, better RMSE values are obtained for the longest available warming period associated with 36 h.

In the 2010 flood event (Figure 12), the best RMSE results are achieved with the 24 h warming with real precipitation.

In the 2011 flood event (Figure 13), better results are obtained with the 24 h antecedent precipitation, which is the longest antecedent precipitation available. In this event, both the real and the ERA-5 antecedent precipitation perform equally well.

In the 2018 flood event (Figure 14), only ERA-5 warming precipitation is available, as the real antecedent precipitation for the period before the beginning of the flood event is zero for all of the time steps. In this episode, the smallest RMSE values are obtained for the longest available warming, which is 48 h.

In summary, in the five flood events considered in the study, the RMSE value decreases as the length of the antecedent precipitation period increases. In addition, for the five events studied, the MAE and MBE values obtained are closer to zero when the longer previous precipitation is considered. Therefore, based on the results obtained for the three options considered to estimate the initial soil moisture content in the catchment, it was determined that longer warming periods yield better outcomes. Consequently, the longest available antecedent precipitation period for each event will be used as the optimal warming period

for generating the probabilistic forecasts. It should be noted that while the longest existing antecedent rainfall is 24 h for some flood events, it covers 36 or 48 h in other flood events.

4.4. Probabilistic Forecasts

After selecting the best method to consider the antecedent precipitation, in order to estimate the initial moisture content in the catchment at the beginning of a flood event, a probabilistic forecast is obtained for each flood event. Such a probabilistic flood forecast has been obtained considering the ensemble of analog and extreme analog rainfall field forecasts as input data in the RIBS hydrological model.

Figures 15–19 present the probability distribution of possible response discharges in the catchment for each flood event considered in the study by obtaining discharge percentiles in each time step. The percentile graphs indicate the probability distributions of the flow predictions. For example, between the 10% and 90% percentile curves, it is expected that 80% of the flood response predictions would fall between such two limits. Therefore, such a range is associated with a confidence interval of 80%.

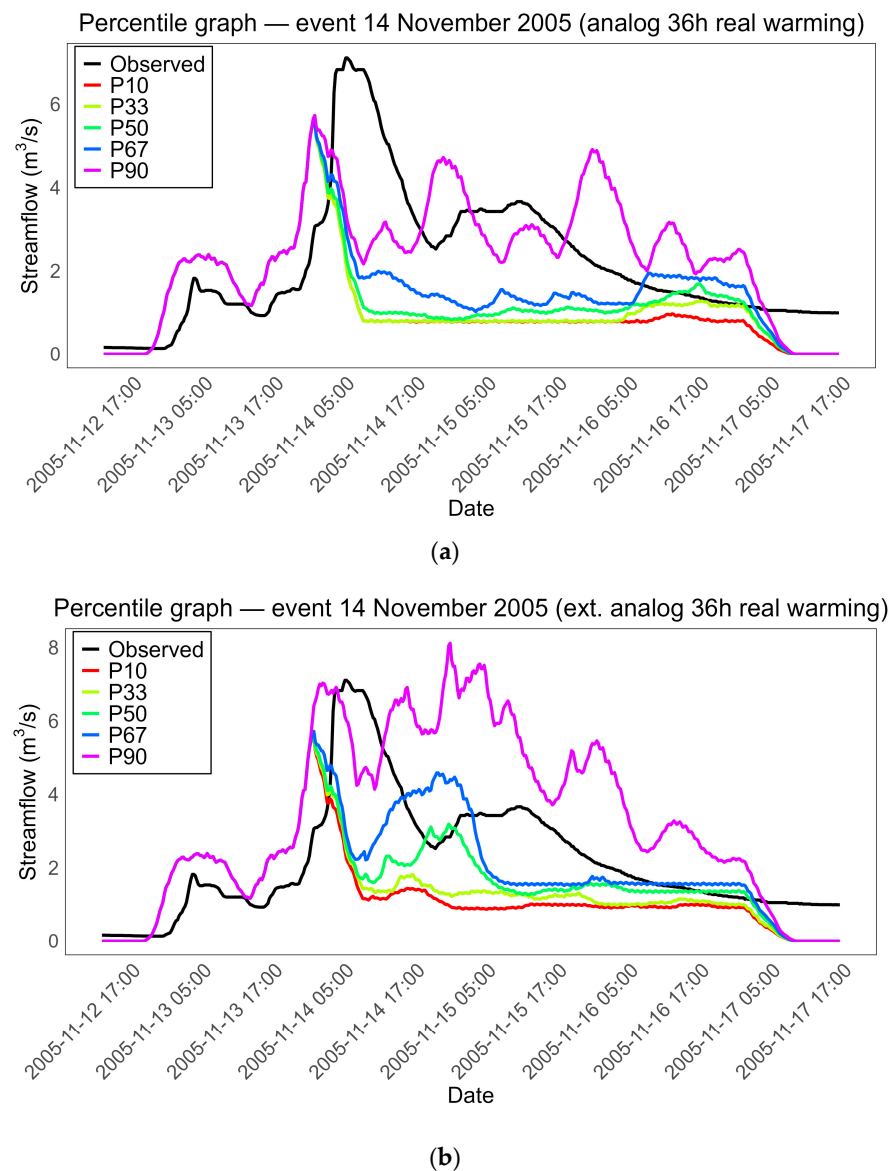


Figure 15. Probabilistic flood forecast for the 14 November 2005 flood event. (a) Analog rainfall field forecasts; (b) extreme analog rainfall field forecasts.

The percentile graph of the 14 November 2005 event (Figure 15) shows better results for the extreme analog events, in which a significant portion of the observed hydrograph falls within the confidence intervals. However, the forecast tends to underestimate given aspects of the hydrological response.

The probabilistic forecast of the 12 September 2006 flood event (Figure 16) greatly underestimates the observed flood response. Such an underestimation can be caused by a considerable precipitation underestimation, compared with the real rainfall, of both analog and extreme analog rainfall field forecasts in this flood event (Figure S9).

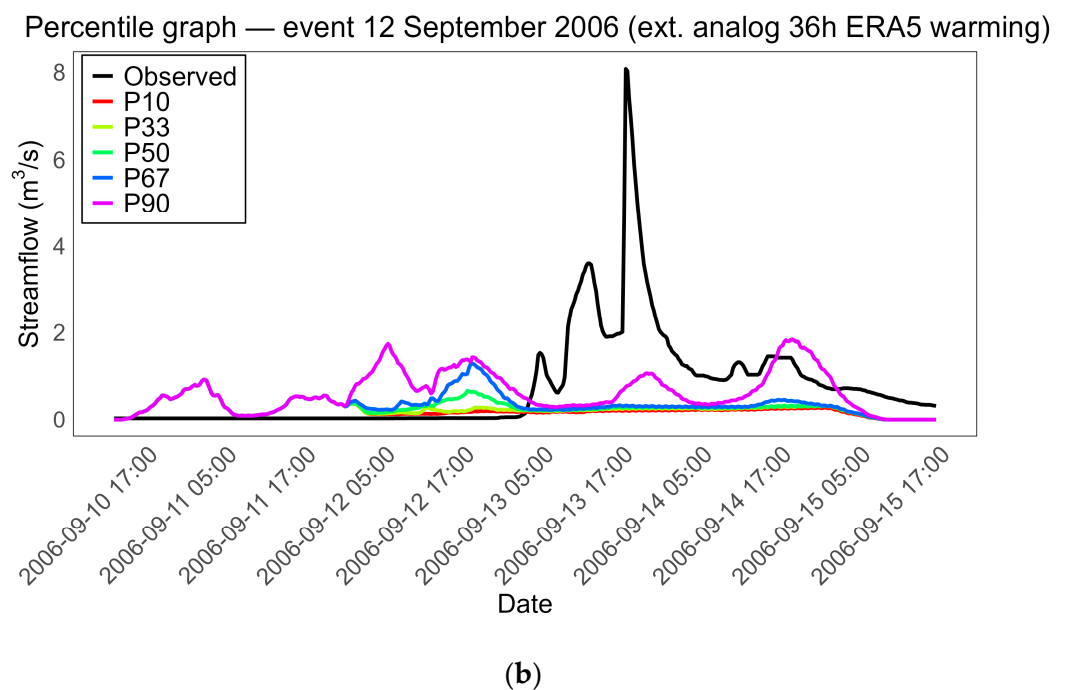
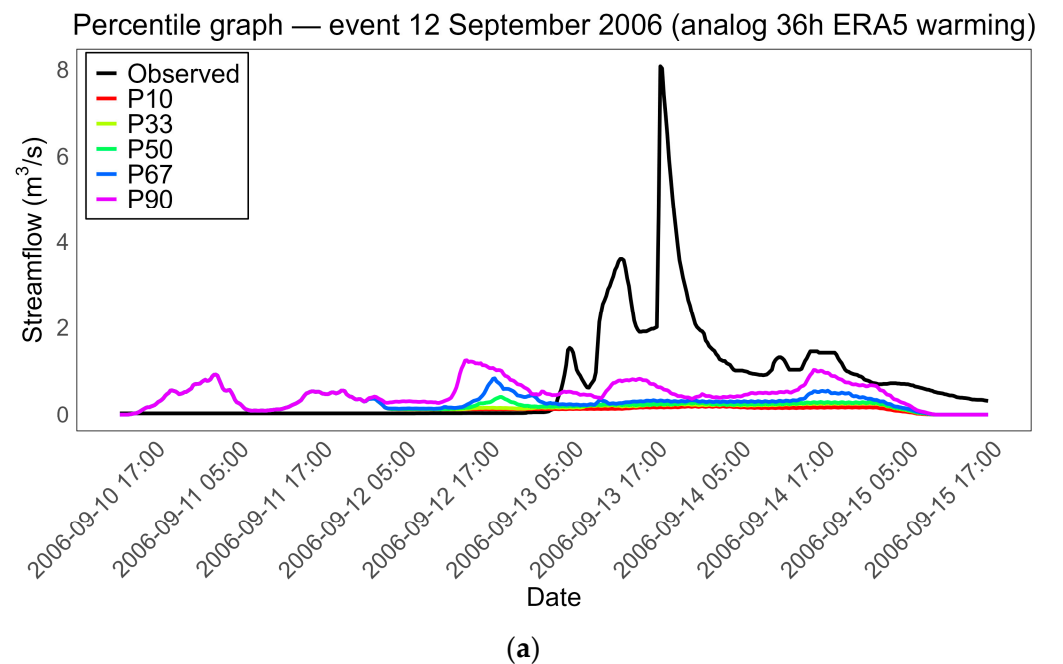


Figure 16. Probabilistic flood forecast for the 12 September 2006 flood event. (a) Analog rainfall field forecasts; (b) extreme analog rainfall field forecasts.

The percentile graph obtained for the forecast response of the 17 September 2010 flood event (Figure 17), clearly underestimates the discharges recorded in the observed event. In

this case, the underestimation can also be caused by considerably less precipitation than the real rainfall in both analog and extreme analog rainfall field forecasts (Figure S10).

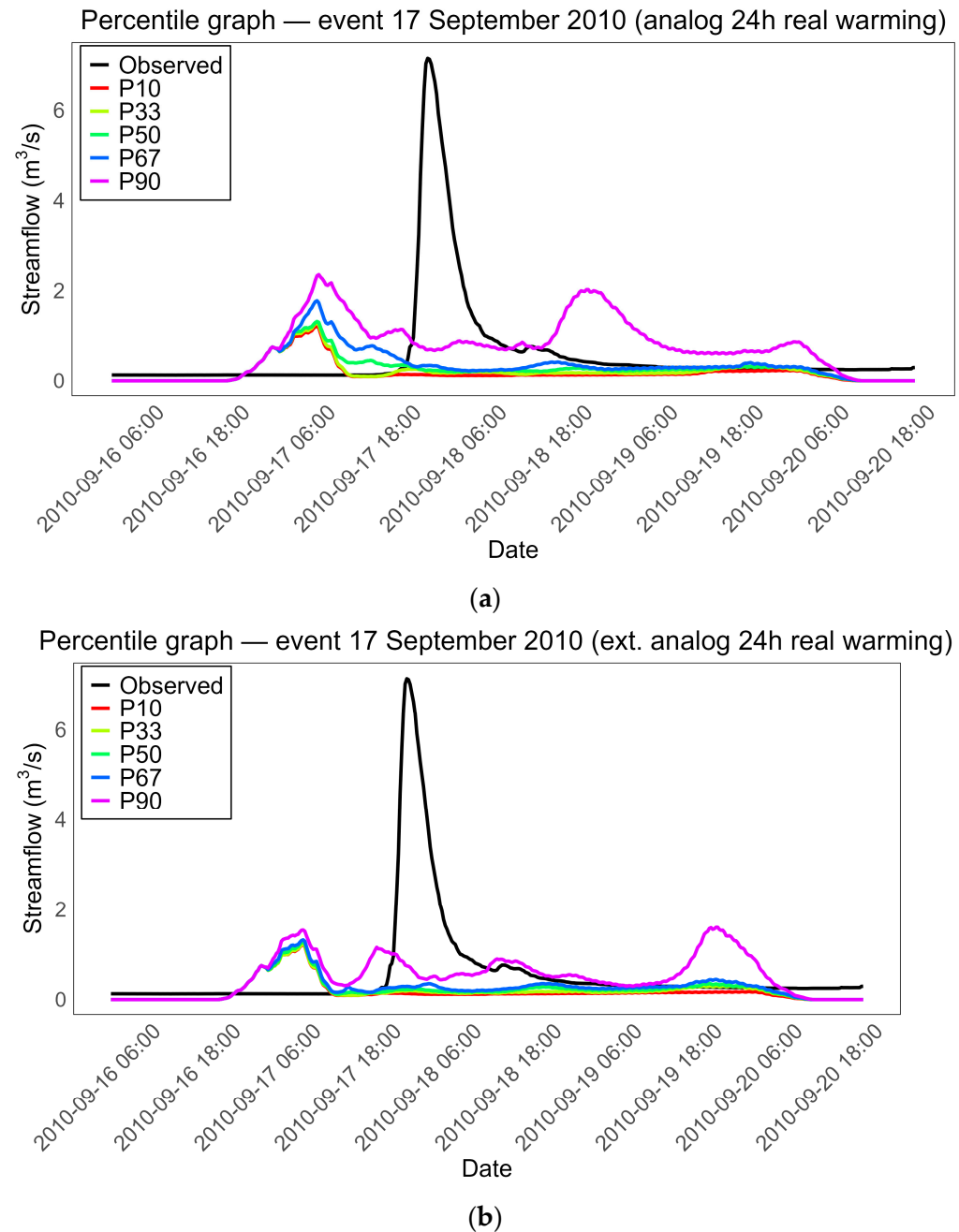
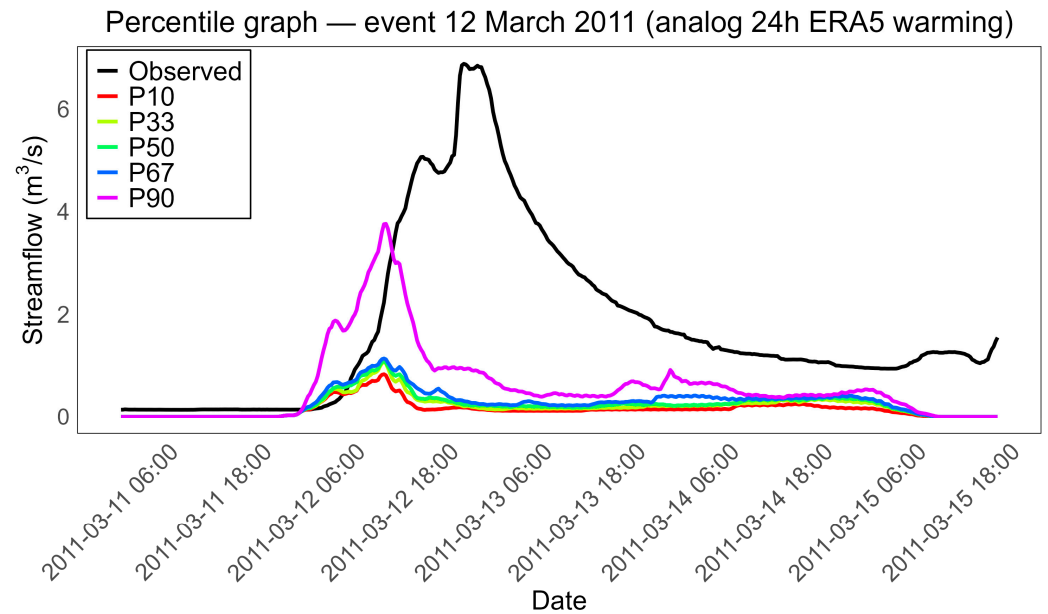
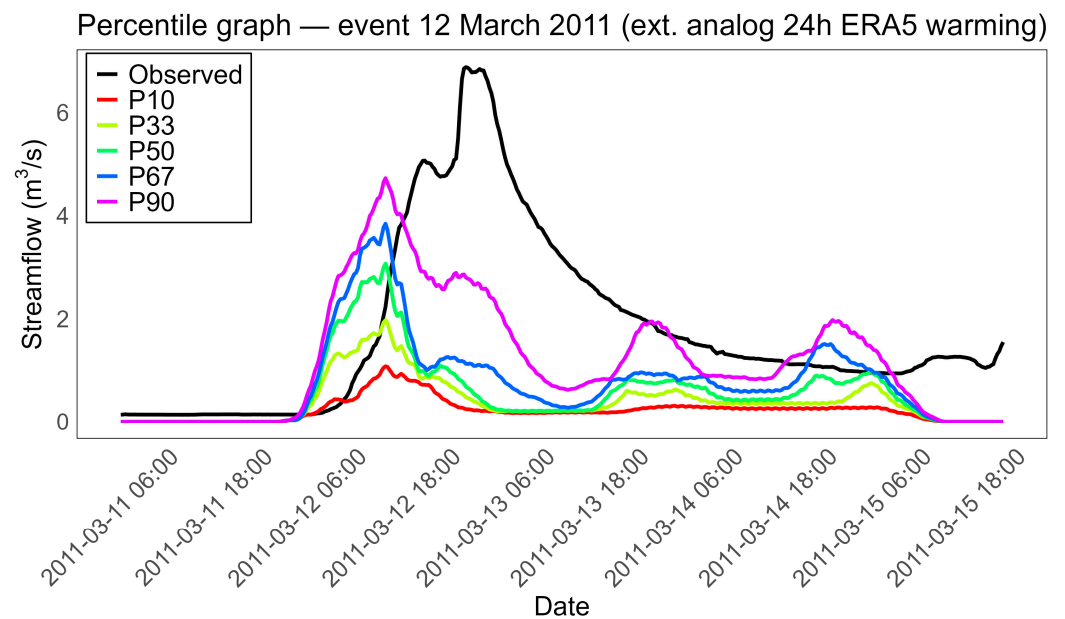


Figure 17. Probabilistic flood forecast for the 17 September 2010 flood event. (a) Analog rainfall field forecasts; (b) extreme analog rainfall field forecasts.

In the 12 March 2011 flood event (Figure 18), the probabilistic forecast produces a predicted discharge response that approximates the shape of the observed hydrograph, though it tends to underestimate the peak discharge reached in the real situation. However, the results are more similar to the observed hydrograph than the previous two flood events. Figure S11 shows that the mean areal precipitation of analogs and extreme analogs is smaller than, but more similar to, the mean areal precipitation obtained with real rainfall than in the previous two flood events.



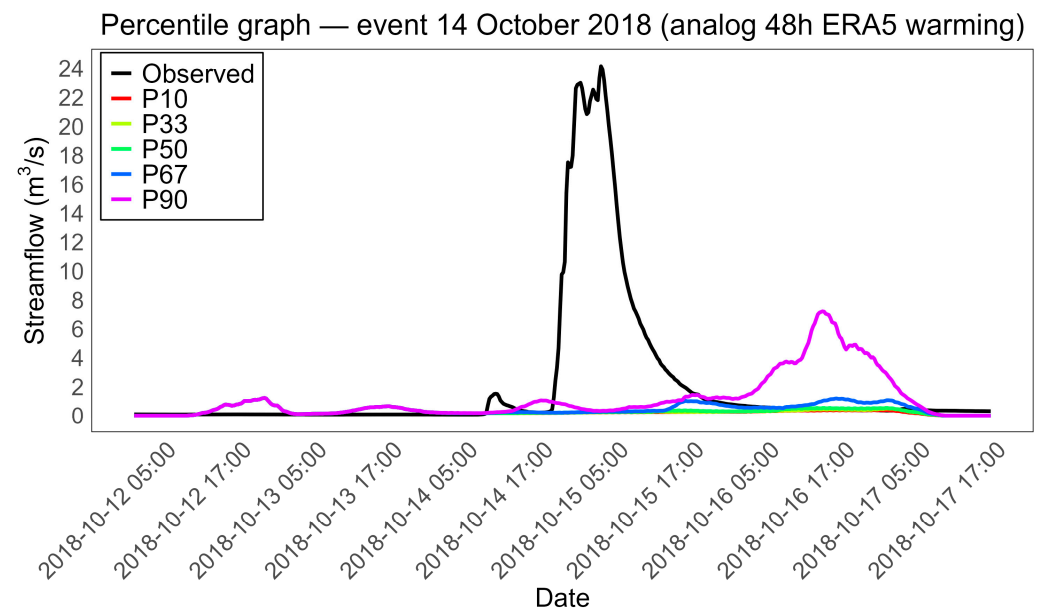
(a)



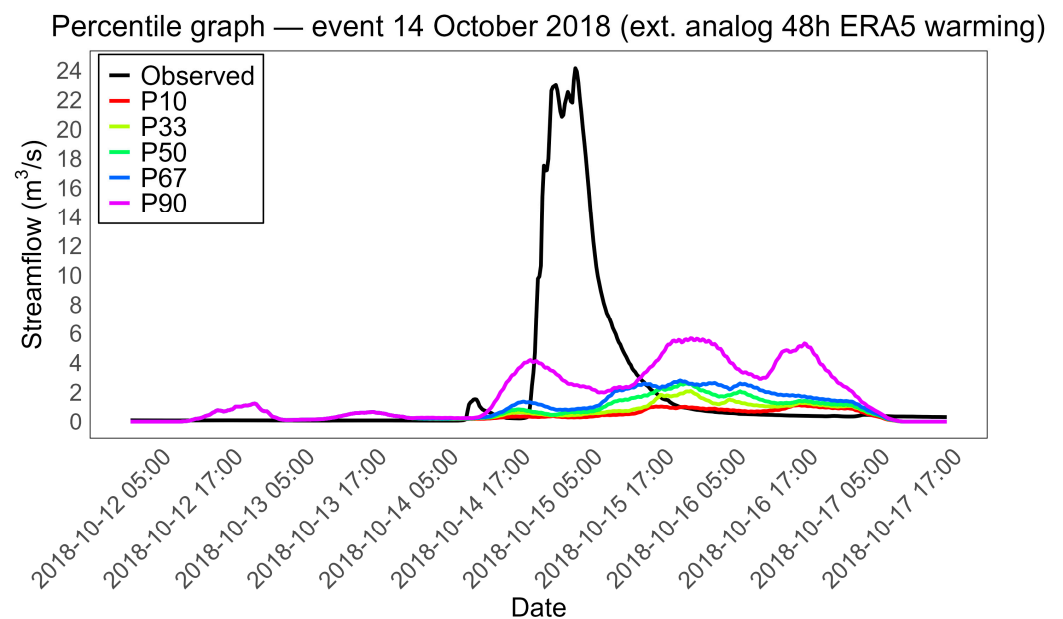
(b)

Figure 18. Probabilistic flood forecast for the 12 March 2011 flood event. (a) Analog rainfall field forecasts; (b) extreme analog rainfall field forecasts.

The probabilistic forecast of the 14 October 2018 flood event (Figure 19) underestimates the observed flood response. Figure S12 shows that the mean areal precipitation obtained with both analog and extreme analog field forecasts is much smaller than the mean areal precipitation obtained with the real rainfall. Therefore, flood forecasts are underestimated because the rainfall forecasts are also underestimated.



(a)



(b)

Figure 19. Probabilistic flood forecast for the 14 October 2018 flood event. (a) Analog rainfall field forecasts; (b) extreme analog rainfall field forecasts.

5. Discussion

In this section, the results included in the previous section are discussed, highlighting the limitations of the study.

5.1. Model Calibration

It should be noted that in some flood events, optimal calibration results have not been achieved, due to the torrential behavior of the catchment, subject to flash floods driven by short, high-intensity, and localized storms. In addition, such storms are characterized by a high spatial variability in rainfall. Therefore, in some cases, the precipitation recorded at rainfall gauging stations might not be able to characterize the rainfall spatial distribution

in the catchment. For example, this would be the case in the 2010 flood event (Figure S1), in which the simulated hydrograph overestimates the water volume compared with the observed hydrograph. In addition, this could also be the situation for the 2015 flood event (Figure S4), in which a similar hydrograph shape is obtained, but the simulated peak flow occurs about 6 h before the observed peak flow.

However, in other flood events, such as the 2013, 2014, and 2018 flood events (Figure S2, Figure S3, and Figure 5, respectively), a strong similarity between the simulated and observed hydrographs is achieved, as evidenced by the small RMSE and high NSE values obtained (Table 4). Furthermore, it can be highlighted that the best calibration results were achieved for the 2018 flood event, resulting in an accurate calibration.

The RIBS model parameter values included in Table 7 were chosen as the result of the calibration process, after evaluating a set of model parameter value combinations (Figures 6 and S5–S8). Such a parameter value combination led to the best overall calibration results in the five flood events considered in the study, performing better than the other combinations considered in at least three of the five flood events (Table 6). For almost all of the five calibration flood episodes, the RMSE and NSE objective function results (Table 8) obtained with the chosen RIBS model parameter values (values of calibration 2 in Table 6), closely approximate those obtained for each of the five flood events using the best calibration parameter values found individually.

5.2. Analysis of Simulations

As it was expected, it could be emphasized that the simulations obtained with real precipitation as input data in the RIBS model produce flood hydrographs that are more similar both graphically and in magnitude to the observed hydrograph.

After reviewing the simulations of the five flood episodes considered in this paper, it could be concluded that, in general, the forecasts of the flows are improved when a longer time series of previous precipitation is introduced in the model (Figures 10–14). Therefore, it can be concluded that adding longer available time series of antecedent precipitation leads to the best estimate of the catchment initial soil moisture content.

It is also important to understand which type of antecedent precipitation source leads to the best prediction results. While real precipitation performs better in the 2005 and 2010 flood events (Figures 10 and 12), ERA-5 and real precipitations obtain similar predictions for the 2011 flood event (Figure 13). On the other hand, only warming with ERA-5 precipitation was considered for the 2006 and 2018 flood events (Figures 11 and 14), because the antecedent real precipitation was zero in all time steps for these flood events.

In the five flood episodes considered in the study, the flood forecasts tend to underestimate the observed flow. In addition, better prediction results are obtained using extreme analog rainfall field forecasts, which can be caused by using past events that produced more catastrophic floods with similar atmospheric configuration to the analyzed event.

In the 2006, 2010, and 2018 flood events, the flood response prediction with the precipitation rainfall fields generated with the meteorological analog methodology tend to significantly underestimate the observed values (Figures 16, 17 and 19). For example, the probabilistic forecast of the 2011 flood event gives a similar shape for the hydrograph, though predicted percentiles are approximately 50% smaller than observed values (Figure 18b). Such an underestimation of flood forecasts is caused by a considerable underestimation of precipitation supplied by the rainfall field forecasts compared with real precipitation.

The best prediction results are achieved for the 2005 flood event with the extreme analog rainfall forecasts (Figure 15b). For this flood event, most of the observed hydrograph

is between the 10 and 90% percentiles, though the shape and the hydrograph volume could be improved.

Ideally, the observed hydrograph should fall within the confidence limits of the percentile lines. However, this rarely occurs in most simulations. Therefore, future work will focus on improving both, the calibration process and the analog method for providing rainfall forecasts, to achieve more accurate response discharge forecasts and be able to obtain more reliable flood predictions.

5.3. Applicability of the Methodology

The methodology presented in this study for providing a probabilistic flood forecast for the Francolí basin can be replicated in other basins, as ERA5 reanalysis is available globally and the hydrological study can be carried out using the RIBS model for small and medium-sized basins. In other Mediterranean basins, with such special climatic characteristics and due to the lack of historical data and the occurrence of rapid and intense flash floods, the implementation of such methodology is essential for early flood detection and providing valuable information for decision-making.

The applicability of the proposed methodology in flood scenarios would be applied as follows. Several hours or days before the flood event, forecasts of expected meteorological conditions in the following hours or days would be available (including information on the 500 hPa and 1000 hPa geopotential height fields provided by the GFS). Thus, using these data, potential rainfall fields are derived within minutes by applying the analog-based approach. These rainfall fields are then input into the RIBS model, which can simulate the hydrological response of the basin in a few minutes. Therefore, the results of this flood forecast for the Francolí River basin could be generated and delivered in approximately 15 min.

In addition, this approach can be also extended to other Spanish basins with major floods and other climatic conditions (different conditions than this Mediterranean area, where it is more difficult to reproduce the flooding phenomena accurately). Therefore, in other catchments, predictions are likely to yield higher accuracy. In future studies, this methodology will be adapted to another basin in Spain.

6. Conclusions

This study proposes a flood forecasting tool in the Francolí river catchment. The distributed hydrological Real-time Interactive Basin Simulator (RIBS) model was calibrated in the catchment. The calibrated hydrological model parameter values reasonably replicate the basin hydrological response for a set of past events.

In this study, a series of rainfall field forecasts based on the analog method were developed and used as input data in the calibrated hydrological RIBS model. Rainfall forecasts show significant variability among analogs, reflecting the inherent uncertainty in meteorological prediction. Additionally, there exist uncertainties associated with the hydrological model, parameter estimation, and meteorological prediction, which will be analyzed in future research. Therefore, it is important to highlight the limitations of the present paper regarding uncertainty and flood frequency statistical analyses.

In addition, a considerable underestimation of precipitation has been found in four of five flood events compared with the real precipitation recorded at rainfall gauging stations.

Results show that increasing the duration of the antecedent precipitation considered in the hydrological simulations enhances forecast accuracy. Such an antecedent precipitation achieves enhanced predictions with the real precipitation, mainly in the 2005 and 2010 flood episodes.

The forecast provides a probability distribution of possible response discharges of the Francolí river basin in advance for a given flood event. In the future, the calibration and the analog method will be improved to achieve better results that will improve the precision of the predictions. Thus, the forecast tool can be useful in real time for flood early warning and could be incorporated in decision-making processes.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/hydrology12080220/s1>. Figure S1. Comparison between the observed and calibrated hydrographs for the event of 12 August 2010. Figure S2. Comparison between the observed and calibrated hydrographs for the event of 6 March 2013. Figure S3. Comparison between the observed and calibrated hydrographs for the event of 29 November 2014. Figure S4. Comparison between the observed and calibrated hydrographs for the event of 3 November 2015. Figure S5. Hydrographs obtained for the different model parameter combinations considered for the event of 12 August 2010. The observed hydrograph is presented in red and the hydrograph for the selected calibration is presented in green (calibration 2). Figure S6. Hydrographs obtained for the different model parameter combinations considered for the event of 6 March 2013. The observed hydrograph is presented in red and the hydrograph for the selected calibration is presented in green (calibration 2). Figure S7. Hydrographs obtained for the different model parameter combinations considered for the event of 29 November 2014. The observed hydrograph is presented in red and the hydrograph for the selected calibration is presented in green (calibration 2). Figure S8. Hydrographs obtained for the different model parameter combinations considered for the event of 3 November 2015. The observed hydrograph is presented in red and the hydrograph for the selected calibration is presented in green (calibration 2). Figure S9. Mean areal precipitation in the Francolí catchment: (a) analog rainfall forecasts; (b) extreme analog rainfall forecasts. The real precipitation in the catchment is presented by a dark green line. Event of 12 September 2006. Figure S10. Mean areal precipitation in the Francolí catchment: (a) analog rainfall forecasts; (b) extreme analog rainfall forecasts. The real precipitation in the catchment is presented by a dark green line. Event of 17 September 2010. Figure S11. Mean areal precipitation in the Francolí catchment: (a) analog rainfall forecasts; (b) extreme analog rainfall forecasts. The real precipitation in the catchment is presented by a dark green line. Event of 12 March 2011. Figure S12. Mean areal precipitation in the Francolí catchment: (a) analog rainfall forecasts; (b) extreme analog rainfall forecasts. The real precipitation in the catchment is presented by a dark green line. Event of 14 October 2018. Figure S13. Simulated hydrograph for analog and extreme analog rainfall forecasts (simulation with 36 h ERA-5 antecedent precipitation) for the 12 September 2006 flood event. (a) Analog rainfall forecasts; (b) extreme analog rainfall forecasts. The red line represents the observed hydrograph. The green line is the hydrograph obtained with the real precipitation as input in the RIBS model. The remaining colored lines represent the analog and extreme analog rainfall forecasts. Figure S14. Simulated hydrograph for analog and extreme analog rainfall forecasts (simulation with 24 h real antecedent precipitation) for the 17 September 2010 flood event. (a) Analog rainfall forecasts; (b) extreme analog rainfall forecasts. The red line represents the observed hydrograph. The green line is the hydrograph obtained with the real precipitation as input in the RIBS model. The remaining colored lines represent the analog and extreme analog rainfall forecasts. Figure S15. Simulated hydrograph for analog and extreme analog rainfall forecasts (simulation with 24 h ERA-5 antecedent precipitation) for the 12 March 2011 flood event. (a) Analog rainfall forecasts; (b) extreme analog rainfall forecasts. The red line represents the observed hydrograph. The green line is the hydrograph obtained with the real precipitation as input in the RIBS model. The remaining colored lines represent the analog and extreme analog rainfall forecasts. Figure S16. Simulated hydrograph for analog and extreme analog rainfall forecasts (simulation with 48 h ERA-5 antecedent precipitation) for the 14 October 2018 flood event. (a) Analog rainfall forecasts; (b) extreme analog rainfall forecasts. The red line represents the observed hydrograph. The green line is the hydrograph obtained with the real precipitation as input in the RIBS model. The remaining colored lines represent the analog and extreme analog rainfall forecasts.

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