Can assimilation of crowdsourced streamflow observations in hydrological modelling improve flood prediction?

M. Mazzoleni[1], M. Verlaan[2], L. Alfonso[1], M. Monego[3], D. Norbiato[3], M. Ferri[3] and D. P. Solomatine[1,4]

[1]{UNESCO-IHE Institute for Water Education, Delft, The Netherlands}

[2]{Deltares, Delft, The Netherlands}

[3]{Alto Adriatico Water Authority, Venice, Italy}

[4]{Delft University of Technology, Water Resources Section, Delft, The Netherlands}

Correspondence to: M. Mazzoleni (m.mazzoleni@unesco-ihe.org)

Abstract

Monitoring stations have been used for decades to properly measure hydrological variables and better predict floods. To this end, methods to incorporate such observations into mathematical water models have also being developed, including data assimilation. Besides, in recent years, the continued technological improvement has stimulated the spread of low-cost sensors that allow for employing crowdsourced and obtain observations of hydrological variables in a more distributed way than the classic static physical sensors allow. However, such measurements have the main disadvantage to have asynchronous arrival frequency and variable accuracy. For this reason, this is one of the first studies that aims to demonstrate that crowdsourced streamflow observations can improve flood prediction if integrated in hydrological models. Two different types of hydrological models, applied to two case studies, are considered. Realistic (albeit synthetic) streamflow observations are used to represent crowdsourced streamflow observations in both case studies. Overall, assimilation of such observations within the hydrological model results in a significant improvement, up to 21% (flood event 1) and 67% (flood event 2) of the Nash-Sutcliffe efficiency index, for different lead times. It is found that the accuracy of the observations influences the model results more than the actual (irregular) moments in which the streamflow observations are assimilated into the hydrological models.

This study demonstrates how networks of low-cost sensors can complement traditional networks of physical sensors and improve the accuracy of flood forecasting.

1 Introduction

Observations of hydrological variables measured by physical sensors have been increasingly integrated into mathematical models by means of model updating methods. The use of these techniques allows for the reduction of intrinsic model uncertainty and improves the flood forecasting accuracy (Todini et al., 2005). The main idea behind model updating techniques is to either update model input, states, parameters or outputs as new observations become available (Refsgaard, 1997; WMO, 1992). Input update is the classical method used in operational forecasting as uncertainties of the input data can be considered as the main source of uncertainty (Bergström, 1991; Canizares et al., 1998; Todini et al., 2005). Regarding the state updating, Kalman filtering approaches such as Kalman filter (Kalman, 1960), extended Kalman filter (Aubert et al., 2003; Kalman, 1960; Madsen and Cañizares, 1999; Verlaan, 1998) or Ensemble Kalman filter (EnKF, Evensen, 2006) are ones of the most used when new observations are available.

Due to the complex nature of the hydrological processes, spatially and temporally distributed measurements are needed in the model updating procedures to ensure a proper flood prediction (Clark et al., 2008; Mazzoleni et al., 2015; Rakovec et al., 2012). However, traditional physical sensors require proper maintenance and personnel which can be very expensive in case of a vast network. For this reason, the technological improvement led to the spread of low-cost sensors used to measure hydrological variables such as water level or precipitation in a distributed way. An example of such sensors, defined in the following as "social sensor", is a smart-phone camera used to measure the water level at a staff gauge with an associate QR code used to infer the spatial location of the measurement (see Figure 1). The main advance of using these type of sensors is that they can be used not only by technicians but also by regular citizens, and that due to their reduced cost a more spatially distributed coverage can be achieved. The idea of designing such alternative networks of low-cost social sensors and using the obtained crowdsourced observations is the base of the EU-FP7 WeSenseIt project (2012-2016), which also sponsors this research. Various other projects have also been initiated in order to assess the usefulness of crowdsourced observations inferred by low-cost sensors owned by citizens. For instance, in the project CrowdHydrology (Lowry and Fienen, 2013), a method to monitor stream stage at designated gauging staffs using crowd source-based text messages of water levels is developed using untrained observers. Cifelli et al. (2005) described a community-based network of volunteers (CoCoRaHS), engaged in collecting precipitation measurements of rain, hail and snow. An example of hydrological monitoring, established in 2009, of rainfall and streamflow values within the Andean ecosystems of Piura, Peru, based on citizen observations is reported in Célleri et al. (2009). Degrossi et al. (2013) used a network of wireless sensors in order to map the water level in two rivers passing by Sao Carlos, Brazil. Recently, the iSPUW Project is aims to integrate data from advanced weather radar systems, innovative wireless sensors and crowdsourcing of data via mobile applications in order to better predict flood events in the urban water systems of the Dallas-Fort Worth Metroplex (ISPUW, 2015; Seo et al., 2014). Other examples of crowdsourced the water-related information include the so-called Crowdmap platform for collecting and communicating the information about the floods in Australia in 2011 (ABC, 2011), and informing citizens about the proper time to drink water in an intermittent water system (Alfonso, 2006; Au et al., 2000; Roy et al., 2012). A detailed and interesting review of the examples of citizen science applications in hydrology and water resources science is provided by Buytaert et al. (2014)

The traditional hydrological observations from physical sensors have a well-defined structure in terms of frequency and accuracy. On the other hand, crowdsourced observations are provided by citizens with varying experience of measuring environmental data and little connections between each other, and the consequence is that the low correlation between the measurements might be observed. So far, in operational hydrology practice, the added value of crowdsourced data it is not integrated into the forecasting models but just used to compare the model results with the observations in a post-event analysis. This can be related to the intrinsic variable accuracy, due to the lack of confidence in the data quality from such heterogeneous sensors, and the variable life-span of the crowdsourced observations.

Regarding data quality, Bordogna et al. (2014) and Tulloch and Szabo (2012) stated that quality control mechanisms should consider contextual conditions to deduce indicators about reliability (expertise level), credibility (volunteer group) and performance of volunteers such as accuracy, completeness and precision level. Bird et al. (2014) addressed the issue of data quality in conservation ecology by means of new statistical tools to assess random error and bias in such observations. Cortes et al. (2014) evaluated data quality by distinguishing the in-situ data collected between a volunteer and a technician and comparing the most frequent value reported at a given location. They also gave some range of precision according to the rating scales. With in-situ exercises, it might be possible to have an indication of the reliability of data collected (expertise level). However, this indication does not necessarily lead to a conclusion of high, medium or low accuracy every time a streamflow observation of a contributor is received. In addition, such approach is not enough at operational level to define accuracy in data quality. In fact, every time a crowdsourced observation is received in real-time, the reliability and accuracy of observations should be identified. To do so, one possible approach could be to filter out the measurements following a geographic approach which defines semantic rules governing what can occur at a given location (e.g. Vandecasteele and Devillers, 2013). Another approach could be to compare measurements collected within a pre-defined time-window in order to calculate the most frequent value, the mean and the standard deviation.

Regarding the variable life-span, crowdsourced observations can be defined as *asynchronous* because do not have predefined rules about the arrival frequency (the observation might be sent just once, occasionally or at irregular time steps which can be smaller than the model time step) and accuracy. In a recent paper, Mazzoleni et al. (2015) presented results of the study of the effects of distributed synthetic streamflow observations having synchronous intermittent temporal behaviour and variable accuracy in a semi-distributed hydrological model. It has been shown that the integration of distributed uncertain intermittent observations with single measurements coming from physical sensors would allow for the further improvements in model accuracy. However, we have not considered the possibility that the asynchronous observations might be coming at the moments not coordinated with the model time steps. A possible solution to handle asynchronous observations in time with EnKF is to assimilate them at the moments coinciding with the model time steps (Sakov et al., 2010). However, as these authors mention, this approach requires the disruption of the ensemble integration, the ensemble update and a restart, which may not feasible for large-scale forecasting applications. Continuous approaches, such as 3D-Var or 4D-Var methods, are usually implemented in oceanographic modeling in order to integrate asynchronous observations at their corresponding arrival moments (Derber and Rosati, 1989; Huang et al., 2002; Macpherson, 1991; Ragnoli et al., 2012). In fact, oceanographic observations are commonly collected at not pre-determined, or asynchronous, times. For this reason, in variational data assimilation, the past asynchronous observations are simultaneously used to minimize the cost function that measures the weighted difference between background states and observations over the time interval, and identify the best estimate of the initial state condition (Drecourt, 2004; Ide et al., 1997; Li and Navon, 2001).

In addition to the 3D-Var and 4D-Var methods, Hunt et al. (2004) proposed a Four Dimensional Ensemble Kalman Filter (4DEnKF) which adapts EnKF to handle observations that have occurred at non-assimilation times. In this method the linear combinations of the ensemble trajectories are used to quantify how well a model state at the assimilation time fits the observations at the appropriate time. Furthermore, in case of linear dynamics 4DEnKF is equivalent to instantaneous assimilation of the measured data (Hunt et al., 2004). Similarly to 4DEnKF, Sakov et al. (2010) proposed the Asynchronous Ensemble Kalman Filter (AEnKF), a modification of the EnKF, mainly equivalent to 4DEnKF, used to assimilate asynchronous observations (Rakovec et al., 2015). Contrary to the EnKF, in the AEnKF current and past observations are simultaneously assimilated at a single analysis step without the use of adjoint model. Yet another approach to assimilate asynchronous observations in models is the so-called First-Guess at the Appropriate Time (FGAT) method. Like in 4D-Var, the FGAT compares the observations with the model at the observation time. However, in FGAT the innovations are assumed constant in time and remain the same within the assimilation window (Massart et al., 2010). Having reviewed all the described approaches, in this study we have decided to use a straightforward and pragmatic method, due to the linearity of the hydrological models implemented in this study, similar to the AEnKF to assimilate the asynchronous crowdsourced observations.

The main objective of this novel study is to assess the potential use of crowdsourced observations within hydrological modelling. In particular, the specific objectives of this study are to a) assess the influence of different arrival frequency of the crowdsourced observations and their related accuracy on the assimilation performances in case of a single social sensor; b) to integrate the distributed low-cost social sensors with a single physical sensor to assess the improvement in the flood prediction performances in an early warning system. The methodology is applied in the Brue (UK) and Bacchiglione (Italy) catchments, considering lumped and semi-distributed hydrological models respectively. Due to the fact that streamflow observations from social sensors are not available in the Brue catchment while in the Bacchiglione catchment the sensors are being recently installed, the synthetic time series, asynchronous in time and with random accuracy, that imitate the crowdsourced observations, are generated and used.

The study is organized as follows. Firstly, the case studies and the datasets used are presented. Secondly, the hydrological models used are described. Then, the procedure used to integrate the crowdsourced observations is reported. Finally, the results, discussion and conclusions are presented.

2 Case studies and datasets

In this paper we choose two different case studies in order to validate the obtained results for areas having diverse topographical and hydrometeorological features and represented by two different hydrological models. The Brue catchment is considered because of the availability of precipitation and streamflow data, while the Bacchiglione river is one of the official case studies of the WeSenseIt Project (Huwald et al., 2013), which is funding this research.

2.1 Brue catchment

The first case study is located in the Brue catchment (Figure 2), in Somerset, with a drainage area of about 135 km^2 at the catchment outlet in Lovington. Using the SRTM DEM with the 90m resolution it is possible to derive the streamflow network and the consequent time of concentration, by means of the Giandotti equations (Giandotti, 1933), which is about 10 hours. The hourly precipitation (49 rainfall stations) and streamflow data used in this study are supplied by the British Atmospheric Data Centre from the HYREX (Hydrological Radar Experiment) project (Moore et al., 2000; Wood et al., 2000). The average precipitation value in the catchment is estimated using the Ordinary Kriging (Matheron, 1963).

2.2 Bacchiglione catchment

The second case study is the upstream part of the Bacchiglione River basin, located in the North-East of Italy, and tributary of the River Brenta which flows into the Adriatic Sea at the South of the Venetian Lagoon and at the North of the River Po delta. The study area has an overall extent and river length of about 400 km2 and 50 km (Ferri et al., 2012). The main urban area located in the downstream part of the study area is Vicenza. The analysed part of the Bacchiglione River has four main tributaries. On the Western side the confluences with the Bacchiglione are the Leogra, the Orolo and the Retrone River, whose junction is located in the urban area itself. In Figure 2 the Retrone River it is not shown since it does not influence the water level measured at the gauged station of Vicenza (Ponte degli Angeli in Figure 3). On the Eastern side there is the Timonchio River (see Figure 3). The Alto Adriatico Water Authority (AAWA) has implemented an Early Warning System to properly forecast the possible future flood events. Recently, within the activities of the WeSenseIt Project (Huwald et al., 2013), , one physical sensor and three staff gauges complemented by a QR code (social sensor, as represented in Figure 1) were installed in the Bacchiglione River to measure the water level. In particular, the physical sensor is located at the outlet of the Leogra catchment while the three social sensors are located at the Timonchio, Leogra and Orolo catchments outlet respectively (see Figure 3).

2.3 Datasets

In the Brue catchment two different flood events which occurred between 28/10/1994 to 16/11/1994 (flood event 1) and from 14/01/1995 to 04/02/1995 (flood event 2) are considered. The observed precipitation values are treated as the "perfect forecasts" and are fed into the hydrological model. The observed streamflow data for the considered flood event are available as well.

In case of Bacchiglione catchment, the flood event which occurred in May 2013 is considered; it had the high intensity and resulted in several traffic disruptions at various locations upstream Vicenza. For flood forecasting, AAWA uses the 3-day weather forecast as the input to the hydrological model. The observed values of streamflow and water level at Ponte degli Angeli are used to assess the performance of the hydrological model.

3 Hydrological modelling

3.1 Brue catchment

A lumped conceptual hydrological model is implemented to estimate the flood hydrograph at the outlet section of the Brue catchment. The choice of the model is based on previous studies performed on the Brue catchment in case of assimilation of streamflow observations from dynamic sensors (Mazzoleni et al., 2015). Direct runoff is used as input in the conceptual model and assessed by means of the Soil Conservation Service Curve Number (SCS-CN) method (Mazzoleni et al., 2015). The average value of CN within the catchment is calibrated by minimizing the difference between the simulated volume and observed quickflow, using the method proposed by Eckhardt (2005), at the outlet section.

The main module of the hydrological model is based on the Kalinin-Milyukov-Nash (KMN), Szilagyi and Szollosi-Nagy (2010), equation:

$$Q(t) = \frac{1}{k} \cdot \frac{1}{(n-1)!} \int_{t_0}^{t} \left(\frac{\tau}{k} \right)^{n-1} \cdot e^{-\tau / k} (\tau) \cdot I(t-\tau) \cdot d\tau \qquad (1)$$

where I is the model forcing (in this case direct runoff), n (number of storage elements) and k (storage capacity) are the two parameters of the model and Q is the model output (streamflow). In this study, the parameter k is assumed as a linear function between the time of concentration, assessed using the Giandotti equation (Giandotti, 1933) and a coefficient c_k. Szilagyi and Szollosi-Nagy (2010) derived the discrete state-space system of Eq. (1) that is used in this study in order to apply the data assimilation (DA) approach (Mazzoleni et al., 2014, 2015).

The model calibration is performed maximizing the correlation between the simulated and observed value of discharge, at the outlet point of the Brue catchment, during the flood events occurred from the 23-10-1994 to 17-03-1995. The results of such calibration provided a value of the parameters n and c_k equal to 4 and 0.026 respectively.

3.2 Bacchiglione catchment

The hydrological and routing models used in this study are based on the early warning system implemented by the AAWA and described in Ferri et al. (2012). One the main goal of this study is also to test our methodology using synthetic observations to then apply it, in the framework of the WeSenseIt Project, on the existing early warning system implemented by AAWA on the Bacchiglione catchment.

In the schematization of the Bacchiglione catchment, the location of physical and social sensors corresponds to the outlet section of three main sub- catchment s, Timonchio, Leogra and Orolo, while the remaining sub-catchments are considered as inter-catchment. For both sub-catchments and inter-catchments, a conceptual hydrological model, described below, is used to estimate the outflow hydrograph. The outflow hydrograph of the three main sub-catchments is considered as upstream boundary conditions of a hydraulic model used to estimate water level in the main river channel (see Figure 3), while the outflow from the inter-catchment is considered as internal boundary condition to account for their corresponding drained area. In the following, a brief description of the main components of the hydrological and routing models is provided.

The input for the hydrological model consists of precipitation only. The hydrological response of the catchment is estimated using a hydrological model that considers the routines for runoff generation and a simple routing procedure. The processes related to runoff generation (surface, sub-surface and deep flow) are modelled mathematically by applying the water balance to a control volume representative of the active soil at the sub-catchment scale. The water content *Sw* in the soil is updated at each calculation step *dt* using the following balance equation:

$$Sw_{t+dt} = Sw_t + P_t - R_{sur,t} - R_{sub,t} - L_t - ET_t \tag{2}$$

where *P* and *ET* are the components of precipitation and evapotranspiration, while R_{sur}, R_{sub} and *L* are the surface runoff, sub-surface runoff and deep percolation model states respectively (see Figure 3). The surface runoff is expressed by the equation based on specifying the critical threshold beyond which the mechanism of dunnian flow (saturation excess mechanism) prevails:

$$R_{sur,t} = \begin{cases} C \cdot \left(\dfrac{Sw_t}{Sw_{\max}} \right) \cdot P_t \Rightarrow P(t) \leq f = \dfrac{Sw_{\max} \cdot \left(Sw_{\max} - Sw_t\right)}{\left(Sw_{\max} - C \cdot Sw_t\right)} \\ P_t - \left(Sw_{\max} - Sw_t\right) \Rightarrow P_t > f \end{cases}. \tag{3}$$

where *C* is a coefficient of soil saturation obtained by calibration, and Sw_{max} is the content of water at saturation point which depends on the nature of the soil and on its use.

The sub-surface flow is considered proportional to the difference between the water content *Sw*(*t*) at time *t* and that at soil capacity S_c:

$$R_{sub,t} = c \cdot \left(Sw_t - S_c\right). \tag{4}$$

while the estimated deep flow is evaluated according to the expression proposed by Laio et al. (2001):

$$L_t = \frac{K_s}{e^{\beta \cdot \left(1 - \frac{S_c}{Sw_{\max}}\right)} - 1} \cdot \left(e^{\beta \cdot \left(\frac{Sw_t - S_c}{Sw_{\max}}\right)} - 1 \right). \tag{5}$$

where, K_s is the hydraulic conductivity of the soil in saturation conditions, β is a dimensionless exponent characteristic of the size and distribution of pores in the soil. The evaluation of the real evapotranspiration is performed assuming it as a function of the water content in the soil and potential evapotranspiration, calculated using the formulation of Hargreaves and Samani (1982).

Knowing the values of R_{sur}, R_{sub} and L, it is possible to model the surface Q_{sur}, sub-surface Q_{sub} and deep flow Q_g routed contributes according to the conceptual framework of the linear reservoir at the closing section of the single sub-catchment. In particular, in case of Q_{sur} the value of the parameter k, which is a function of the residence time in the catchment slopes, is estimated relating the slopes velocity of the surface runoff to the average slopes length L. However, one of difficulties involved is the proper estimation of the surface velocity, which should be calculated for each flood event (Rinaldo and Rodriguez-Iturbe, 1996). According to Rodríguez-Iturbe et al. (1982), such velocity is a function of the effective rainfall intensity and event duration. In this study, the estimate of the surface velocity is performed using the relation between velocity and intensity of rainfall excess proposed in Kumar et al. (2002). In this way it is possible to estimate the average time travel and the consequent parameter k. However, such formulation is applied in a lumped way for a given sub-catchment. As reported in McDonnell and Beven (2014) more reliable and distributed models should be used to reproduce the spatial variability of the residence times within the catchment over the time. That is why, in the advanced version of the model implemented by AAWA, in each sub-catchment the runoff propagation is carried out according to the geomorphological theory of the hydrologic response. In such model, the overall catchment travel time distributions is considered as nested convolutions of statistically independent travel time distributions along sequentially connected, and objectively identified, smaller sub-catchments. The parameter k assumes different values for each time step as the rainfall changes. In fact, the variability of residence time is considered according to Rodríguez-Iturbe et al. (1982) by assuming the surface velocity as a function of the effective rainfall intensity (Kumar et al., 2002). Anyway, the correct estimation of the residence time should be derived considering the latest findings reported in McDonnell and Beven (2014). In case of Q_{sub} and Q_g the value of k is calibrated comparing the observed and simulated discharge at Vicenza as previously described.

In the early warning system implemented by AAWA in the Bacchiglione catchment, the flood propagation along the main river channel is represented one-dimensional hydrodynamic model, MIKE 11 (DHI, 2005). This model solves the Saint Venant Equations in case of unsteady flow based on an implicit finite difference scheme proposed by Abbott and Ionescu (1967). However, in order to reduce the computational time required by the analysis performed in this study MIKE11 is replaced by a hydrological routing Muskingum-Cunge model (see, e.g. Todini 2007), considering river cross-sections as rectangular for the estimation of hydraulic radios, wave celerity and the other hydraulic variables.

Calibration of the hydrological and hydrodynamic model parameters is performed by AAWA, and described in Ferri et al. (2012), considering the time series of precipitation from 2000 to 2010 in order to minimize the root mean square error between observed and simulated values of water level at Ponte degli Angeli gauged station. In order to stay as close as possible to the early warning system implemented by AAWA, we used the same calibrated model parameters proposed by Ferri et al. (2012).

4 Data assimilation procedure

4.1 Kalman Filter

In Data Assimilation (DA) it is typically assumed that the dynamic system can be represented in the state-space as follows:

$$\mathbf{x}_t = M(\mathbf{x}_{t-1}, \vartheta, I_t) + w_t \qquad w_t \sim N(0, \mathbf{S}_t). \tag{6}$$

$$\mathbf{z}_t = H(\mathbf{x}_t, \vartheta) + v_t \qquad v_t \sim N(0, R_t). \tag{7}$$

where, $\mathbf{x}_t$ and $\mathbf{x}_{t-1}$ are state vectors at time t and t-1, M is the model operator that propagates the states $\mathbf{x}$ from its previous condition to the new one as a response to the inputs I_t, while H is the operator which maps the model states into output $\mathbf{z}_t$. The system and measurements errors w_t and v_t are assumed to be normally distributed with zero mean and covariance $\mathbf{S}$ and R. In a hydrological modelling system, these states can represent the water stored in the soil (soil moisture, groundwater) or on the earth surface (snow pack). These states are one of the governing factors that determine the hydrograph response to the inputs into the catchment.

In case of the linear systems used in this study, the discrete state-space system of Eq. (1) can be represented as follows (Szilagyi and Szollosi-Nagy, 2010):

$$\mathbf{x}_t = \mathbf{\Phi}\mathbf{x}_{t-1} + \mathbf{\Gamma} I_t + w_t. \tag{8}$$

$$Q_t = \mathbf{H}\mathbf{x}_t + v_t. \tag{9}$$

where t is the time step, $\mathbf{x}$ is vector of the model states (stored water volume in m^3), $\mathbf{\Phi}$ is the state-transition matrix (function of the model parameters n and k), $\mathbf{\Gamma}$ is the input-transition matrix, $\mathbf{H}$ is the output matrix, and I and Q are the input (forcing) and model output (discharge in this case). For example, for n=3 the matrix $\mathbf{H}$ is expressed as $\mathbf{H} = [0 \quad 0 \quad k]$. Expressions for matrices $\mathbf{\Phi}$ and $\mathbf{\Gamma}$ can be found in Szilagyi and Szollosi-Nagy (2010).

For the Bacchiglione model, the preliminary sensitivity analysis on the model states (soil content S and the storage water x_{sur}, x_{sub} and x_L related to Q_{sur}, Q_{sub} and Q_g) is performed in order to decide on which of the states to update. The results of this analysis (shown in the next section) pointed out that the stored water volume x_{sur} (estimated using Eq. (8) with n=1, H=k and I_t replaced by R_{sur}) is the most sensitive state and for this reason we decided to update only this state.

The Kalman Filter (KF, Kalman, 1960) is a mathematical tool which allows estimating, in an efficient computational (recursive) way, the state of a process which is governed by a linear stochastic difference equation. KF is optimal under the assumption that the error in the process is Gaussian; in this case KF is derived by minimizing the variance of the system error (error in state) assuming that the model state estimate is unbiased. In an attempt to overcome these limitations, various variants of the Kalman filter, such as the extended Kalman filter (EKF), unscented Kalman filter and ensemble Kalman filter (EnKF) have been proposed.

Kalman filter procedure can be divided in two steps, namely forecast equations, (Eqs. (10) and (11)), and update (or analysis) equations (Eqs. (12), (13) and (14)):

$$\mathbf{x}_t^- = \mathbf{\Phi}\mathbf{x}_{t-1}^+ + \mathbf{\Gamma}\mathbf{I}_t . \tag{10}$$

$$\mathbf{P}_t^- = \mathbf{\Phi}\mathbf{P}_{t-1}^+\mathbf{\Phi}^T + \mathbf{S} . \tag{11}$$

$$\mathbf{K}_t = \mathbf{P}_t^-\mathbf{H}^T\left(\mathbf{H}\mathbf{P}_t^-\mathbf{H}^T + R\right)^{-1} . \tag{12}$$

$$\mathbf{x}_t^+ = \mathbf{x}_t^- + \mathbf{K}_t\left(Q_t^o - \mathbf{H}\mathbf{x}_t^-\right). \tag{13}$$

$$\mathbf{P}_t^+ = \left(\mathbf{I} - \mathbf{K}_t\mathbf{H}\right)\mathbf{P}_t^- . \tag{14}$$

where $\mathbf{K}_t$ is the Kalman gain matrix, $\mathbf{P}$ is the error covariance matrix, Q^0 is the new observation and $\mathbf{M}_Q$ is the model error matrix. The prior model states $\mathbf{x}$ at time t are updated, as the response to the new available observations, using the analysis equations Eqs. (12) to (14). This allows for estimation of the updated states values (with superscript +) and then assessing the background estimates (with superscript –) for the next time step using the time update equations Eqs. (10) and (11). The proper characterization of the model covariance matrix $\mathbf{S}$ is a fundamental issue in Kalman filter. In this study, in order to evaluate the effect of assimilating crowdsourced observations, the model is considered more accurate than the observations and, a covariance matrix $\mathbf{S}$ with diagonal values of 10^2 is considered.

4.2 Assimilation of asynchronous streamflow observations with irregular accuracy

In most of the hydrological applications of DA, observations from physical sensors are integrated into water models at a regular, synchronous, time step. However, as showed in Figure 1, a social sensor can be used by different operators, having different accuracy, to measure water level at a specific point. For this reason, social sensors provide crowdsourced observations which are asynchronous in time and with a higher degree of uncertainty than the one of observations from physical sensors. In particular, crowdsourced observations have three main characteristics: a) irregular arrival frequency (asynchronicity); b) random accuracy; c) random number of observations received by the static device within two model time steps.

As described in the Introduction, various methods have been proposed in order to include asynchronous observations in models. Having reviewed them, in this study we are proposing a somewhat simpler DA approach for integrating Crowdsourced Observations into hydrological models (DACO). This method is based on the assumption that the change in the model states and in the error covariance matrices within the two consecutive model time steps t_0 and t (observation window) is linear, while the inputs are assumed constant. All the data received during the observation window are assimilated in order to update the model states and output at time t. Therefore, assuming that one observation would be available at time t_0^*, the first step of such a filter (A in Figure 4) is the definition of the model states and error covariance matrix at t_0^* as:

$$\mathbf{x}_{t_0^*}^- = \mathbf{x}_{t_0}^+ + \left(\mathbf{x}_t^- - \mathbf{x}_{t_0}^+\right) \cdot \frac{t_0^* - t_0}{t - t_0}. \tag{15}$$

$$\mathbf{P}_{t_0^*}^- = \mathbf{P}_{t_0}^+ + \left(\mathbf{P}_t^- - \mathbf{P}_{t_0}^+\right) \cdot \frac{t_0^* - t_0}{t - t_0} \tag{16}$$

The second step (B in Figure 4) is the estimation of the updated model states and error covariance matrix, as the response to the streamflow observation $Q_{t_0^*}^o$. The estimation of the posterior values of $\mathbf{x}_{t_0^*}^-$ and $\mathbf{P}_{t_0^*}^-$ is performed by Eqs. (13) and (14) respectively. The Kalman gain is estimated by Eq. (12), where the prior values of model states and error covariance matrix at t_0^* are used. Knowing the posterior value $\mathbf{x}_{t_0^*}^+$ and $\mathbf{P}_{t_0^*}^+$ it is possible to predict the value of states and covariance matrix at one model step ahead, t^* (C in Figure 4) using the model forecast equations Eqs. (10) and (11).

The last step (D in Figure 4) is the estimation of the interpolated value of **x** and **P** at time step t. This is performed by means of a linear interpolation between the current values of **x** and **P** at t_0^* and t^*:

$$\tilde{\mathbf{x}}_t^- = \mathbf{x}_{t_0^*}^- + \left(\mathbf{x}_{t^*}^- - \mathbf{x}_{t_0^*}^+\right) \cdot \frac{t - t_0^*}{t^* - t_0^*}. \tag{17}$$

$$\tilde{\mathbf{P}}_t^- = \mathbf{P}_{t_0^*}^- + \left(\mathbf{P}_{t^*}^- - \mathbf{P}_{t_0^*}^+\right) \cdot \frac{t - t_0^*}{t^* - t_0^*}. \tag{18}$$

The symbol ~ is added on the new matrices **x** and **P** in order to differentiate them from the original forecasted values in t. Assuming that a new streamflow observation is available at an intermediate time t_1^* (between t_0^* and t), the procedure is repeated considering the values at t_0^* and t for the linear interpolation. Then, in case when no more observations are available, the updated value of $\tilde{\mathbf{x}}_t^-$ is used to predict the model states and output at t+1 (Eqs. (10) and (11)).

Finally, in order to account for the intermittent behaviour of such observations, the approach proposed by Mazzoleni et al. (2015) is applied. In this method, the model states matrix **x** is updated and forecasted when observations are available, while without observations the model is run using Eq. (10) and covariance matrix **P** propagated at the next time step using Eq. (11)

4.3 Observation accuracy

In this section, the uncertainty related to the streamflow crowdsourced observations is characterised. The observational error is assumed to be the normally distributed noise with zero mean and given standard deviation:

$$\sigma_t^Q = \alpha_t \cdot Q_t^{true} \tag{19}$$

where the coefficient α is related to the degree of uncertainty of the measurement (Weerts and El Serafy, 2006).

One of the main and obvious issues in citizen-based observations is to maintain the quality control of the water observations (Cortes et al., 2014; Engel and Voshell, 2002). In Introduction a number of methods to estimate (calibrate) the model of observational uncertainty have been referred to. In this study coefficient α is assumed a random variable uniformly distributed between 0.1 and 0.3, so we leave more thorough investigation of uncertainty level of the crowdsourced data for future studies. Cortes et al. (2014) argue (and this is a reasonable suggestion) that the uncertainty of a measurement provided by a well-trained technician is smaller than the one coming from a normal citizen. For this reason we assumed that the maximum value of α is three times higher than the uncertainty coming from the physical sensors. The value of Q^{true} is the streamflow value measured at a asynchronous time step and it is described in the next section.

5 Experimental setup

In this section, two sets of experiments are performed in order to test the proposed method and assess the benefit to integrate crowdsourced observations, asynchronous in time and with variable accuracy, in real-time flood forecasting.

In the first set of experiments, called “Experiments 1”, assimilation of streamflow observations at one social sensor location is carried out to understand the sensitivity of the employed hydrological model (KMN) under various scenarios of such observations.

In the second set of experiments, called “Experiments 2”, the distributed observations coming from social and physical sensors, at four locations within the Bacchiglione catchment, are considered, with the aim of assessing the improvement in the flood forecasting accuracy. The social sensors, showed in Figure 1 and Figure 3, were installed in the summer of 2014 within the framework of the WeSenseIt project.

5.1 Experiments 1: Assimilation of crowdsourced observations from one social sensor

The focus of Experiments 1 is to study the performance of the hydrological model (KMN) assimilating crowdsourced observations, having lower arrival frequencies than the model time step and random accuracies, coming from a social sensor located in a specific point of the Brue catchment.

Due to the fact that crowdsourced observations are not available in the case studies of Brue at the moment of this study, realistic synthetic streamflow observations having different characteristics are generated. For this reason, observed hourly streamflow observations at the catchment outlet are interpolated to represent observations coming at arrival frequency higher than hourly. A similar approach, termed “observing system simulation experiment” (OSSE), is commonly used in meteorology to estimate synthetic “true” states and measurements by introducing random errors in the state and measurement equations (Arnold and Dey, 1986; Errico et al., 2013; Errico and Privé, 2014). OSSEs have the advantage of making it possible to directly compare estimates to “true” states and they are often used for validating DA algorithms.

To analyse all possible combinations of arrival frequency, number of observations within the observation window (1 hour) and accuracy, a set of scenarios are considered (Figure 5), changing from regular arrival frequency of observations with high accuracy (scenario 1) to random and chaotic asynchronous observations with variable accuracy (scenario 11). In each scenario a varying the number of observations from 1 to 100 is considered. It is worth noting that in case of one observation per hour and regular arrival time, scenario 1 corresponds to the case of physical sensors with an observation arrival frequency of one hour.

Scenario 2 corresponds to the case of observations having fixed accuracy (α equal to 0.1) and irregular arrival moments, but in which at least one observation coincides with the model time step. In particular, scenario 1 and 2 are exactly the same in case of one observation available within the observation window since it is assumed that the arrival frequency of that observation has to coincide with the model time step. On the other hand, the arrival frequency of the observations in scenario 3 is assumed to be random and observations might not arrive at the model time step.

Scenario 4 considers observations with regular frequency but random accuracy at different moments within the observation window, whereas in scenario 5 observations have irregular arrival frequency and random accuracy. In all the previous scenarios the arrival frequency, the number and accuracy of the observations are assumed to be periodic, i.e. repeated between consecutive observation windows along all the time series. However such periodic repetitiveness might not occur in real-life, and for this reason, a non-periodic behaviour is assumed in scenarios 6, 7, 8 and 9. The non-periodicity assumptions of the arrival frequency and accuracy are the only factors that differentiate scenarios 6, 7, 8 and 9 from the scenarios 2, 3, 4, and 5 respectively. In addition, the non-periodicity of the number of observations within the observation window is introduced in scenario 10.

Finally, in scenario 11 the observations, in addition to all the previous characteristics, might have an intermittent behaviour, i.e. not being available for one or more observation windows.

5.2 Experiments 2: Spatially distributed physical and social sensors

Synthetic hourly streamflow observations are calculated using measured precipitation recorded during the May 2013 flood event (post-event simulation) as input in the hydrological model of the Bacchiglione catchment. Interpolated streamflow observations having characteristics reported in scenarios 10 and 11, in Experiments 1, are generated due to the unavailability of crowdsourced observations at the moment of this study. In order to evaluate the model performances, observed and simulated streamflows are compared, for different lead times.

Streamflow observations from physical sensors are assimilated in the hydrological model of AMICO system at an hourly frequency, while crowdsourced observations from social sensors are assimilated using the DACO method previously described. The updated hydrograph estimated by the hydrological model is used as the input into Muskingum-Cunge model used to propagate the flow downstream, to the gauged station at Ponte degli Angeli, Vicenza.

The main goal of Experiments 2 is to understand the contribution of distributed crowdsourced observations to the improvement of the flood prediction at a specific point of the catchment, in this case at Ponte degli Angeli. For this reason, five different experimental settings are introduced, and represented in Figure 6, corresponding to different types of employed sensors.

Firstly, only the observations coming from the physical sensor at the Leogra sub-catchment are used to update the hydrological model of sub-catchment B (setting A). Secondly, in setting B, the model improvement in case of assimilation of crowdsourced observations at the same location of setting A is analysed. In setting C only the distributed crowdsourced observations within the catchment are assimilated into the hydrological model. Then, setting D accounts for the integration of crowdsourced and physical observations, contrary to the setting C where the physical sensors is dropped in favour of the social sensor at Leogra. Finally, setting E considers the complete integration between physical and social sensors in Leogra, Timonchio and Orolo sub-catchments.

6 Results and discussions

6.1 Experiments 1: Influence of crowdsourced observations on flood forecasting

The observed and simulated hydrographs at the outlet section of the Brue catchment with and without the model update (considering hourly streamflow observations) are reported in Figure 7 for two different flood events. As expected, it can be seen that the updated model tends to better represent the flood events than model without updating.

The results of scenario 1 for flood event 1, assimilating from 1 to 30 observations within the observation window, are represented in Figure 8. As it can be seen, increasing the number of observations within the observation window results in the improvement of the NSE for different lead time values. However, such improvement becomes negligible for more than five observations. This means that the additional observations do not add information useful for improving the model performance. In both flood events we found similar trends in the dependency of Nash index on the number of observations. However, it is not possible to define a priori number of observations needed to improve model. In fact, after a threshold number of observations (five for flood event 1 and fifteen for flood event 2), NSE asymptotically approaches to a certain value meaning that no improvement is achieved with additional observations. However, the only difference between the two flood events is that such asymptotic NSE values are different because model performances can change according to the considered flood events.

This asymptotic behaviour when extra information is added has also been observed using other metrics by Krstanovic and Singh (1992), Ridolfi et al. (2014), Alfonso et al. (2013)), among others.

The same type of analysis is performed with the scenarios 2 to 9 (Figure 9). The results obtained in Figure 9 show that in case of irregular arrival frequency (scenarios 2 and 3) the NSE is higher than in scenarios 4 and 5, where observations vary in accuracy. These results point out that the model performance is more sensitive to the accuracy of the observations than to the moment in time at which the streamflow observations become available. However, it can be observed from scenarios 2 to 5 that the trend it is not as smooth as the one obtained with scenario 1. This can be related to the fact that NSE may vary with varying arrival frequency and observations accuracy. In fact, in scenario 1 the arrival frequency is set as regular for different model runs, so the moments in which the observations became available is always be the same for any model run. On the other hand, in the other scenarios, the irregular moment in which the observation becomes available within the observation window is randomly selected and is changing according to the different model runs. This means that for a given number of observations (for example 5), the five observations arrive at different moments, for different model runs, and this results in five different values of NSE. A smooth trend is also obtained for scenarios 6, 7, 8 and 9 but this is related to the periodic behaviour of the observations as explained below.

In order to remove the random behaviour related to the irregular arrival frequency and observation accuracy, different model runs (100 in this case) are carried out, assuming different random values of arrival and accuracy (coefficient α) during each model run, for a given number of observations and lead time. The NSE value is estimated for each model run, so μ(NSE) and σ(NSE) represent the mean and standard deviation of the different values of NSE. Overall, σ(NSE) tends to decrease for the high number of observations. Scenario 2 has the lower standard deviation for low values of discharge observations due to the fact that the arrival frequency has to coincide with the model time step and this tends to stabilize the NSE. In addition, the irregular arrival frequency (scenarios 2 and 3) has a higher impact on the σ(NSE) than on the mean NSE value μ(NSE). Besides, the variable observations accuracy (scenario 4) influences more μ(NSE) than σ(NSE), as described before. The combined effects of irregular frequency and uncertainty are reflected in scenario 5 which has the lower mean and higher standard deviation of NSE if compared to the first four scenarios.

An interesting fact is that passing from periodic (Figure 10a and b) to non-periodic (Figure 10c and d) behaviour of the crowdsourced observations, the standard deviation is significantly reduced, while the mean remains the same. A non-periodic behaviour of the observations, common in real life, helps to reduce the fluctuation of the NSE generated by the random behaviour of streamflow observations. Table 1 shows the NSE values and model improvement obtained for the different experimental scenarios during flood event 1 and 2.

Finally, the results obtained for scenarios 10 and 11 are showed in Figure 11. The NSE values obtained for the flood event 1 are higher than the ones obtained for the flood event 2. The assimilation of irregular number of observations in scenario 10, in each observation window, seems to provide the same μ(NSE) than the ones obtained with scenario 9. One the main outcome is that the intermittent nature of the observations (scenario 11) induces a drastic reduction of the NSE and an increase in its noise in both considered flood events.

6.2 Experiments 2: Influence of distributed physical and social sensors

In order to find out what model states leads to a maximum increase of the model performance, a preliminary sensitivity analysis is performed. The four model states, x_S, x_{sur}, x_{sub} and x_L, related to Sw, Q_{sur}, Q_{sub} and Q_g, are perturbed by ±20% around the true state value using the uniform distribution, every time step from the initial time step up to the perturbation time (PT). No correlation between time steps is considered. After PT, the model realizations are run without perturbation in order to assess the perturbation effect on the system memory. No assimilation, and consequent model update, is performed at this step. From the results reported in Figure 12, it can be observed that the model state x_{sur} is the most sensitive states if compared to the other ones. In addition, the perturbations of all the states seem to affect the model output even after the PT (high system memory). For this reason, in this experiments, only the model state x_{sur} is updated by means of the DACO method.

The physical and crowdsourced observations are assimilated in order to improve the poor flow prediction in Vicenza due to the underestimation of the 3-days rainfall forecast used as input in flood forecasting practice in this area. Scenarios 10 and 11, described in the previous sections, are used to represent the irregular and random behaviour of the crowdsourced observations.

The results of this analysis are showed in Figure 13. Different model runs (100) are performed for the Leogra sub-catchment to account for the effect induced by the random arrival frequency and accuracy of the crowdsourced observations within the observation window as described above. It can be seen that the assimilation of observations from the physical sensor provides a better flood prediction at the Leogra catchment if compared to the assimilation of a small number of crowdsourced observations. In particular, Figure 13a and Figure 13b show that the same NSE values achieved with assimilation of physical observations (hourly frequency and high accuracy) can be obtained by assimilating between 10 and 20 crowdsourced observations per hour. However, the overall reduction of NSE in case of intermittent observations is such that even with a high number of observations (even higher than 50 per hour) the NSE is always lower than the one obtained assimilating physical observations for any lead time. Figure 13c and Figure 13d show analogous results expressed in terms of different lead times.

Figure 14 and Figure 15 show the results obtained from the experiments settings represented in Figure 6 in case of physical and crowdsourced observations. Also in this case, different simulation runs (100) of random values of arrival frequency and uncertainty are performed.

One of the main outcomes of these analyses is that the replacement of a physical sensor for a social sensor at only one location (settings B) does not improve the model performance in terms of NSE for different lead time values. Distributed locations of social sensors (setting C) can provide higher values of NSE than a single physical sensor, even for low number of observations in both regular and intermittent crowdsourced observations. It is interesting to note that integrating social and physical sensors (setting D) the NSE is higher than in case of setting C for low number of observations. However, with higher number of observations, setting C is the one providing the best model improvement for low lead time values. This can be due to the fact that the physical sensor at Leogra provides constant improvement, for a given lead time, while the social sensor tends to achieve better results with a higher number of observations. This dominant effect of the social sensor, in case of high number of observations, tends to increase for the higher lead times. The best model improvement is achieved in case of setting E, i.e. fully integrating physical sensor with distributed social sensors. In case of intermittent observations (Figure 14d, e and f), it can be noticed that the setting D provides always higher improvement than setting C. In case of high lead time value (12h) results of setting C tend to be similar to the ones obtained with setting B. As in case of scenario 10, also in case of scenario 11 the best results are achieved in case of setting E.

Figure 15 shows the standard deviation of the NSE obtained for the different settings in case of lead time 4h. In case of setting A σ(NSE) is equal to zero since observations are coming from physical sensor at regular time steps. Higher σ(NSE) values are obtained in case of setting B, while including different crowdsourced observations tend to decrease the value of σ(NSE). It can be observed that σ(NSE) decreases for high value of crowdsourced observations. As expected, the lowest values of σ(NSE) are achieved including the physical sensor in the DA procedure. Similar considerations can be drawn in case of scenario 11, where an higher and more perturbed σ(NSE) values are obtained.

7 Conclusions

This innovative study demonstrates that crowdsourced observations, asynchronous in time and with variable accuracy, can improve flood prediction if integrated in hydrological models. Such observations are assumed to be inferred using low-cost social sensors as, for example, staff gauge connected to a QR code on which people can read the water level indication and send the observations via a mobile phone application. This type of social sensor is tested within the framework of the WeSenseIt FP7 Project. Two different case studies, the Brue (UK) and Bacchiglione (Italy) catchments, are considered, and the two types of hydrological models are used. In the Experiments 1 (Brue catchment) the sensitivity of the model results to the different frequencies and accuracies of the crowdsourced observations coming from a hypothetical social sensor at the catchment outlet is assessed. On the other hand, in the Experiments 2 (Bacchiglione catchment), the influence of the combined assimilation of crowdsourced observations, coming from a distributed network of social sensors, and existing streamflow observations from physical sensors, used in the Early Warning System implemented by AAWA, is evaluated. Due to the fact that crowdsourced streamflow observations are not yet available in both case studies, realistic synthetic observations with various characteristics of arrival frequency and accuracy are introduced.

Overall, we demonstrated that the results we have obtained are very similar in terms of model behaviour assimilating asynchronous observations in both cases studies.

In Experiments 1 it is found that increasing the number of crowdsourced observations within the observation window increases the model performance even if these observations have irregular arrival frequency and accuracy. Therefore, observations accuracy affects the average value of NSE more than the moment in which these observations are assimilated. However, the arrival frequency of the observations results in a significant noise in the NSE estimation. This noise is reduced when the assimilated observations are considered having non-periodic behaviour. In addition, the intermittent nature of the observations tends to drastically reduce the NSE of the model for different values of lead times. In fact, if the intervals between the observations are too large then the abundance of crowdsourced data at other times and places is no longer able to compensate their intermittency.

Experiments 2 showed that, in the Bacchiglione catchment, the integration of observations from social sensors and single physical sensor can improve the flood prediction even in case of a small number of intermittent crowdsourced observations. In case of both physical and social sensors located at the same place the assimilation of crowdsourced observations give the same model improvement than the assimilation of physical observations only in case of high number and non-intermittent behaviour. . In particular, the integration of existing physical sensors with a new network of social sensors can improve the model predictions, as shown in the Bacchiglione case study. We agree the cases and models are indeed different, but the presented study demonstrated that the results obtained are very similar in terms of model behaviour assimilating asynchronous observations.

In our study we have obtained interesting results, however, this work has still certain limitations. Firstly, the proposed method used to assimilate crowdsourced observations is applied to the linear parts of hydrological models, so the proposed methodology has to be tested on models with explicit non-linearities. Secondly, additional analyses on different case studies and the longer time series of flood events should be carried out in order to draw more general conclusions about assimilation of the crowdsourced observations and their value in different types of catchments and model setups. Thirdly, while quite realistic synthetic streamflow observations have been used in this study, the developed methodology was not tested on real-life data (observations coming from actual social sensors) so there is a need to check if the drawn conclusions are still valid. Finally, advancing methods for a more accurate assessment of the data quality and accuracy of streamflow observations coming from social sensors need to be considered (e.g. developing a pre-filtering module aimed to select only observations having good accuracy while discarding the one with low accuracy).

The future work will be aimed at addressing the limitations formulated above, which would hopefully allow for a better characterisation of the crowdsourced observations (citizens observatories) and making them a more reliable source of data for model-based forecasting.

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Tables

Table 1. NSE values in case of different experimental scenarios during flood event 1 and 2.

	Flood event 1			Flood event 2		
Scenario	1 obs	100 obs	Improvement	1 obs	100 obs	Improvement
1	0.775	0.896	0.135	0.537	0.879	0.390
2	0.775	0.895	0.134	0.537	0.876	0.388
3	0.760	0.895	0.151	0.501	0.875	0.428
4	0.699	0.888	0.212	0.318	0.856	0.629
5	0.692	0.885	0.218	0.304	0.850	0.642
6	0.775	0.895	0.134	0.537	0.877	0.388
7	0.758	0.895	0.153	0.486	0.876	0.445
8	0.708	0.888	0.203	0.338	0.857	0.605
9	0.696	0.885	0.214	0.283	0.852	0.667

Figures

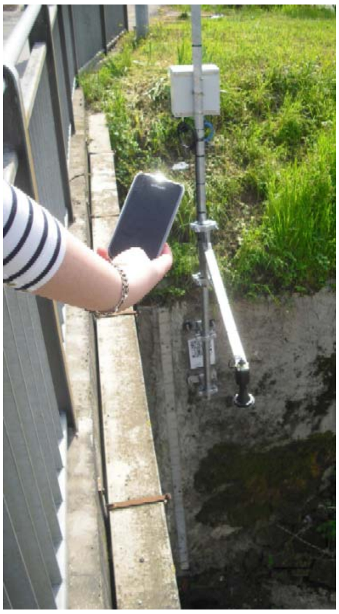

Figure 1. Example of a low-cost social sensor, and crowdsourced observations, implemented in the Bacchiglione river, Italy, under the WeSenseIt project

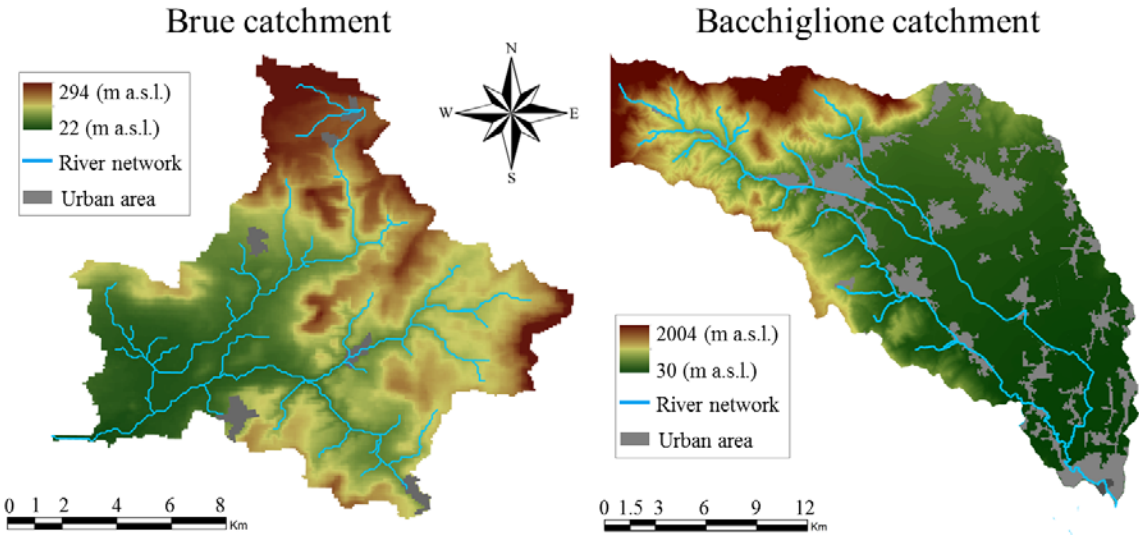

Figure 2. The two case studies considered in this study

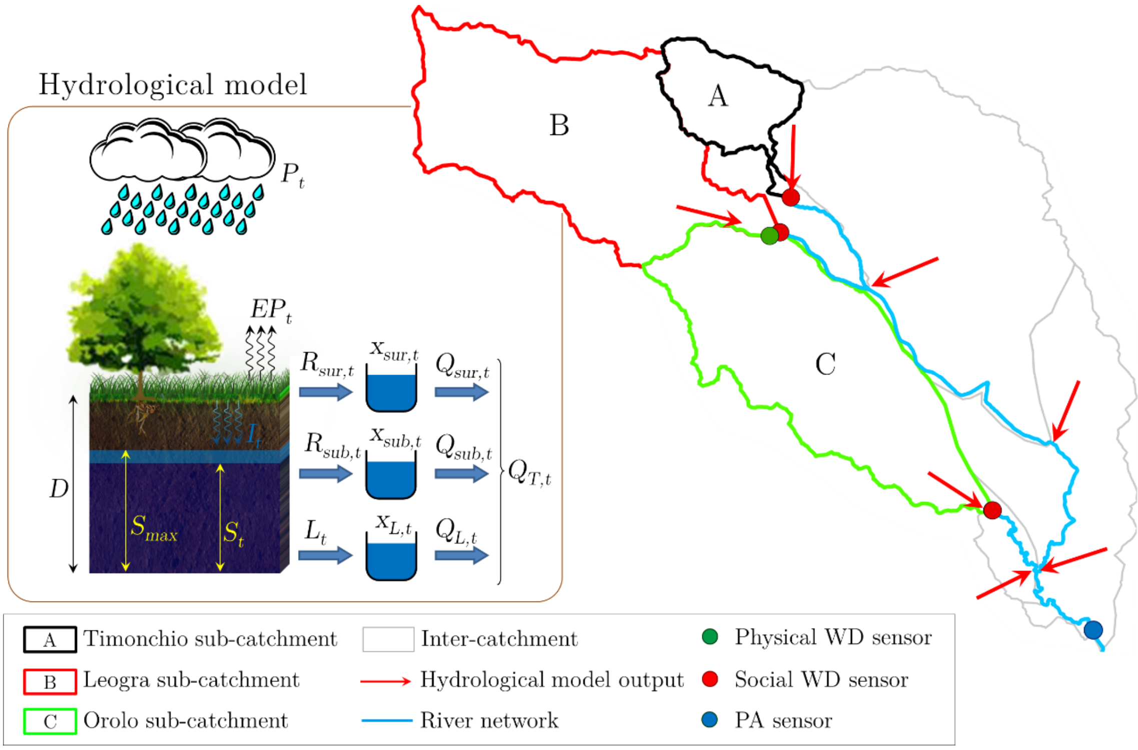

Figure 3. Structure of the early warning system AMICO and location of the physical, social and Ponte degli Angeli (PA) sensors implemented in the Bacchiglione catchment by the Alto Adriatico Water Authority

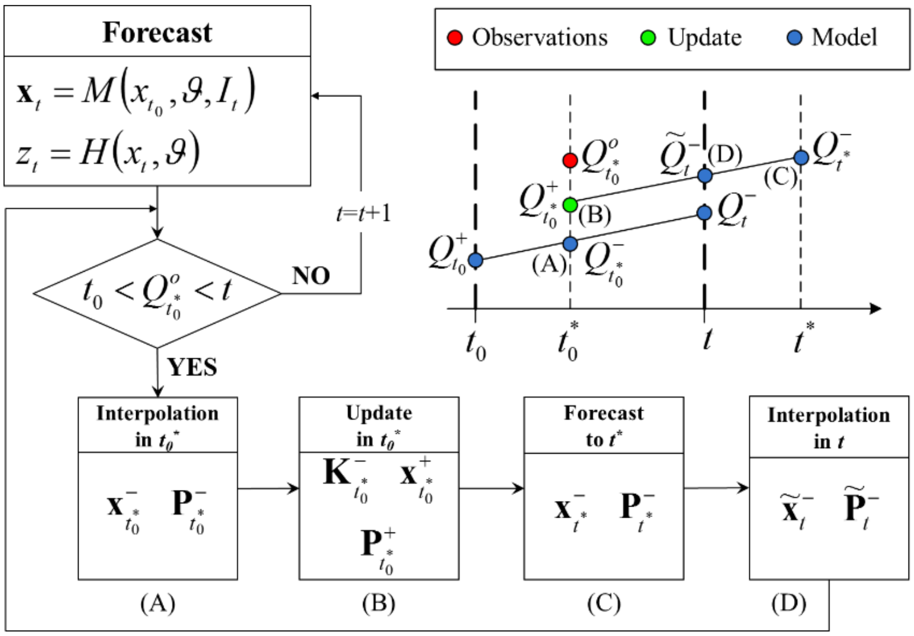

Figure 4. Graphical representation of the DACO method proposed in this study to assimilate crowdsourced asynchronous observations

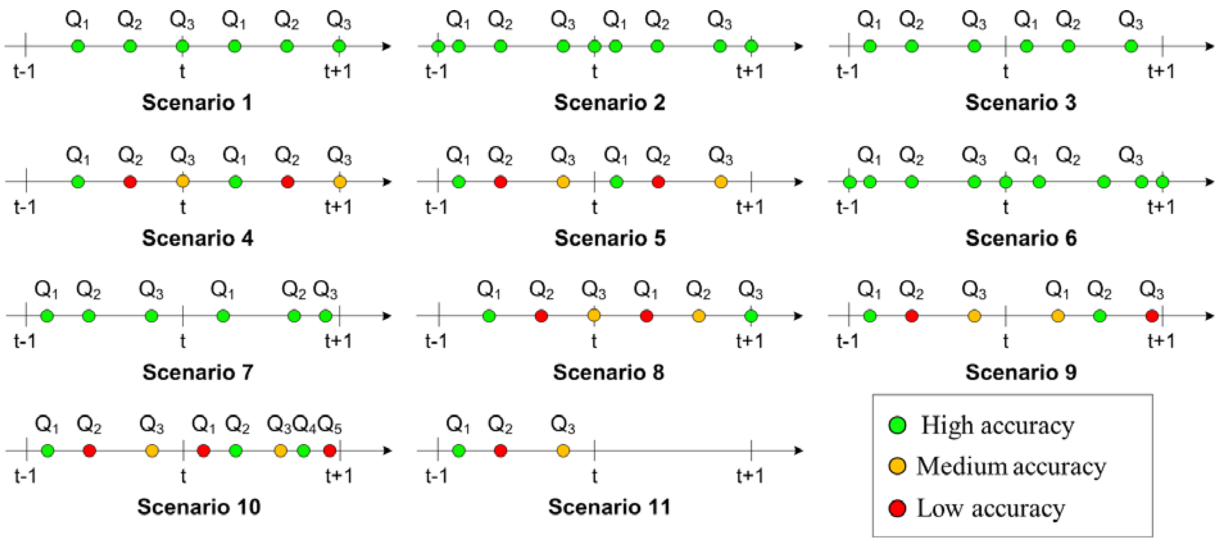

Figure 5. The experimental scenarios representing different configurations of arrival frequency, number and accuracy of the streamflow observations

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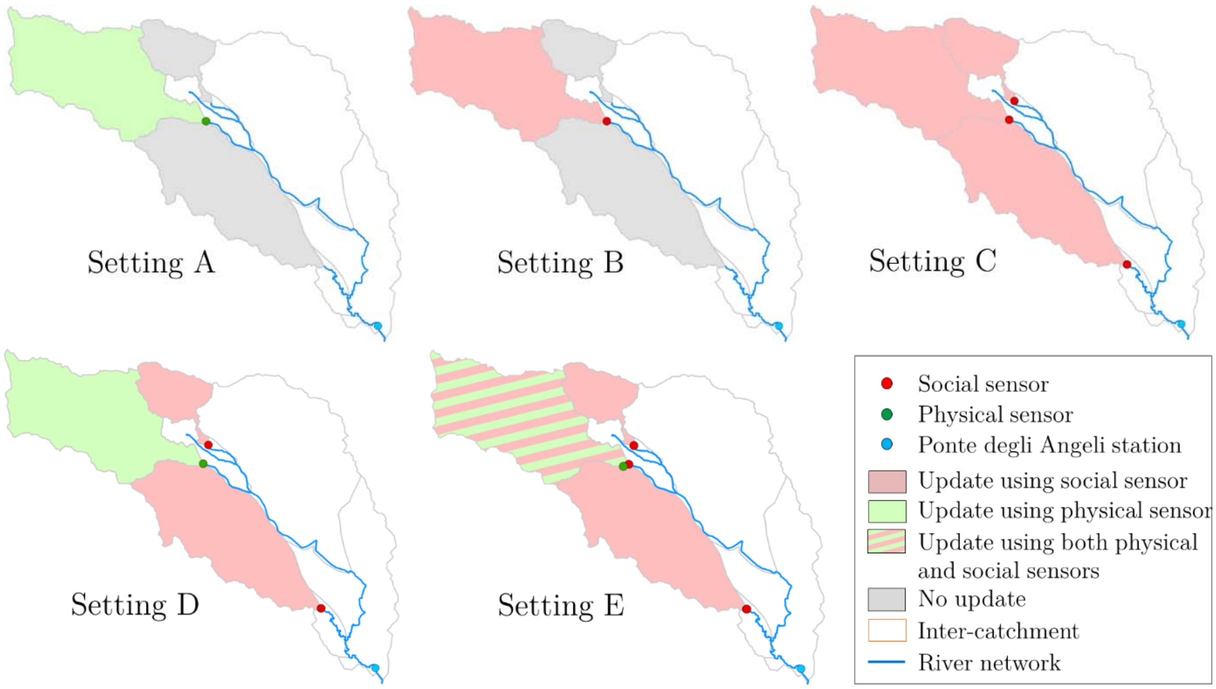


904 Figure 6. Different experimental settings implemented within the Bacchiglione catchment
905 during Experiments 2

906

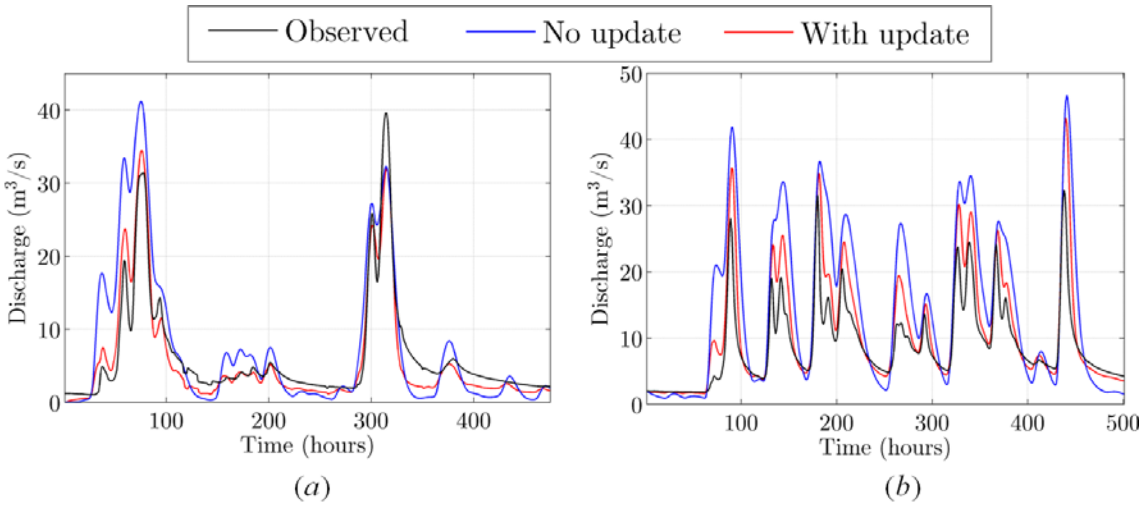
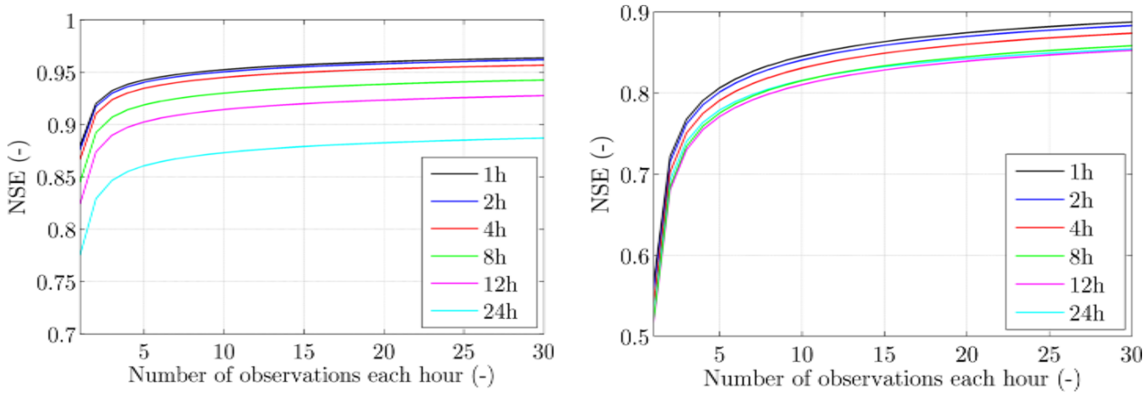


Figure 7. The observed and simulated hydrographs, with and without assimilation, for flood event 1 (a) and 2 (b) in the Brue catchment



(flood event 1) *(flood event 2)*

Figure 8. Model improvement in terms of NSE during flood event 1 and 2, in case of different lead times, assimilating streamflow observations according to scenario 1

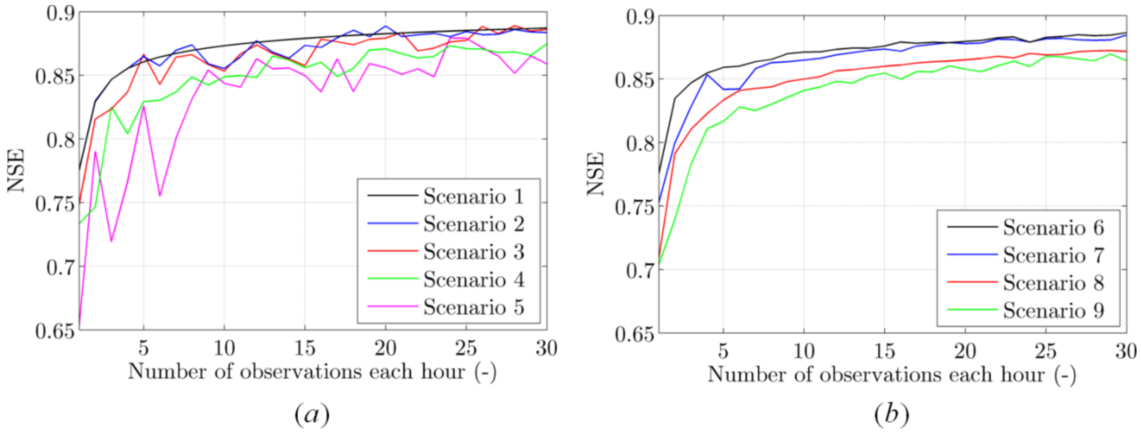


Figure 9. Model improvement during flood event 1 (lead time of 24h), assimilating diverse values of streamflow observations according to the experimental scenarios from 1 to 9 with (a) observations with periodic behaviour, (b) observations with non-periodic behaviour

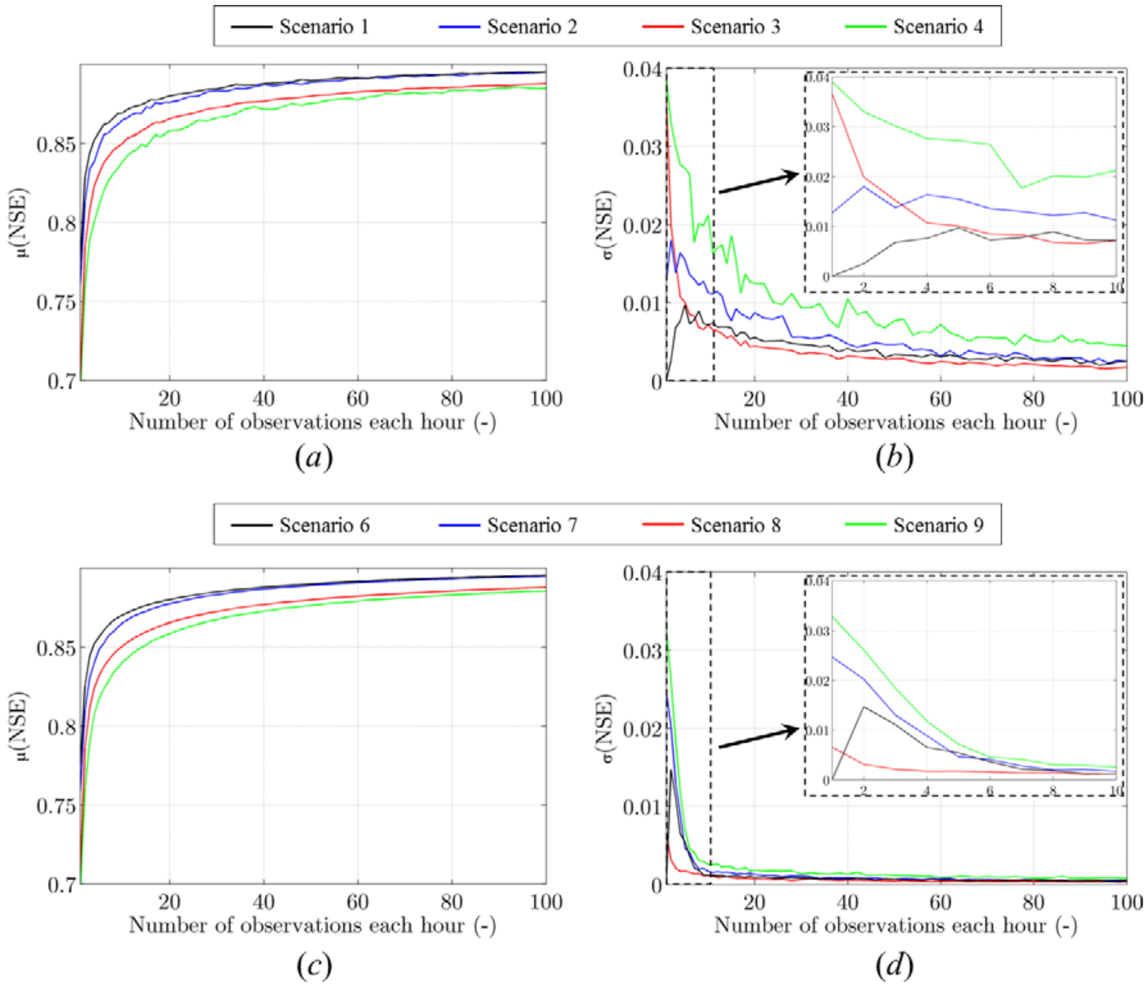


Figure 10. Dependency of μ(NSE) and σ(NSE) on the number of observations, for the scenarios 2, 3, 4, 5, 6, 7, 8 and 9 in case of flood event 1

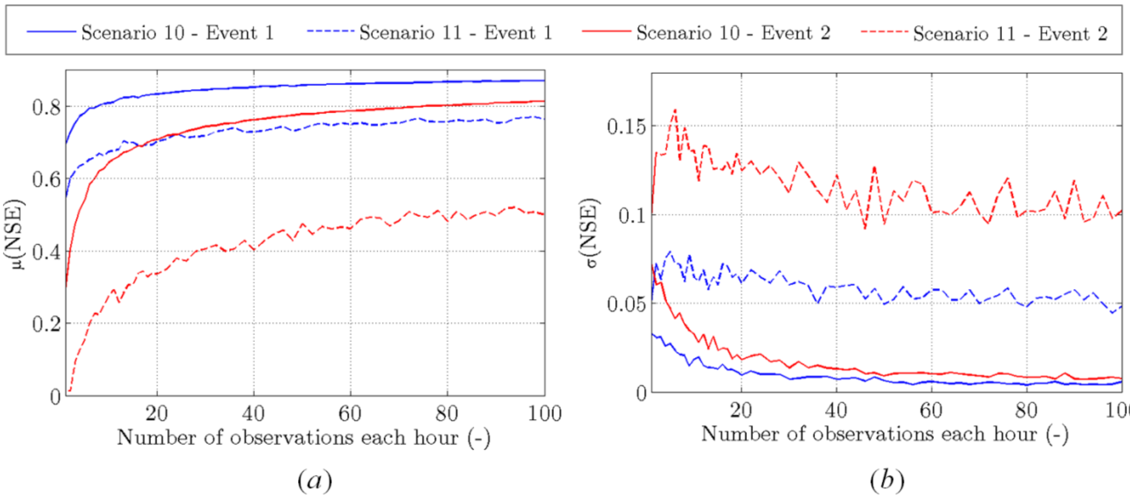


Figure 11. Dependency of the μ(NSE) and σ(NSE) on the number of observations, for the scenarios 10 and 11 in case of flood events 1 (a) and 2 (b)

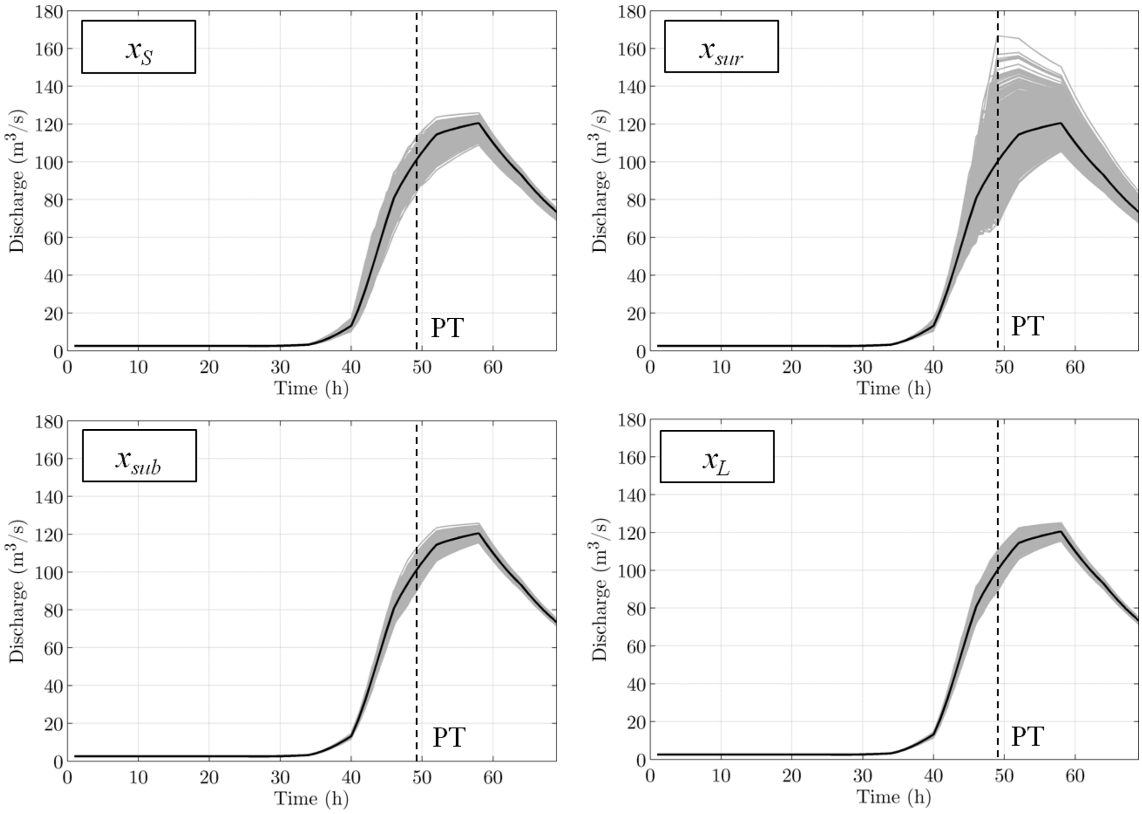


Figure 12. Effect of perturbing the model states on the model output, Bacchiglione case study. PT=Perturbation Time

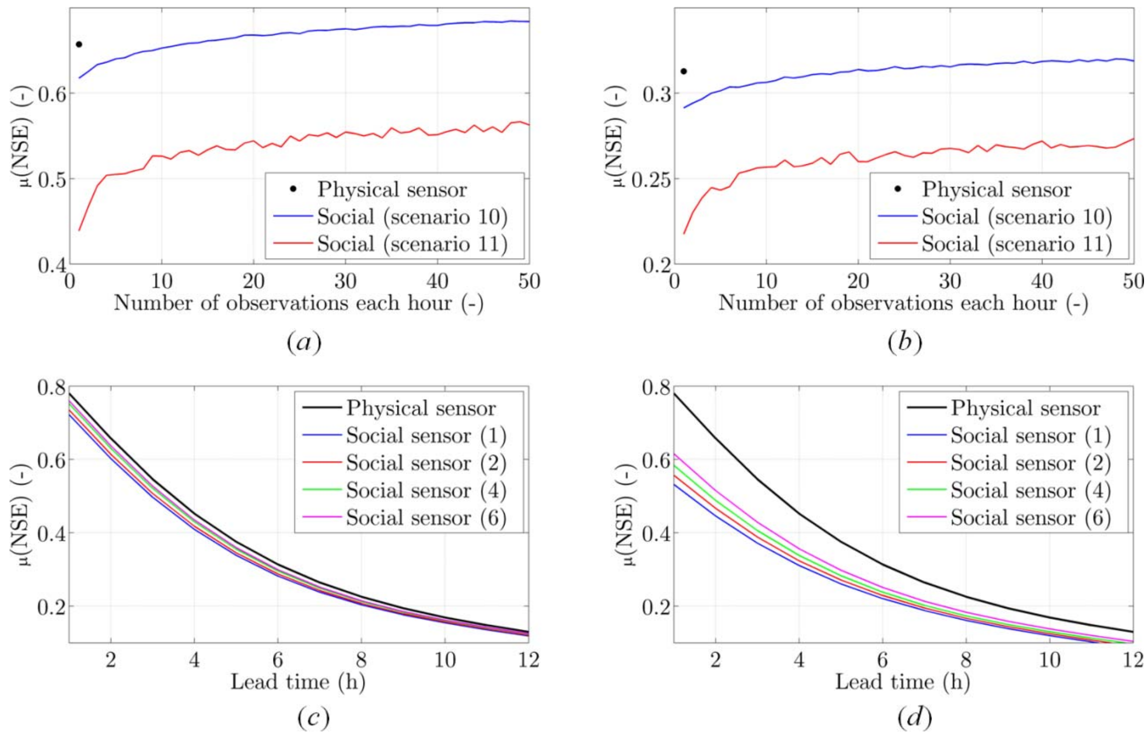


Figure 13. Model performance expressed as μ(NSE) values – assimilating observations from physical and social sensors, continuous (a) or intermittent (b) in time, at Leogra gauged station having characteristic described in scenarios 10 (c) and 11 (d)

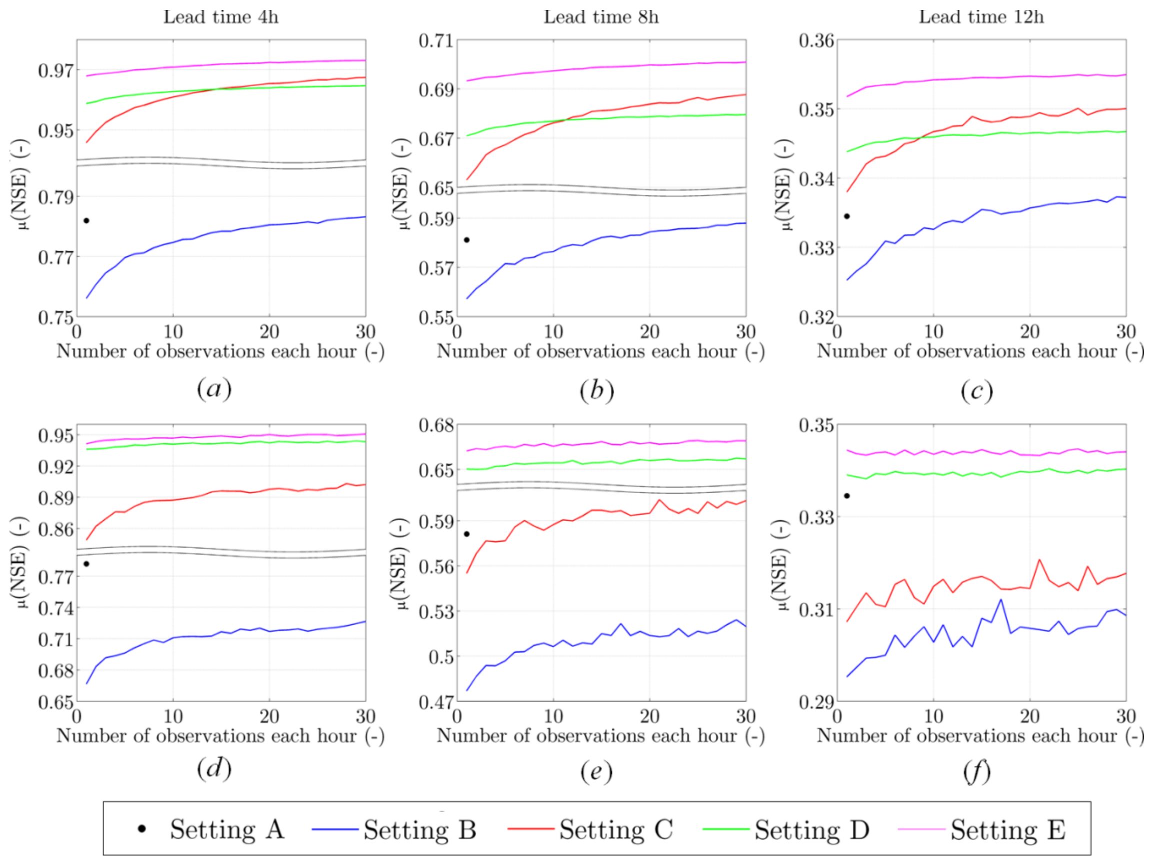


Figure 14. Model performance expressed as μ(NSE) – assimilating different number of crowdsourced observations, for the three lead time values, having characteristic of scenario 10 (first row) and 11 (second row)

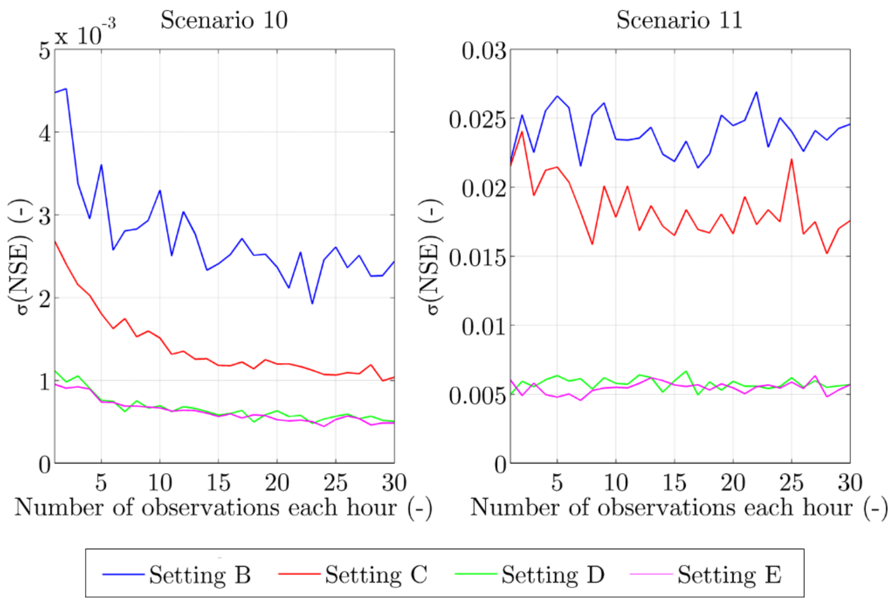


Figure 15. Variability of performance expressed as σ(NSE) – assimilating crowdsourced observations within setting A, B, C and D, assuming the lead time of 4h, for scenarios 10 and 11