A reliable rainfall–runoff model for flood forecasting: review and application to a semi-urbanized watershed at high flood risk in Italy

Daniele Masseroni, Alessio Cislaghi, Stefania Camici, Christian Massari and Luca Brocca

ABSTRACT

Many rainfall–runoff (RR) models are available in the scientific literature. Selecting the best structure and parameterization for a model is not straightforward and depends on a broad number of factors, including climatic conditions, catchment characteristics, temporal/spatial resolution and model objectives. In this study, the RR model 'Modello Idrologico Semi-Distribuito in continuo' (MISDc), mainly developed for flood simulation in Mediterranean basins, was tested on the Seveso basin, which is stressed several times a year by flooding events mainly caused by excessive urbanization. The work summarizes a compendium of the MISDc applications over a wide range of catchments in European countries and then it analyses the performances over the Seveso basin. The results show a good fit behaviour during both the calibration and the validation periods with a Nash–Sutcliffe coefficient index larger than 0.9. Moreover, the median volume and peak discharge errors calculated on several flood events were less than 25%. In conclusion, we can be assured that the reliability and computational speed could make the MISDc model suitable for flood estimation in many catchments of different geographical contexts and land use characteristics. Moreover, MISDc will also be useful for future support of real-time decision-making for flood risk management in the Seveso basin.

Key words | calibration, flood forecasting, rainfall–runoff, semi-urbanized catchment, Seveso

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INTRODUCTION

A model can be considered as a simplified representation of a real world system (Devi *et al.* 2015). Even physically based models, solving complex systems of differential equations describing the occurring physical processes, need simplifications related to the identification of the parameter values, the uncertainties in input/output observations, the point-scale nature of physically based equations, and so forth. Therefore, the best model might be the one which gives results close to reality with the use of a minimum number of parameters and reduced model complexity. Hydrological models are mainly used for predicting and understanding various runoff processes. A rainfall–runoff (RR) model consists of a set of equations that, starting from rainfall and evapotranspiration data, allows the estimation of runoff as a function of various parameters used for describing watershed characteristics. The common inputs required for all models are the meteorological variables, such as rainfall and evapotranspiration data, and the watershed variables like drainage area, soil properties, vegetation cover and watershed topography.

In the scientific literature, a plethora of RR models are available: each one characterized by a different level of complexity and data requirement. RR models can be subdivided as a function of their spatial structure (lumped versus semi-distributed or distributed), time representation (continuous time versus event-based) or process description (physically

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meaningful versus data-driven) (Brocca et al. 2011a). A comprehensive compendium of presently available catchment models can be found in Singh & Woolhiser (2002) and Kampf & Burges (2007). Although the number of available RR models is large, the discussion about the accuracy and the reliability is still open and it is a topic of increasing scientific interest. In addition, the hydrological models have a key role in water and environment resource management. In particular, the issue of flood protection and the awareness of runoff volumes in urban catchments have continued to rise in the policy priorities over the last decade, accompanied by an effort for improving flood forecasts (Cloke & Pappenberger 2009). To accomplish this task, researchers generally use different hydrological model typologies that have to be calibrated and validated using experimental watersheds. Choosing the model structure, identifying the parameter values and reducing the model's predictive uncertainty are considered paramount elements within hydrological modelling. The model structure must be parsimonious in terms of parameters to easily identify a stable and representative parameter set and to quantify the calibration uncertainty (e.g., Perrin et al. 2001). Moreover, the computational time has to be low if the purpose of the model is to support real-time decision-making for flood risk management. Several reviews of hydrological modelling have been published about this topic (e.g., Wheater et al. 1993; Beven & Freer 2001; Singh & Woolhiser 2002; Wagener et al. 2004). However, some aspects of the hydrological modelling field are changing rapidly, including new developments in distributed and lumped modelling, treatment of the uncertainty, and modelling ungauged and nonstationarity basins. Hence, an updated review of the case studies examining the modelling capabilities and limitations for different geographical contexts is very welcome.

The main purposes of this study are: (1) presenting the structure of the simple RR model named 'Modello Idrologico Semi-Distribuito in continuo' (MISDc), developed by Brocca et al. (2011a, 2011b); (2) giving a brief compendium of its applications for discharge prediction in many geographical contexts over different basins; and (3) evaluating the MISDc performances on the Seveso basin, one of the most vulnerable catchments in northern Italy, that is highly susceptible to flooding Milan municipality.

MISDC MODEL STRUCTURE

The MISDc model is a spatially distributed RR model that was designed for the simulation of flood events at hourly time scale. Currently, two model versions have been published. The original version simulates continuously the soil moisture while discharge is simulated only during flood events (Brocca et al. 2011a). A second version was developed for simulating also discharge continuously in time (Brocca et al. 2013a). However, both models have basically the same structure, which is described in the following, with the new version that only adds a component for the simulation of baseflow to the original structure. Two different components constitute the core of MISDc. The first component is a soil water balance (SWB) model (Brocca et al. 2008) that simulates the soil moisture temporal pattern and sets the initial conditions for the second component, an event-based RR model for flood hydrograph simulation. The two models are coupled through a simple linear relationship between the saturation degree ($W(t)$) and the soil retention parameter (S) of the Soil Conservation Service-Curve Number (SCS-CN) method. The experimental relationship was derived from intense monitoring activity of soil moisture and runoff over experimental catchments located in Mediterranean areas (Brocca et al. 2011c). The model considers the surface soil layer as a spatially lumped system with the following characteristics: (1) the infiltration rate is estimated using the Green–Ampt equation; (2) the drainage rate is described by the relation of Famiglietti & Wood (1994); and (3) the potential evapotranspiration is computed through the empirical relation of Blaney and Criddle as modified by Doorenbos & Pruitt (1977). Moreover, the model employs the SCS-CN method to estimate the losses and the geomorphological instantaneous unit hydrograph (IUH) and the linear reservoir IUH for routing excess rainfall in the catchment and in the area draining directly into the main channel, respectively (Corradini et al. 1997). MISDc does not include the component of snowmelt. A schematic and conceptual structure of the simulated processes is illustrated in Figure 1; however, the reader can refer to Brocca et al. (2011a, 2011b) and Camici et al. (2011) for more details.

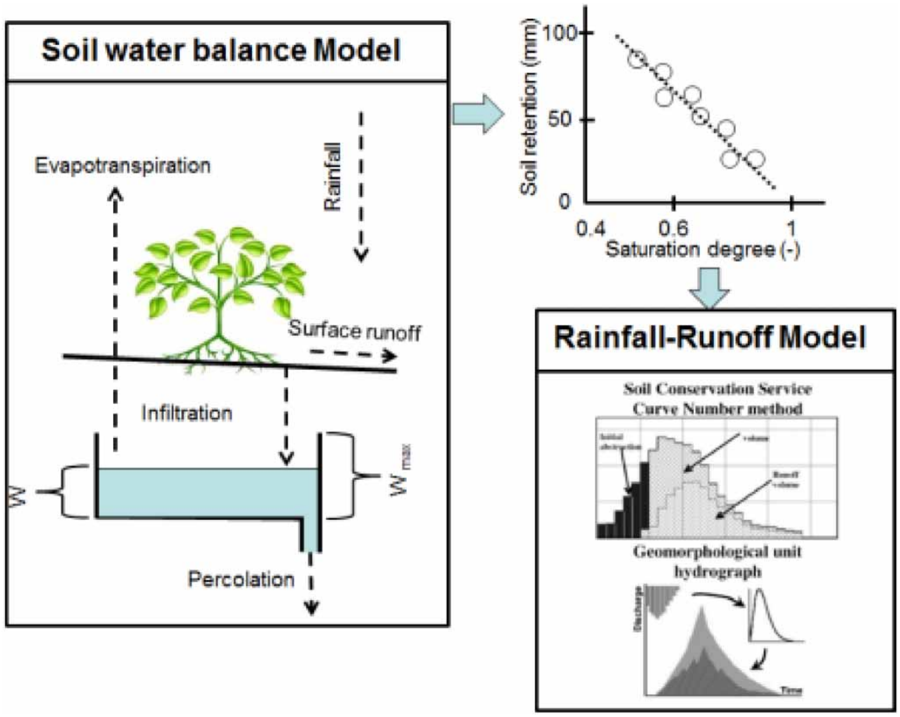


Figure 1 | Schematic diagram of the MISDc components. The structures of the SWB model and the RR model are shown on the left and on the right, respectively. The experimental relationship linking the output of the SWB model and the initial conditions of the RR model is shown in the top right part of the figure.

MISDc incorporates eight parameters (Brocca *et al.* 2013a), and it is characterized by a low computational effort, making it very attractive for hydrological practice. Indeed, the model can be conveniently adopted for the evaluation and simulation of multiyear (>20) discharge time series at hourly resolution. The model requires as input continuous time series of hourly precipitation and air temperature data of the whole basin; the temperature data are necessary to evaluate the evapotranspiration rate. For the calibration phase, observed discharge time series are necessary.

A positive feature is that both versions of MISDc model are freely available and can be downloaded at http://hydrology.irpi.cnr.it/people/l.brocca (or by contacting the authors). The code was developed in MATLAB programming language and is fully commented; an executable version of the model is also available.

Model parameters

The second version of the model, hereinafter simply MISDc (Brocca *et al.* 2013a), was used in this study for simulating continuous discharge time series at the closure section of the Seveso basin. The SWB component incorporates five parameters: W_{max} (maximum water capacity of the soil layer), K_s (saturated hydraulic conductivity), m (drainage exponent), Nu (fraction of drainage versus interflow) and b (correction factor for actual evapotranspiration). The RR component requires only three parameters: η (lag-time parameter), λ (initial abstraction coefficient) and S_r (parameter of S versus $W(t)$ relationship). As shown in Brocca *et al.* (2011a), during the calibration process, each parameter can vary over a physical admissible range as reported in Table 1.

COMPENDIUM OF THE MISDC HYDROLOGICAL APPLICATIONS

Geographical contexts

Both versions of MISDc model were applied over different basins that belong to the European countries, i.e., 46 basins in different parts of Italian territories, two in Spain, one in French, one in Greece and one in Luxembourg

Table 1 | Description, unit of measure and range of the calibration parameters for MISDc

Model component	Parameter	Description	Unit	Range
SWB	W_{max}	Maximum water capacity of the soil layer	Mm	100–1,000
	K_s	Saturated hydraulic conductivity	mm h^{-1}	0.01–20
	M	Drainage exponent	–	5–60
	Nu	Fraction of drainage versus interflow	–	0–1
	b	Correction factor for actual evapotranspiration	–	0.4–2
RR	γ	Lag-time parameter	–	0.5–6.5
	λ	Initial abstraction coefficient	–	0.0001–0.2
	S_r	Parameter of S versus $W(t)$ relationship	–	1–4

(Brocca *et al.* 2010, 2013b, 2013c; Massari *et al.* 2014a, 2014b, 2015a, 2015b; Ciabatta *et al.* 2016) (Figure 2). In addition, a small basin located in the western USA was analysed (Brocca *et al.* 2013b). A recent study by Massari *et al.* (2015c) was carried out in the Niger River basin in Africa.

The model performance over the Italian basins was analysed using a dataset constituted by hourly streamflow, precipitation and temperature observations provided by the Italian Department of Civil Protection in the period between 2010 and 2013 (Massari *et al.* 2015a). In other cases, the range of years could be different but not less than 3 years.

In general, the size of catchments where MISDc was applied ranges from 1 hectare to 7,400 km^2 (2,507 km^2, on average). The mean catchment elevation ranges between 350 and 1,300 m above sea level. The model was applied in a range of climates from temperate in Luxembourg and temperate Mediterranean in northern Italy to drier climate in southern Italy, Greece and USA (Arizona). Cumulative annual rainfall over the catchments varied from 250 (in USA) to 2,800 mm (in Northern Italy). Many catchments

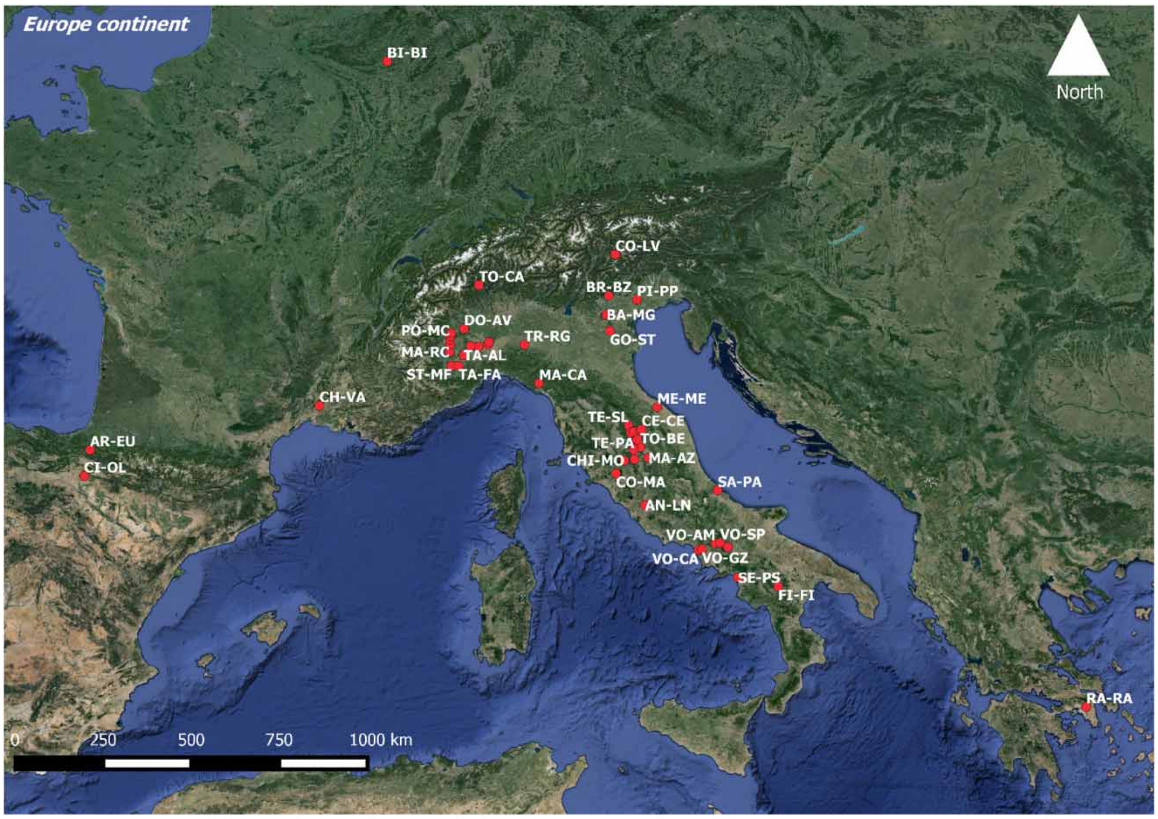


Figure 2 | European catchment positions. See Appendix for the complete name of basins (available with the online version of this paper).

are covered by different and often conflicting land uses. More specifically, they intertwine forests, croplands, grasslands and urban areas. The urban tissue of each basin was on average 5% of the total area.

MISDc application areas

The MISDc model has three major areas of application: (1) flood risk management and design flood estimation (e.g., Brocca *et al.* 2011a, 2013a; Camici *et al.* 2011); (2) climate change impact assessment on flood occurrence (e.g., Camici *et al.* 2014); and (3) soil moisture data assimilation (e.g., Massari *et al.* 2015b). A brief description of each application area is given below.

Concerning flood risk management, the parsimony and the simplicity of the model make it an efficient tool for flood forecasting. In addition, thanks to its structure, it can be easily run by end users and stakeholders. For these reasons, MISDc was applied to several basins of central Italy within civil protection purposes (Brocca *et al.* 2011a, 2011b). Furthermore, using the MISDc model, Brocca *et al.* (2013a) developed a framework composed of a comprehensive synthetic RR database in support of flood risk assessment and management able to provide discharge hydrograph scenarios without having to run any kind of models, thereby saving time and effort to warning issues. This methodology provided a tool, easy to use also by non-technical end users who are not familiar with hydrological modelling. This tool allows the retrieval of the discharge hydrograph scenarios from the database without having to run any kind of models, thereby saving time and effort to warning issues. In a similar context, by coupling MISDc to a stochastic model for generating synthetic time series of rainfall and temperature, Camici *et al.* (2011) generated long time series of discharge and calculated the different flood frequency. This study finally allowed assessment of the peak flow values for specific recurrence intervals, i.e., the design flood values.

In a different context, using the same tools developed for flood forecasting, the MISDc model was also employed for assessment of the impact of climate change on flood occurrence in central Italy (Camici *et al.* 2012, 2014). Camici *et al.* (2014) used different climate models and downscaling techniques for evaluating the climate change impact in different basins of central Italy. Results revealed that the hydrological characteristics of the study catchments play an important role in the assessment of the climate change impacts. For that, the need to use ensemble climate model results and multiple downscaling methods is underlined.

Finally, in order to improve the ability of the MISDc model in predicting river discharges, a large collection of works concerning data assimilation of *in situ* and satellite soil moisture data has been developed since 2010 (Brocca *et al.* 2010). In particular, in the works of Massari *et al.* (2014a, 2014b, 2015b), MISDc performances are analysed under different hypothesis, i.e., by assimilating soil moisture measurements from *in situ* sensors, land surface models and remote sensing. These studies provide promising outcomes, and represent the first attempt to integrate ground observed and satellite soil moisture datasets for flood simulation.

MISDc performances

MISDc has ensured quick and reliable results for all tested catchments. To quantify the goodness of the model's performance, most authors used the median value of different performances, such as the Nash–Sutcliffe efficiency (NSE) coefficient, the relative error in peak discharge (Err_{peak}) and the median relative error in volume (Err_{vol}), obtained by the applications to the reviewed catchments. Figure 3(a)–3(c) show the frequency distribution of such performance indices. NSE, Err_{peak}, Err_{vol} were divided in 11 classes according to observed minimum and maximum index values obtained over all experimental basins. A general agreement occurs between observed and simulated discharge at the closure section of the basins, with NSE values ranging from 0.5 to 0.9. In particular, 25% of basins have a NSE range of values between 0.85 and 0.89. Peak discharge and volumetric errors on flood events are in a range of 0.01–0.45, with a maximum frequency occurring at the class 0.21–0.24 for Err_{peak} and 0.17–0.21 for $Errr_{vol}$. Based on these results, we can consider the model accurate in simulating the most significant flood events for small to large catchments with different land uses and climatological conditions.

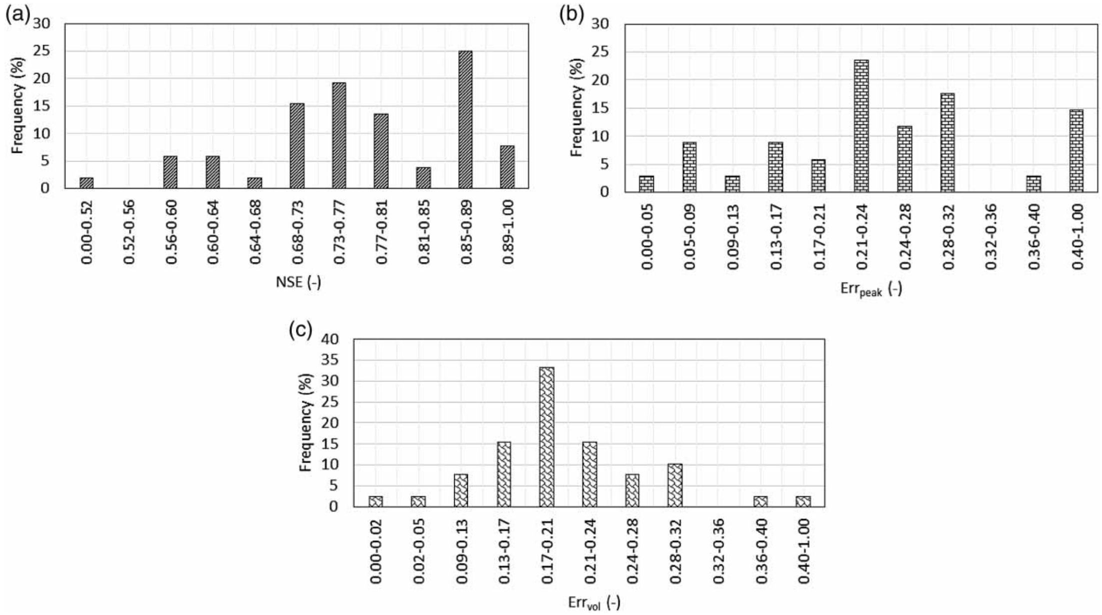


Figure 3 | Median performance indices of MISDc model for the selected catchments: (a) NSE = median Nash–Sutcliffe coefficient; (b) Err_{peak} = median relative error in peak discharge; and (c) Err_{vol} = median relative error in volume.

CASE STUDY

Seveso basin context

The Seveso basin, located inside the wider catchment of Lambro-Seveso-Olona, in the Lombardy territory, northern Italy, was selected for evaluating the performance of the MISDc model. This portion of the Po Valley, marked by intense urbanization and industrialization, is affected by extraordinary hydraulic-environmental problems subsequent to land use change (Lombardy Region 2009). The Lambro-Seveso-Olona catchment covers 2,500 km^2 and has a population not less than four million people. The intense presence of industrial, agricultural and livestock businesses of great national and international importance significantly affects the hydraulic-environmental equilibrium (Bocchi *et al.* 2012). The critical situations affecting the waterways, which are also widely discussed in documents of the Lombardy Region (2007, 2009), are: (1) the inadequacy of the discharge capacity of the watercourses, resulting in risks of overflowing large urban areas, even when the precipitation intensity is not high; (2) the poor physical-chemical quality of the water; (3) the poor biological quality of the river environment; (4) the poor hydro-morphological quality of the watercourses; (5) the absence of the aesthetic function in the landscape; and (6) the absence of recreational function. In this context, the support of modelling tools that can be adopted to mitigate the risk of flooding, activating political and technical decisions, is therefore essential.

In particular, the Seveso River basin is characterized by a natural portion that extends from the slopes of Monte Sasso to the municipality of Paderno Dugnano (in the province of Milan) where, in the locality of Palazzolo, the closure section is situated (Figure 4(a)). The total basin area is approximately 190 km^2, and the river length into the natural catchment is approximately 35 km. The ground elevation varies within the study catchment, from 10 to 375 m above sea level.

Land use characteristics

With respect to land use, about 54% of the surface is impervious due to expansion of the urban fabric. The remaining 46% is pervious and includes the agricultural and the wooded areas that together account for 36% of the whole basin. The agricultural land and the forests are present especially in the northern portion close to the cities in Monza-Brianza province.

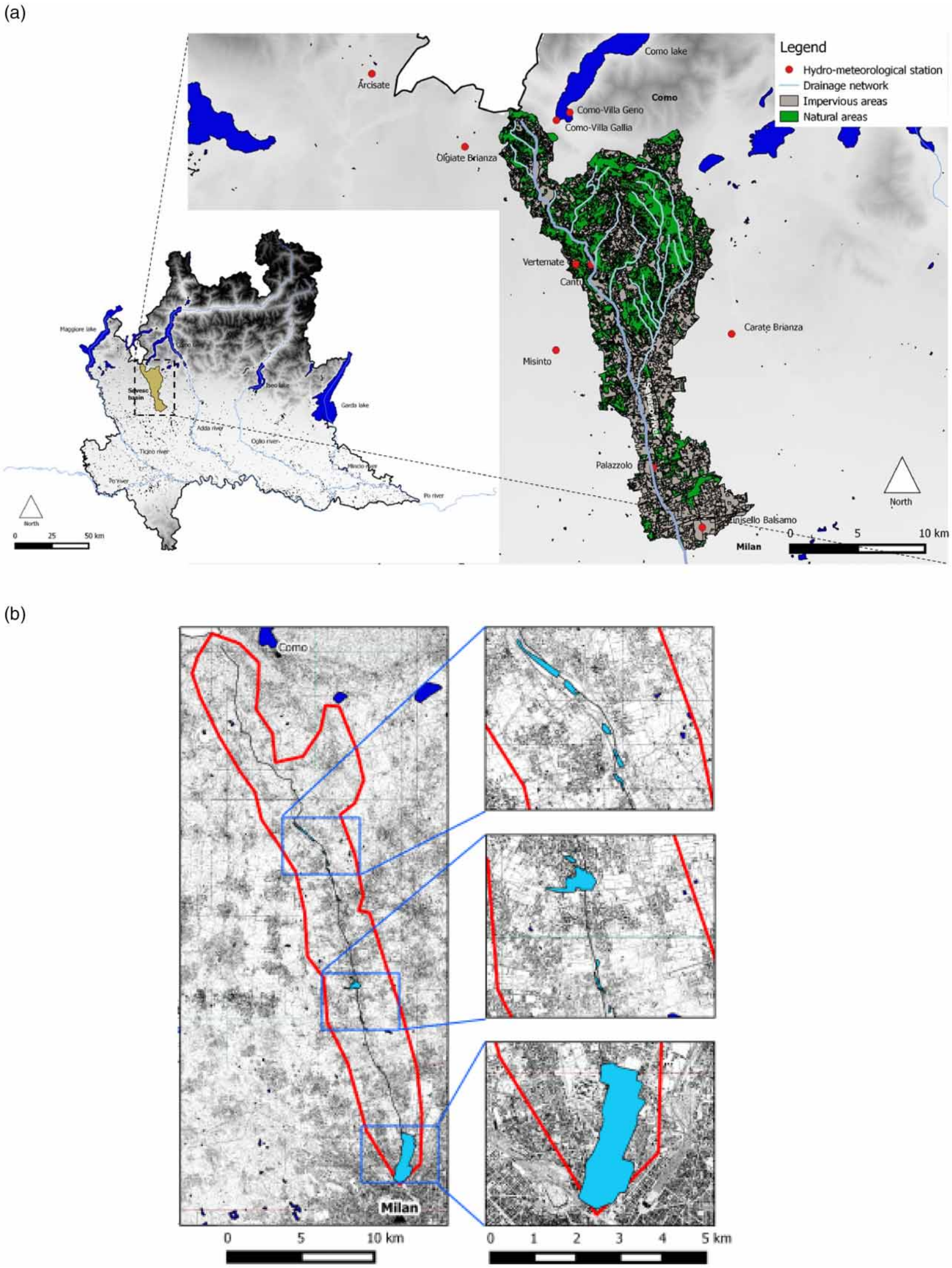


Figure 4 | (a) Location of the natural portion of Seveso catchment in the Lombardy region (on the left), hydro-meteorological stations and the land use (on the right). (b) Example of flooded areas along Seveso river during the event of November 14–15, 2014.

The continuous increase of the urbanized surfaces in the Seveso basin causes a consequent increase of the flow discharges into the sewer system and saturates the drainage capacity, even in situations characterized by weather events with modest return periods (from 2–10 years). These characteristics produce flooding events in some areas near the Seveso River, especially in the municipalities of Bovisio-Masciago, Lentate sul Seveso and Seveso. From the year 1976 to the present, approximately 90 floods have occurred, with an average of 2.5 floods per year (according to the Regional Agency for the Environmental Protection of the Lombardy Region (ARPA) data). The frequency of overflows has increased in recent years; in fact, from 2005 to the present, approximately 30 serious overflows have occurred, with an average of three per year. Particularly critical events were those of 2010 and 2014, during which more than five overflows per year occurred. Figure 4(b) shows the flooded areas on November 15, 2014 inside a Seveso river buffer of about 5 km in radius (Bocchi *et al.* 2012). In Figure 4(b), the urbanized portion of the basin, which extends up to the centre of Milan, is considered. The image shows a hydraulic criticality evenly distributed along the watercourse. The most vulnerable zone is located in the northern part of Milan: during the event of November 14–15, 2014, the extent of the flooded area reached a size of about 2.5 km^2. Over the total basin surface, the flooded areas exceeded 3.5 km^2.

Meteorological and flow regime

The Seveso basin has a humid subtropical climate according to the Köppen classification system. In fact, the Po Valley presents a transitional climate between the Mediterranean climate dominated by anticyclonic patterns and the Central European climate dominated by the oceanic influence of westerly circulations (Confalonieri *et al.* 2009). A real-time hydro-meteorological system monitored by ARPA Lombardy records measurements of rainfall, temperature and river stage with a time interval of 60 minutes and is freely available on the ARPA Lombardy's website. In the study basin, nine meteorological stations and one hydrometric site at the locality of Palazzolo (Paderno Dugnano, MI) are present, as shown in Figure 4. The stage–discharge relationship has been evaluated comparing the river stage and the flow discharge observations, measured by radar equipment recently installed by ARPA Lombardy. Successively, each time series of data has been analysed to detect multiple abrupt change points or trends according to the procedure described in detail by Rienzner & Gandolfi (2013). Figure 5(a) and 5(b) show the monthly averaged pattern obtained over 10 years (from June 2005 to June 2015) of the hourly data of the air temperature, rain and runoff volume. Higher monthly rainfall values generally occur during the spring and autumn periods. In particular, the average rainfall in April and May is equal to 140 mm/month, whereas the peak occurs in November, with 210 mm/month on average. In terms of the runoff volume, the monthly averaged pattern is approximately 5 Mm^3, but in autumn, as a consequence of widespread rainfalls, the mean runoff volume increases to 10 Mm^3 in November.

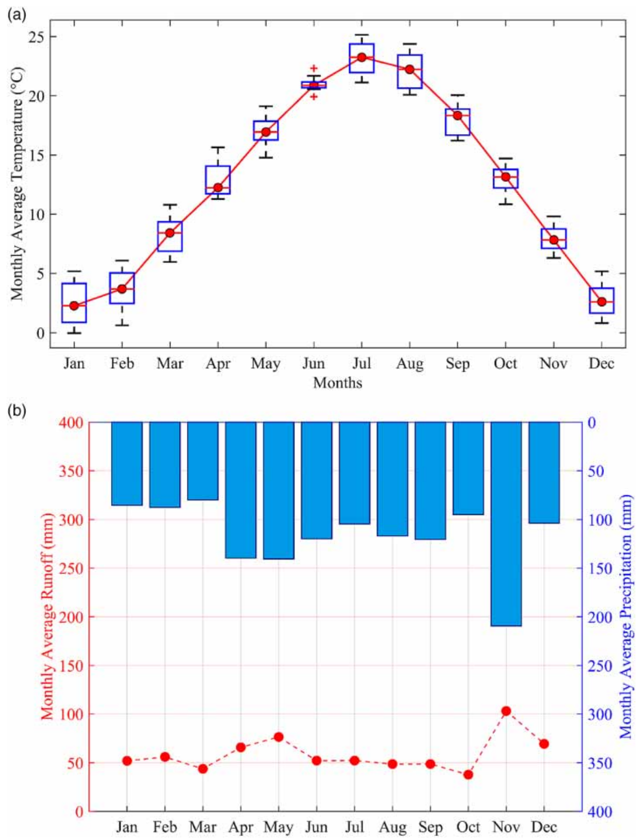


Figure 5 | (a) The line represents the monthly average temperature, while the boxplots indicate the distribution of the monthly temperature over the last 10 years. (b) In the upper part, the bars represent the monthly average rainfall, while in the lower part, the lines indicate the monthly average runoff.

The maximum air temperature values are in July, when the monthly mean temperature reaches approximately 23 °C, whereas the minimum of slightly above 0 °C occurs in January.

MODEL IMPLEMENTATION FOR THE CASE STUDY

Model calibration

For the case study the lumped configuration of the MISDc model was used in consequence of the small size of the basin. For the model calibration, the adopted algorithm is a standard gradient-based automatic optimization method implemented in MATLAB software package ('fmincon' function) as suggested by Brocca et al. (2011a) and Massari et al. (2014a). We set the maximum number of iterations equal to 100 times per parameter and the termination tolerance equal to 1×10^{-5}. The relatively low number of involved parameters make this process particularly suitable. The produced results are similar to those obtained by using more efficient, but slower, algorithms, such as the shuffled complex evolution algorithm as in Brocca et al. (2013a). The hydrological model parameters were calibrated comparing the simulated and the observed discharges at the closure section of the basin. The selected objective function is to maximize the NSE coefficient (Nash & Sutcliffe 1970).

Model performance evaluation

According to Smith et al. (2013), it has been difficult to specify ranges of values of the goodness-of-fit indicators that determine whether a model simulation is acceptable, good, or very good. However, the recent work of Ritter & Muñoz-Carpena (2013) presented an interesting framework for the statistical interpretation of hydrological model performance. The developed statistic software, named FITEVAL, calculates the root mean square error (RMSE) and NSE indices, the latter coupled with the approximated probability distributions function derived with bootstrapping (Efron 1979), followed by the bias corrected and accelerated method (Di Cicco & Efron 1996) for calculating the confidence intervals. Hypothesis testing of the indicators exceeding threshold values is proposed in a unified framework for statistically accepting or rejecting the model performance. The goodness of fit is subdivided into four performance classes based on the NSE ranges. These groups are denoted as unsatisfactory, acceptable, good and very good. The corresponding NSE limits were first derived based on a value of $NSE_{threshold} = 0.65$, which has been reported in the literature as a lower limit of a valid goodness of fit (e.g., Moriasi et al. 2007). The NSE adapted to high flow conditions (ANSE) (Hoffmann et al. 2004) was evaluated, and the absolute peak discharge and volumetric errors (hereafter indicated respectively with ε_{Qp} and ε_V) were also computed for some characteristic flood events over the observation years. In addition, a statistical method based on contingency table analysis was used to estimate forecasting performance as suggested by many authors (e.g., Martina et al. 2006; Ravazzani et al. 2007; Bartholmes et al. 2009; AghaKouchak & Mehran 2013; Demirel et al. 2015). The contingency table compares the observed flood events with the forecasted. The possible outcomes are: hit (H) indicates that both measurement and simulation detect the flood events, miss (M) refers to events identified by observation, but missed by the simulation, false alarm (F) represents flood events identified by simulation, but do not occur and true null events (Q) denotes when both measurement and simulation do not identify flood events.

To build such a table, it is necessary to fix a rainfall threshold that is the cumulative volume of rainfall during a storm event which can generate a critical water stage at a specific section (Martina et al. 2006) and a discharge threshold that corresponds to a hazardous water level (consequently it becomes appropriate to issue a flood alert). In this study, the value of rainfall threshold is equal to 10 mm as suggested by Camici et al. (2011), whereas the discharge limit is 50 m^3/s that corresponds to the bank-full discharge at the closure section of Palazzolo.

Based on this analysis, a series of skill scores including the probability of detection (POD), the frequency of hits (FOH), the frequency of misses (FOM), the false alarm ratio (FAR) and the critical success index described by AghaKouchak & Mehran (2013) and Bartholmes et al. (2009) were calculated. Their mathematical formula are summarized as follows:

$$POD = H/(H+M) \quad \text{range}\,[0, 1]\,\text{best:1} \tag{1}$$

$$FOH = H/(H+F) \quad \text{range}\,[0, 1]\,\text{best:1} \tag{2}$$

$$FOM = M/(H+M) \quad \text{range}\,[0, 1]\,\text{best:0} \tag{3}$$

$$FAR = F/(H+F) \quad \text{range}\,[0, 1]\,\text{best:0} \tag{4}$$

RESULTS AND DISCUSSION

Model calibration and validation

The application of MISDc provides a good simulation of the discharge for the whole dataset at the closure section of Palazzolo, as shown in Figure 6.

Calibration was performed over 6 years from 2005 to 2010. For the calibration procedure, the required computation time was approximately 5 minutes while the model runs over the 5 years of the validation procedure in a few seconds.

Considering the available data, the agreement between the observed and simulated discharge is very good, with NSE and RMSE values of 0.92 and 1.36 $m^3 s^{-1}$, respectively (Table 2). The 95% confidence interval for NSE [0.88–0.94] indicates that the goodness-of-fit evaluation moves from good to very good with no bias or outliers. The value of ANSE equal to 0.81 shows that the model was reliable in reproducing both the peak and the shape of the observed hydrographs, particularly during high flow conditions that correspond to flood events.

The reliability of the model is also confirmed in the validation period (from the year 2011 to 2015), with NSE and RMSE values of 0.91 and 1.58 $m^3 s^{-1}$, respectively. The 95% confidence interval for NSE [0.87–0.95] indicates that the goodness-of-fit evaluation does not change in the validation phase. Although the ANSE value is equal to 0.84, there is a slight underestimation concerning the discharges that exceed the value of 40 $m^3 s^{-1}$ (as shown in Figure 6), while the estimation of the base flow is very good. Moreover, the results show that the p-value is approximately zero in both cases. Therefore, the median NSE is significantly larger than the NSE threshold, below which the goodness of fit is not acceptable (equal to 0.65 according to Ritter & Muñoz-Carpena (2013)).

Performance during flood events

Using the same set of calibrated parameters, the MISDc model was assessed during flood events. Its performance

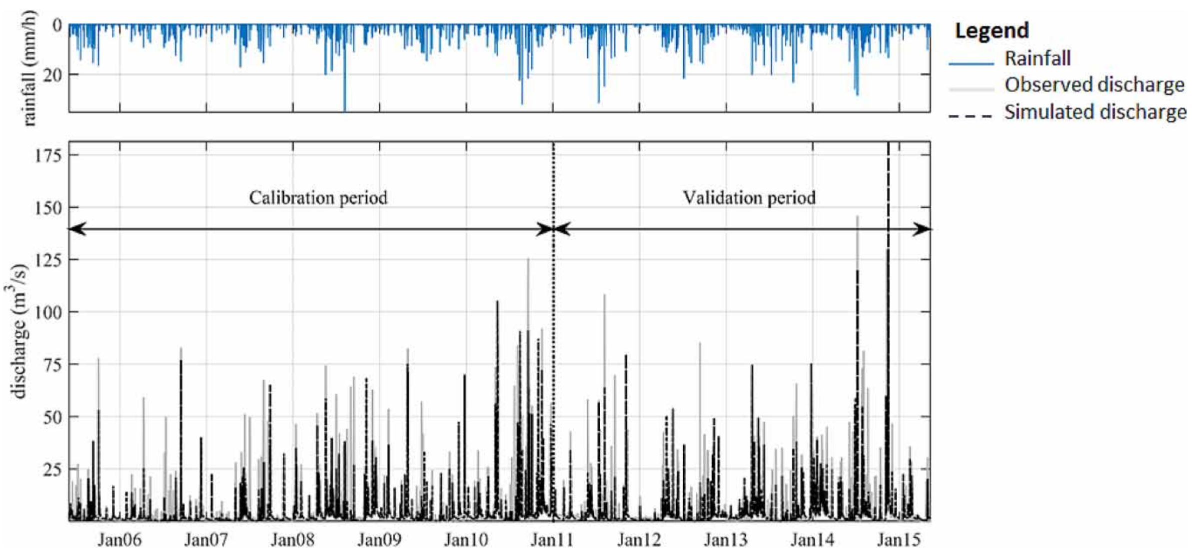
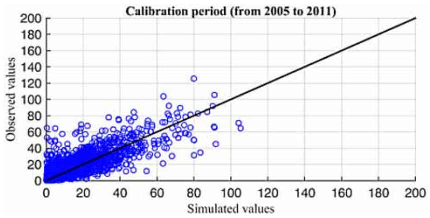
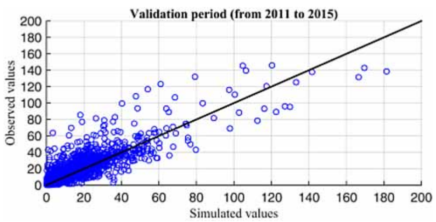


Figure 6 | Simulated versus observed discharge using MISDc for the entire available period.

Table 2 | Goodness-of-fit evaluation of the MISDc hydrological model applied on the Seveso catchment. The NSE probability distribution obtained by bootstrapping and the corresponding NSE statistical significance are also shown

Performance rating	NSE range by Ritter & Muñoz-Carpena (2013)	Probability of fit being (%)
Calibration period (from 2005 to 2010)		
Very good	0.900–1.000	86.8%
Good	0.800–0.899	13.2%
Acceptable	0.650–0.799	0.0%
Unsatisfactory	< 0.650	0.0% (P-value = 0.000)
		Goodness-of-fit evaluation RMSE: 1.36 [1.14–1.68]* NSE: 0.92 [0.88–0.94]* Presence of outliers: (Q-test): NO Model bias: NO
Validation period (from 2011 to 2015)		
Very good	0.900–1.000	90.5%
Good	0.800–0.899	9.5%
Acceptable	0.650–0.799	0.0%
Unsatisfactory	< 0.650	0.0% (P-value = 0.000)
		Goodness-of-fit evaluation RMSE: 1.58 [1.31–2.06]* NSE: 0.91 [0.87–0.95]* Presence of outliers: (Q-test): YES** Model bias: NO

*95% confidence interval.
**Presence of outliers (Q-test): present and maybe affecting indicators. Potential outlier at: (108.35, 10.81).

was tested over 52 severe flood events that significantly stressed the Seveso basin during the study period. The events were selected according to the suggestions described in Brocca *et al.* (2010). In particular, an event starts at the time when rainfall becomes greater than zero. The ending of an event was determined as the time when the streamflow decreases below a fixed percentage of the peak discharge (30%) or when a period equal to twice the catchment lag time with negligible cumulated rainfall (<1 mm) occurs. Then, the significant floods, i.e., the ones exceeding a rainfall threshold (10 mm) and/or a discharge threshold ($50\,m^3\,s^{-1}$), were selected (Camici *et al.* 2011). Figure 7 shows the behaviour of the MISDc model with respect to the ten more intense events that occurred during the study period. The model shows a good behaviour in six of ten analysed flood events. In particular, the error in peak discharge is higher for the three most important flood events. Unfortunately, it is not clear whether this is due to the model's bad performance or to an inherently larger uncertainty in the rainfall recorded by the raingauges.

In particular, for highlighting the hydrological model performance during flood events, the boxplot of ε_{Qp} and ε_V absolute errors (for the 52 flood events) is shown in Figure 8. The median values for ε_{Qp} and ε_V are 27.37% and 21.86%, respectively, while the first and third quartiles of error values are in a range from 13.58% to 47.30% for ε_{Qp} and from 8.97% to 39.27% for ε_V.

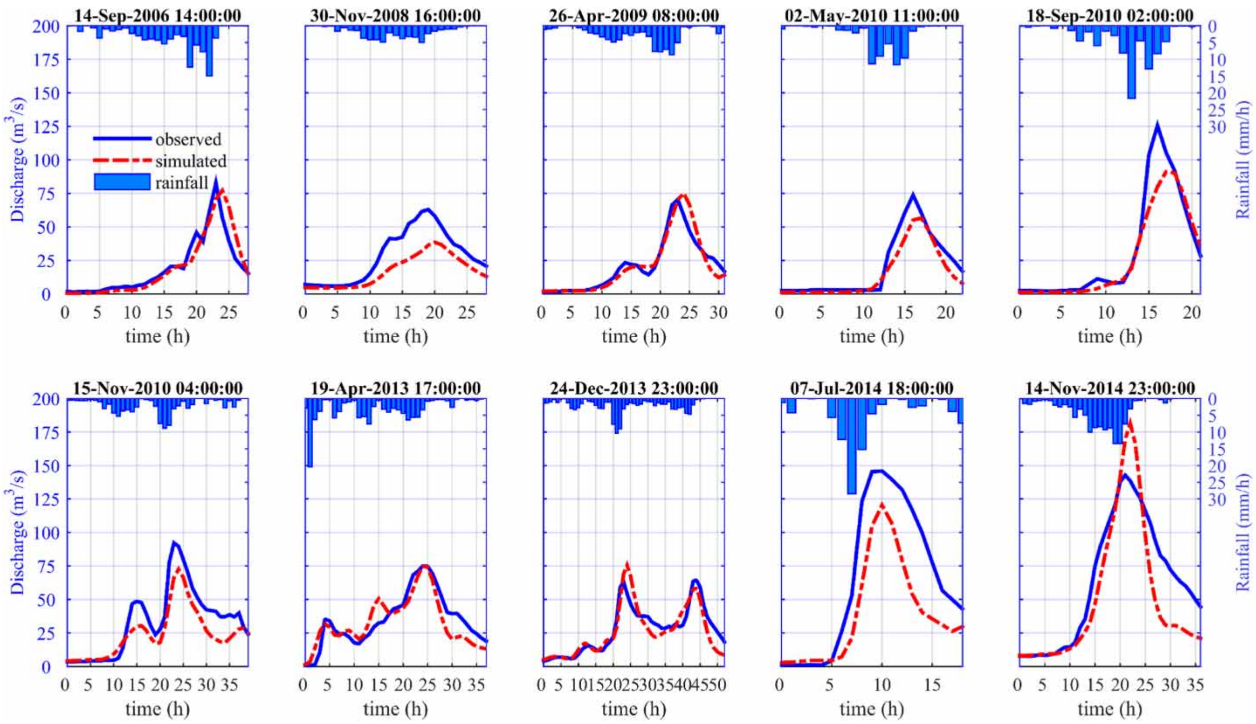


Figure 7 | Comparison of the observed and simulated discharge for some flood events that occurred during the study period at the Seveso River section of Palazzolo. The hourly mean areal rainfall for the Seveso basin is also shown.

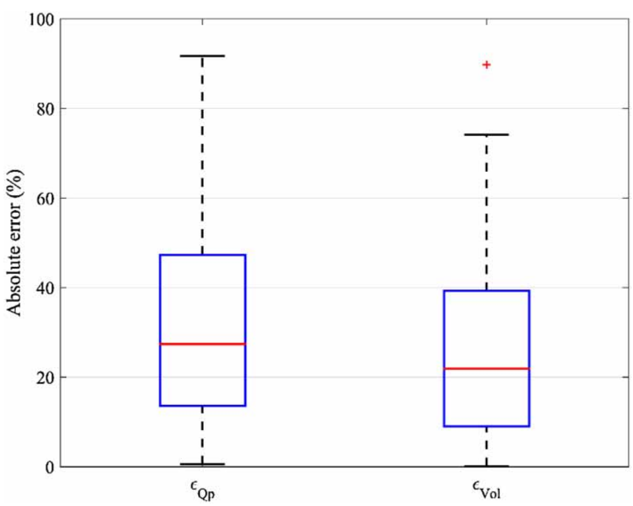


Figure 8 | Box plot of the ε_{Qp} and ε_V relative errors. The whiskers represent the minimum and maximum values of the errors, respectively. The two extremities of the box represent the first and third quartile, and the marked lines in the boxes represent the median value.

The MISDc model can be considered accurate for a flood simulation by comparing the results reported in Reed *et al.* (2004), Moretti & Montanari (2008), and Viviroli *et al.* (2009). For example, the model comparison study by Reed *et al.* (2004) gave a mean absolute peaks error in a typical range of 20–50% depending on the model and the catchment analysed, whereas a median of 27.37% is obtained here.

MISDc was tested for flood forecasting operations considering the whole period of data available. The results of the reliability analysis are shown in Table 3. In terms of skill scores, the results estimate an acceptable performance. POD, FOH, FOM and FAR reached the values of 0.57, 0.88, 0.43 and 0.12, respectively. A positive result is that POD is greater than FAR, therefore the probability of flood event detection is greater than the false alarms. The scores are similar to those obtained by Norbiato *et al.* (2008),

Table 3 | The contingency table adopted to estimate flood forecasting performance

		# Flood observed		
# Flood forecast		Yes	No	Total
	Yes	H = 29	F = 4	33
	No	M = 22	Q = 60	82
	Total	51	64	115

Vincendon *et al.* (2009) and Werner & Cranston (2009), which highlighted a POD value greater than 0.5 and a FAR value lower than 0.5.

CONCLUSIONS

The structure and performance of the MISDc RR model has been illustrated for the Seveso basin and summarized for a wide number of basins from previous studies in the scientific literature. Specifically, the MISDc model has a limited number of parameters, making it highly suitable for long-term simulations. The availability of the model encourages its application in other regions to test its structure and/or to improve the quality of forecasting in basins where other models fail to fit. Moreover, the application of the model to a large number of catchments might allow regionalization of its parameters and address the problem of prediction in ungauged basins.

The performance of the model applied on the Seveso catchment is promising, given that the NSE in both the calibration and validation periods is higher than 0.90, and the median of the peak and volumetric absolute errors for 52 flood events is approximately 25%. The homogeneity of land use and the small size of Seveso catchment could play a role on the goodness of fit, even if good MISDc performance were demonstrated on catchments larger than that studied in this work (see the section 'Compendium of the MISDc hydrological applications'). The good results shown in the sections 'Model calibration and validation' and 'Performance during flood events' for the application of the simple MISDc model for describing the Seveso catchment behaviour confirm the findings of other authors that simple approaches can succinctly represent the response of a catchment to precipitation (Jakeman *et al.* 1993; Perrin *et al.* 2001; Kirchner 2006). The main benefits of the model are that it is freely available (http://hydrology.irpi.cnr.it/people/l.brocca), easy to use, computationally efficient (with the considerable advantage of obtaining quickly a discharge simulation) and a parsimonious approach to data requirements (only rainfall and air temperature data), making it a suitable tool for catchments with poor data availability. Moreover, the novelty of the work is the application of the MISDc model on a more dense urban basin (differently from previous basins in which the urbanized area was on average 5%).

Further works on Seveso basin could be dedicated: (1) to improving the performance on peak discharge prediction by assimilating *in situ* and satellite measurements of soil moisture, as in Massari *et al.* (2015a); (2) to evaluating the changes in discharge runoff according to climate change previsions; and (3) to implementing a risk management database, as in Brocca *et al.* (2013a). Moreover, MISDc can be further tested over small gauged basins of mountainous territories introducing into the model the snow component, and over ungauged basins through the regionalization of MISDc parameters as a function of basin characteristics (i.e., soil texture, land use, slope, geology, etc.).

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