



Towards assimilation of crowdsourced observations for different levels of citizen engagement: the flood event of 2013 in the Bacchiglione catchment

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Abstract

Accurate flood predictions are essential to reduce the risk and damages over large urbanized areas. To improve prediction capabilities, hydrological measurements derived by traditional physical sensors are integrated in real-time within mathematic models. Recently, traditional sensors are complemented with low-cost social sensors. However, measurements derived by social sensors (i.e. crowdsourced observations) can be more spatially distributed but less accurate. In this study, we assess the usefulness for model performance of assimilating crowdsourced observations from a heterogeneous network of static physical, static social and dynamic social sensors. We assess potential effects on the model predictions to the extreme flood event occurred in the Bacchiglione catchment on May 2013. Flood predictions are estimated at the target point of Ponte degli Angeli (Vicenza), outlet of the Bacchiglione catchment, by means of a semi-distributed hydrological model. The contribution of the upstream sub-catchment is calculated using a conceptual hydrological model. The flow is propagated along the river reach using a hydraulic model. In both models, a Kalman filter is implemented to assimilate the real-time crowdsourced observations. We synthetically derived crowdsourced observations for either static social or dynamic social sensors because crowdsourced measures were not available. We consider three sets of experiments: 1) only physical sensors are available; 2) probability of receiving crowdsourced observations and 3) realistic scenario of citizen engagement based on population distribution. The results demonstrated the importance of integrating crowdsourced observations. Observations from upstream sub-catchments assimilated into the hydrological model ensures high model performance for high lead time values. Observations next to the outlet of the catchments provide good results for short lead times. Furthermore, citizen engagement level scenarios moved by a feeling of belonging to a community of friends indicated flood prediction improvements when such small communities are

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located upstream a particular target point. Effective communication and feedback is required between water authorities and citizens to ensure minimum engagement levels and to minimize the intrinsic low-variable accuracy of crowdsourced observations.

1 Introduction

5 A challenge for water management is the reduction of risk related to extreme events such as floods. Flood management needs timely provision of early warning information, for example, to operate control river structures and to regulate water levels. Reliable accurate streamflow simulation and water level prediction by means of hydrological and hydraulic models are therefore of uttermost importance. However, model performance and related predictions are inherently uncertain due to: lack of reliable and sufficient observational data, lack of understanding of the natural hydrological and hydraulic processes, and
10 limitations and assumptions of the modelling system (Merz et al., 2010, p 514). Hence, the accuracy of flood predictions is also variable (Werner et al., 2015). Early warning systems can benefit from spatially and temporally distributed observations of hydrological variables to improve the accuracy of water level predictions (Clark et al., 2008; Rakovec et al., 2012; Mazzoleni et al., 2015a). Particularly in operational early warning, different attempts have been made over to improve the accuracy of flood model predictions by means of: 1) Data assimilation techniques; 2) assimilation of multiple physical sensors; and more
15 recently 3) assimilation of crowdsourced observations from static social and dynamic social sensors.

The main objective of this study is to assess the modelling usefulness in assimilating crowdsourced (CS) observations derived from a distributed network of static physical (StPh), static social (StSc) and dynamic social (DySc) sensors. We analyse the benefits for the flood prediction of the event occurred in May 2013 in the Bacchiglione basin. Observations are assimilated within a cascade of hydrological and hydraulic models in case of different citizen engagement levels (CEL). CEL is further
20 defined as the probability of receiving a CS observation based on the citizen's own interest. We assume that CEL mainly limit the intermittency of observations. Section 2 starts with an overview of background studies both in data assimilation and CS observations. Section 3 introduces the case study and Section 4 describes the modelling and data assimilation approach. Section 5 introduces the experimental setup. Three sets of experiments are carried out with synthetic water level observations. CS observations are not yet operational nor available in the case study for the flood event of 2013. First, it is assumed that only
25 physical sensors are available. Then, CS observations become available according to different Citizen Engagement Levels (CEL). Last, CEL scenarios vary according to the population distribution and citizen's engagement. We assumed three citizens behaviours to collect data: 1) own personal purposes; 2) shared or community interests and 3) societal benefits. Section 6 highlights the modelling benefits of each experimental set up in terms of the model performance as well as the water level prediction. Section 7 draws the conclusions for the event analysed and provides recommendations for further research.



2 Overview in data assimilation and crowdsourced observations

Data assimilation and modularisation concepts are common modelling updating techniques of the model input, parameters or outputs to integrate real-time observations of hydrological variables (WMO, 1992; Refsgaard, 1997). A data assimilation method like Kalman Filter (KF) takes into account the uncertainties in the model and observed data. Such uncertainties are considered within the model update process to update entire states of a modelling system (McLaughlin, 1995; Robinson et al., 1998; McLaughlin, 2002; Madsen and Skotner, 2005; Lahoz et al., 2010; Liu et al., 2012). Observed data derived by static physical sensors, such as pressure sensors, water level sensors, heat flux sensors and pluviometers are assimilated within mathematical models to improve flood predictions. Recent studies have assessed the benefits of assimilating multiple observations from different sensors, in-situ and remote sensors, and different hydrologic variables (Montzka et al., 2012; Pipunic et al., 2013; Andreadis et al., 2015). One of the first attempts to assimilate observations from multiple sources was proposed by Aubert et al. (2003). Daily soil moisture and streamflow data was assimilated from static physical sensors. Afterwards, integration of multiple remote sensing-based observations such as soil moisture (from AMSR-E), precipitation rates (from TRMM and TMI), surface heat fluxes (from MODIS), soil moisture (from AMSR-E) and in-situ observations into dynamic modelling systems are carried out by McCabe et al. (2008), Pan et al. (2008), Lee et al. (2011), Lopez Lopez et al. (2015) and Rasmussen et al. (2015). These previous studies demonstrated the feasibility of assimilating multi-sources data and good model improvement compared against the predictions without any model update.

Besides the increasing availability of remote sensing information, one of the main problems is the scarcity of in-situ data in both spatial and temporal domains (Hannah et al. 2011). Scarcity of in-situ data can be related to the fact that traditional physical sensors require proper maintenance and personnel, which can be very expensive in case of large networks. Over the last couple of decades, technological improvements allow the spread of heterogeneous networks of low-cost sensors. Hydrological variables, such as water level or precipitation, can then be measured in a more distributed way (Yarvis et al., 2005; Fohringer et al., 2015; Smith et al., 2015; Le Boursicaud et al., 2016). The main advantages is that of these types of sensors can be used not only by technicians, but also by “regular” citizens. Due to their reduced cost, more spatially distributed coverage can be achieved.

Recently, citizen science activities have been widely promoted to collect crowdsourced (CS) observations. Bonney et al. (2009) characterised three different approaches for citizen involvement in citizen science, namely contributory, collaborative and co-created. Citizen can contribute with CS observations of hydrological variables to generate additional knowledge of the water cycle and to support decision-making (Howe, 2008; Rotman et al., 2012; Gura, 2013; Bonney et al., 2014; Buytaert et al., 2014). Different projects assess the usefulness of CS observations (Au et al., 2000; Cifelli et al., 2005; Alfonso, 2006; Célleri et al., 2009; ABC, 2011; Roy et al., 2012; Degrossi et al., 2013; Lowry and Fienen, 2013; Seo et al., 2014; Castell et al., 2015; Schneider et al., 2015; Cortes Arevalo, 2016). CS observations should meet easy, safety and reliability requirements (Rossiter et al. 2015). Easy refers to the limited citizen engagement level. Safety refers to the consideration of accessibility and safety



conditions to carry out the CS observations. Reliability refers to both the procedures to carry out the observations and the quality control to minimise low variable accuracies of CS observations.

However, a main problem in citizen science is the motivation that drives citizens to be involved in such activities. Buytaert et al. (2014) pointed out that citizen engagement vary according to geographical location. Flint and Stevenson (2010), highlighted that the different land use and population density between urban and rural areas may also affect citizens' engagement, their interaction and own interests. Cohn (2008) specified that citizens' engagement may be driven by personal interest or community involvement. Batson et al. (2002) further specified it as the interest of: 1) increasing one's own welfare; 2) increasing the welfare of a specific group that one belongs to), 3) increasing the welfare of another individual or group of individuals and 4) upholding one or more principles dear to one's heart or to follow a moral principle. These findings for community engagement in general are confirmed by Gharesifard and Wehn (2016a,b) for citizen science. Their study of the drivers and barriers for sharing citizen-sensed weather data via online amateur networks shows the importance of personal benefits (usefulness of the collected data for personal purpose of belonging to a community of peers with shared interested), social benefits (sharing knowledge about the weather) and altruism (beneficing society at large). Moreover, engagement is dynamic and may evolve and change during the citizen's involvement period. Bonney et al. (2009) characterised three different approaches for citizen involvement, namely contributory, collaborative and co-created. Due to the intrinsic low variable accuracy and intermittency of CS observations, it is important to evaluate the accuracy of CS and to develop quality control mechanisms (Tulloch and Szabo, 2012; Vandecasteele and Devillers, 2013; Bordogna et al., 2014; Bird et al., 2014; Cortes Arevalo et al., 2014).

Data assimilation applications require specific, frequent and high quality measurements, which may not be compatible with the distributed, intermittent and, potentially, lower-quality of citizen-based data (Shanley et al., 2013; Buytaert et al., 2014; Lahoz and Schneider, 2014). That is why interpolation and merging techniques are commonly used to integrate citizen observations within mathematical models. Kovitz and Christakos (2004) assimilated fuzzy data sets assigning probabilities of plausible events based on general knowledge through information maximization and then applying a Bayesian maximum entropy method. Schneider et al. (2015) reported an example of data fusion used to provide a combined concentration field by regressing dynamic air quality observations against model data and spatially interpolating the residuals. Furthermore, Sheffield et al. (2006) and Seibert and Beven (2009) demonstrated that intermittent (or short duration) and distributed data can also be used for model calibration. Aronica et al. (1998) proposed a fuzzy-rule-based calibration to compare model predictions and highly uncertain information about the flood arising from several different types of observations. Seibert and McDonnell (2002) proposed an approach to calibrate hydrological models using both quantitative and qualitative data (e.g. percent of new water, reservoir volume, etc.) provided by expert users. Vaché et al. (2004) demonstrated the usefulness of using qualitative data for multi-objective calibration of hydrological models. Recently, Giuliani et al. (2016) proposed a procedure to automatically extract snow-related information from public webcams and photographs posted on Flickr, to inform water system operations. However, none of the previous studies assessed the usefulness of real-time CS observations in improving flood predictions. First attempts are reported in Mazzoleni et al. (2015a,b; 2016b) and Mazzoleni (2017), where the authors



assimilated distributed streamflow observations from heterogeneous type of sensors within hydrological models. In this study, we evaluate synthetic experiments of citizen engagement level from a heterogeneous network of sensors, including CS observations. To assess the modelling usefulness of CS observations, we evaluate the benefits in the predictions of a flood event in the following case study.

5 3 Case study: The Bacchiglione catchment

The Bacchiglione catchment (Italy) is one of the case studies in which WeSenseIt (WSI) Citizen Observatory of Water Project developed and tested innovative static and low-cost mobile sensors (Ciravegna et al., 2013). The main goal of the WSI project is to allow active citizens to support the work of water authorities by providing CS observations. The new sensors are strategically integrated into the existing monitoring networks for collecting physical and social CS data. WSI also developed mobile phone apps for citizens to send flood reports and sensor readings of precipitation and water level. As a pilot, CS observations collected with these apps are sent to an online platform. Once the pilot becomes operational, the observations can be used in the hydrological and hydraulic models. We assess the usefulness of assimilating CS observations to improve the model performance and consequent flood prediction.

This research focused on the upper part of the Bacchiglione catchment, in Northern-East of Italy, which flows into the Adriatic Sea at the South of the Venetian Lagoon. The case study has an overall extent of about 450km² with a river length of about 50km. The three main tributaries are the Timonchio River on the left side and Leogra and Orolo Rivers on the right side. The main urban areas are located close to the outlet section of the case study area, the city of Vicenza. Distributed rainfall and water level (W_L) information are available from 01/01/2000 in 16 meteorological stations and 2 hydrometric stations. The Alto Adriatico Water Authority (AAWA) is currently using an operational semi-distributed hydrological and hydraulic model for early warning (Ferri et al., 2012, Mazzoleni et al., 2015b). Forecasted and measured precipitation time series are available for a flood event that occurred in May 2013. This event is used to assess the benefits of assimilating CS observations during an extreme event such the one in May 2013. The event is significant due to its high intensity, which resulted in several traffic disruptions at various locations upstream Vicenza.

3.1 Sensor classification

In this study, three types of sensors to measure water level W_L are assimilated within the semi-distributed hydrological and hydraulic model (Section 3). Those are static physical (StPh), static social (StSc) and dynamic social sensors (DySc) sensors (see Figure 1).

The StPh sensors are classic physical sensors such as water level ultrasonic sensors (see example in see Figure 1.a). StPh have a fixed location, regular arrival time and the observational error depends on how well documented the cross section is. Despite of the potential observational error, we assumed high accuracy level as the observation is not affected by the variability of CS data.

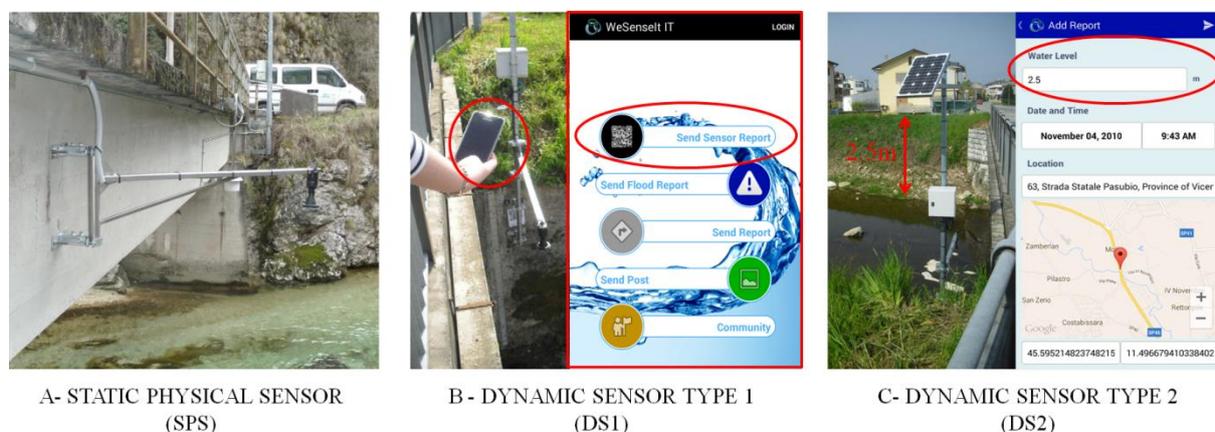


In contrast to StPh, StSc have a larger distribution along the river reach but consist of intermittent CS observations. The StSc sensors are staff gauges located at strategic points and easily accessible (safety) locations along the river reaches. Figure 1 shows an illustrative example of the sensor locations in the Bacchiglione case study. Citizens report observations from these static sensors to estimate W_L values. The WSI mobile phone app (see Figure 1.b) is used to send observations using the QR

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In case of DySc sensors, the location is not fixed but the accessibility (safety) and ease of the observation can be encouraged by following the suggestions of water authorities. In fact, CS observations can provide the distance between the water level and the river bank at random locations along the river. It might be in fact difficult to estimate the W_L value without having any indication about river depth. By assuming a cross section and documenting bank elevations, is possible to estimate the W_L value. For example, by referring to reaches where cross sections are regular or where bank elevations can be inferred from the dimensions of a neighbouring object (see Figure 1.c). To report, citizens can also use the WSI mobile phone app (see Figure 1.c). An example of DySc sensors is reported in Michelsen et al. (2016).

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15 **Figure 1: Representation of different type of sensors implemented in the Bacchiglione catchment under the WeSenseIt project.**

3.2 Crowdsourced observations

The idea of citizen observatories is that StSc and DySc sensors are used by citizen to provide W_L observations. CS observations can have different characteristics of temporal availability and accuracy based on the adopted sensor, as reported in Table 1.

20 Regardless of the social sensor (static or dynamic), the reliability and intermittency of the observation can be affected by the experience, engagement and citizens' own interest. In particular, we assumed a direct relation between intermittency, or temporal availability, and the CEL, i.e. the probability of receiving a CS observation based on the citizen's own interest. Regarding data accuracy, some expertise (training) is still required to read the gauge, take the picture and use the mobile applications developed by WSI. In fact, in case of StSc sensors, due to the low complexity of the observation, we assumed the

25 accuracy level as medium. On the other hand, for DySc sensors, the degree of uncertainty is higher not only because of the



observational error, but also because of the indirect method to estimate the W_L value. The assumed accuracy level is the lowest of all included sensors.

CS may have three expertise levels according to the categories proposed by (Coleman et al., 2009, p5.). We further define these categories in the context of this research as follows:

- 5 1) *Neophyte volunteer*, normal citizen who may have the mobile application but has not yet attended training activities nor experience with sending reports to the basin authority.
- 2) *Interested volunteer*, citizen who has the mobile application, attended the trainings but has limited experience sending reports to the basin authority.
- 3) *Experienced volunteer*, either experienced citizen or technician (the Civil Protection in case of the Bacchiglione catchment),
- 10 who actively uses the application, joins training activities and has enough expertise to provide reliable observations.

Due to the lack of distributed crowdsourced observations at the time the considered flood event occurred, synthetic W_L observations are used.

Table 1. Characteristics of crowdsourced (CS) observations based on sensor classification

Sensor type	Type of observation	Location	Time of availability	Observational error	Assumed accuracy level
Static Physical (StPh)	Water level time series	Fixed, generally in key inlet or outlets	Each model time step	<ul style="list-style-type: none"> - Missing data - Observational noise due to changes in the cross section - Missing or not representative rating curve. 	High
Static Social (StSc)	CS water level and photo of the river gauge.	Fixed but distributed at strategic points along the river reach	Intermittent, according to CEL	<ul style="list-style-type: none"> - Same as StPh - Inaccurate lecture of the river gauge - Inaccurate photo limiting validation - Unknown expertise level of the citizen reporting 	Medium
Dynamic Social (DySc)	Photo and CS estimation of the distance from the river bank to the actual water level	Variable	Intermittent, according to CEL and accessibility level to the river reach	<ul style="list-style-type: none"> - Same as StPh - Same as StSc but inaccurate reference point to estimate distance from the river bank - Photo without a reference measure for validation - Unknown (irregular) cross section and river bank conditions at the reported location 	Low



4 Modelling tools

4.1 Semi-distributed hydrological model

In order to implement the semi-distributed model, the Bacchiglione catchment is divided into different sub-catchments and inter-catchments whose streamflow contributions flow into the main river channel up to the urbanized area of Vicenza. In the schematization of the Bacchiglione catchment (see Figure 2), the location of the StPh and StSc sensors corresponds to the outlet section of three main sub-basins, Timonchio, Leogra and Orolò. The remaining sub-basins are considered as the inter-basin. The rainfall-runoff processes within each sub-catchment and inter-catchment are represented by means of a conceptual hydrological model, initially developed by AAWA. In case of the main river channel, a hydraulic model is used to propagate the flow up to the gauge station of Ponte degli Angeli (PA) in Vicenza. In particular, the river reach is divided into different reaches according to the location of the internal boundary conditions. We used hydrological outputs as upstream (from sub-catchments) and internal boundary conditions (from inter-catchments). Figure 2 shows that the output of the hydrological model (red arrows) are boundary conditions for the proposed hydraulic model.

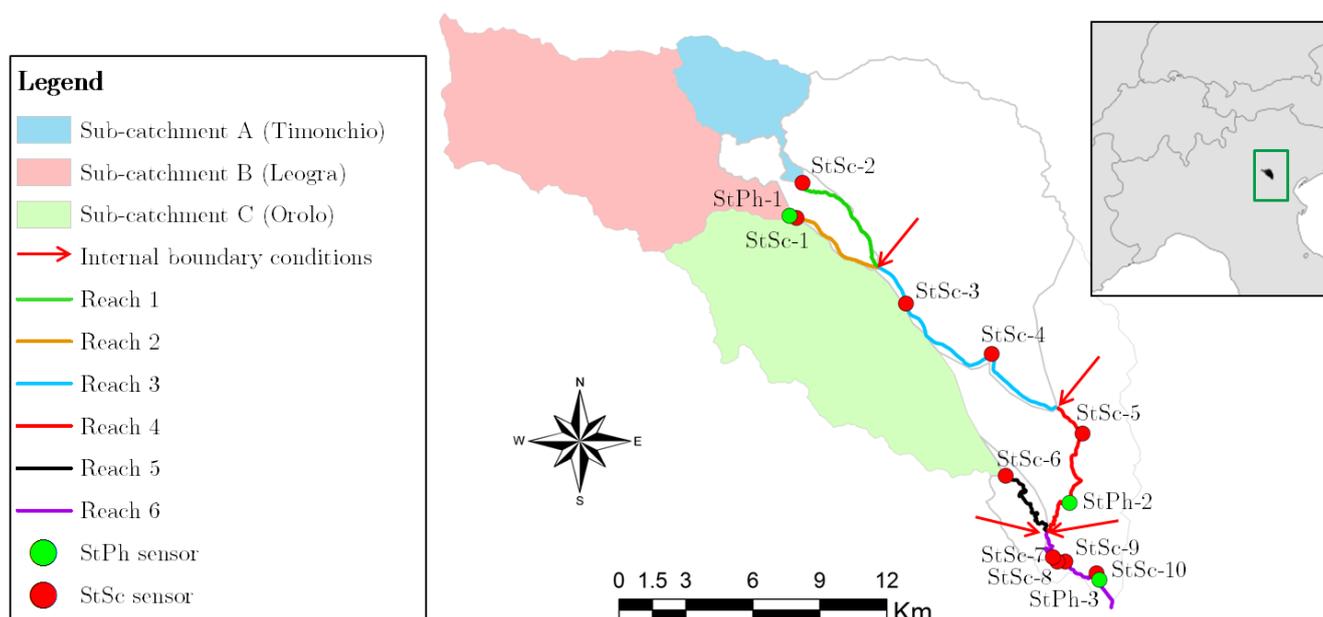


Figure 2. Spatial distribution of the sub-catchments, river reaches, StPh and StSc sensors implemented in the catchment by AAWA

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4.1.1 Hydrological modelling

The hydrological model used in this study is based on the early warning system implemented by AAWA. We briefly relate to the model equation as detailed description is available in Ferri et al. (2012) and Mazzoleni et al. (2015b). Precipitation time series is the only input for the hydrological model implemented in this study. The water balance to a generic control volume of active soil is applied, at the sub-basin scale, to mathematically represent the processes related to runoff generation processes such as surface, sub-surface and deep flow.

$$S_{W,t+dt} = S_{W,t} + P_t - R_{sur,t} - R_{sub,t} - L_t - E_{T,t} \quad (1)$$

where $S_{W,t}$ is the water content at time t , P is the precipitation component, E_T the evapotranspiration, R_{sur} , the surface runoff, R_{sub} the subsurface runoff and L is the deep percolation. The routed contributes of the surface Q_{sur} , sub-surface Q_{sub} and deep flow Q_g are derived from R_{sur} , R_{sub} and L by means of the conceptual framework of the linear reservoir model. In case of Q_{sur} the value of the parameter of this model, i.e. the time constant that defines how fast the water flows out of the reservoir, is estimated as a function of the slopes velocity of the surface runoff to the average slopes length.

In this study, the estimate of the surface velocity is performed using the approach proposed by Kumar et al. (2002). It is worth noting that this formulation is applied at a lumped scale for each sub-catchment and inter-catchment. However, in order to reproduce the spatial variability of the velocity, and consequent resident time, a distributed model should be used as suggested by McDonnell and Beven (2014). Calibration of the hydrological model parameters, including the parameters of the linear reservoir model for Q_{sub} and Q_g , is performed by AAWA minimizing the error between the observed and simulated W_L values at Ponte degli Angeli (Vicenza) for a period between 2000 and 2010. At this point, in order to apply the data assimilation approach and properly integrate crowdsourced W_L observations within the mathematical model, it is necessary to represent the previous dynamic system in a state-space form, i.e.:

$$\mathbf{x}_t = M(\mathbf{x}_{t-1}, \vartheta, \mathbf{I}_t) + w_t \quad (2)$$

$$\mathbf{z}_t = H(\mathbf{x}_t, \vartheta) + v_t \quad (3)$$

where, \mathbf{x}_t and \mathbf{x}_{t-1} are the model state vectors at time t and $t-1$, M is the model operator, \mathbf{I}_t is the vector of the model inputs, while H is the operator which maps the model states into the model output \mathbf{z}_t . The terms w_t and v_t indicate the system and measurements errors which are assumed normally distributed with zero mean and covariance \mathbf{S} and R . In case of the hydrological model used in this study, the states are identified in x_S , x_{sur} , x_{sub} and x_L , i.e. the states to S_W and to the linear reservoir generating Q_{sur} , Q_{sub} and Q_g . In Mazzoleni et al. (2015b), a sensitivity analysis is carried out perturbing the model states $\pm 20\%$ around the true state every time step in order to find out to which model states the output are more sensible. The results of such analysis showed that model output is more sensitive to x_{sur} if compared to the other ones. For this reason, we



decided to update only the model state x_{sur} , which is related to the linear reservoir. Based on the linear nature of the linear reservoir model, the state-space form can be expressed as i.e.

$$\mathbf{x}_t = \Phi \mathbf{x}_{t-1} + \Gamma I_t + w_t \quad (4)$$

$$\mathbf{z}_t = \mathbf{H} \mathbf{x}_t + v_t \quad (5)$$

5 where \mathbf{x} is the vector of the model states (stored water volume in m^3), Φ is the state-transition matrix, Γ is the input-transition matrix, \mathbf{H} is the output matrix. In this case, the model output \mathbf{z} is expressed as streamflow Q at the outlet section of the sub-catchment or inter-catchment. The detailed description of the matrices Φ , Γ and \mathbf{H} can be found in Szilagyi and Szollosi-Nagi (2010).

4.1.1 Hydraulic modelling

10 Flood propagation along the main river channel is represented using a Muskingum-Cunge (MC) model (Cunge, 1969; Ponce and Chaganti, 1994; Ponce and Lugo, 2001; Todini, 2007). MC is derived from the mass balance applied over a prismatic section delimited by the upstream and downstream river section. As described in Cunge (1969) and Todini (2007), a four point time centered scheme is used on the kinematic routing model to derive a first order approximation of a diffusion wave model and express the MC model as:

$$15 \quad Q_{t+1}^{j+1} = C_1 Q_t^j + C_2 Q_t^{j+1} + C_3 Q_{t+1}^j \quad (6)$$

where t and j are the temporal and spatial discretization, Q is the streamflow, while C_1 , C_2 and C_3 are the routing coefficients, function of the geometry of the cross-sections and wave celerity, calculated at each time step t following the approach proposed by Todini (2007) and detailed reported in Mazzoleni et al. (2016a). It is worth noting that in this formulation of MC, the only model parameter is the manning coefficient of the river channel considered in the estimation of the wave celerity. In addition,

20 MC is implemented, independently, along each one of the six river reaches represented in Figure 2.

As in case of the hydrological model previously described, a state-space form of the hydraulic model is used as well in order to apply the data assimilation method. The state and observations process equation are similar to the ones described in Eq.(4) and (5). In case of the hydraulic model, the model state vector is defined as $\mathbf{x}_t = (Q_1^t, Q_2^t, \dots, Q_j^t, \dots, Q_N^t)$, where Q is the discharge along the river in m^3/s , while the input matrix is $\mathbf{I}(t) = (Q_0^t, Q_0^{t+1})$ being Q_0 the discharge at the upstream boundary condition.

25 The state-transition Φ and input-transition Γ matrixes are calculated following the approach derived by Georgakakos et al. (1990). In the observation process of the hydraulic model, \mathbf{z} represents the flow along the river channel, while \mathbf{H} is output matrix equal to $[0 \ 0 \ \dots \ 1]^T$ in case of flow measurements at the outlet section of the river reach. In this study, due to the variable position of social sensors, the matrix \mathbf{H} changes accordingly each time step. The manning equation is used to estimate the W_L in the river channel knowing the value of flow at each spatial discretization, considered 1000m. The value of the manning
 30 coefficient is 0.8 following the calibration process in which observed and simulated rating curve are compared at PA.



4.2 Data assimilation

The Kalman Filter (KF, Kalman 1960) is a mathematical tool widely used to integrate real-time noisy observations, in an efficient computational (recursive), within a dynamic linear system resulting in the best state estimate having minimum variance of the model error. In Liu et al. (2012), a detailed review of KF and other type of data assimilation approaches is reported. The first step in the KF procedure is the forecast of the model state vector, following Eq.(4), and covariance matrix expressed as:

$$\mathbf{P}_t^- = \Phi \mathbf{P}_{t-1}^+ \Phi^T + \mathbf{S}_t \quad (7)$$

where the superscript – indicates the forecasted model error covariance matrix \mathbf{P} and the superscript + indicates the updated state value coming from the previous time step. In fact, whenever an observation z^o becomes available, the second step of the KF, i.e. the update step, the forecasted model states \mathbf{x} and covariance \mathbf{P} are updated as:

$$\mathbf{x}_t^+ = \mathbf{x}_t^- + \mathbf{K}_t(z_t^o - \mathbf{H}_t z_t^o) \quad (8)$$

$$\mathbf{P}_t^+ = (\mathbf{I} - \mathbf{K}_t \mathbf{H}_t) \mathbf{P}_t^- \quad (9)$$

$$\mathbf{K}_t = \mathbf{P}_t^- \mathbf{H}_t^T (\mathbf{H}_t \mathbf{P}_t^- \mathbf{H}_t^T + \mathbf{R}_t)^{-1} \quad (10)$$

where \mathbf{K} is the Kalman gain matrix, the higher this matrix, the more confidence KF gives to the observation z^o and vice versa. Due to the fact that along the river channel only W_L observations are provided, the manning equation is used to express the vector z^o as streamflow based on natural river cross-section geometry.

In this study, crowdsourced observations are considered. As already mentioned, such observations can be irregular both in time and in space. In order to consider the intermittent nature in time within the KF, the approach proposed by Cipra and Romera (1997) and Mazzoleni et al. (2015a) is adopted. According to this approach, when no observation is available, the model state vector \mathbf{x} is estimated using Eq.(4), while the model error covariance \mathbf{P} is forecasted considering no changes at that time step:

$$\mathbf{P}_t^+ = \mathbf{P}_t^- \quad (11)$$

It is worth noting that in case of the hydraulic model, the state variables at each reach are updated separately.

4.3 Synthetic observations

Due to the lack of distributed crowdsourced observations at the time the considered flood event occurred, synthetic W_L observations are used. It is worth noting that, in real-life application, citizens are not supposed to provide directly streamflow observations but W_L . Such W_L values are then converted to streamflow using the rating curve at the location of the social sensors.



In order to generate such synthetic observations, the observed time series of precipitation during the flood event of May 2013 are used as input for the hydrological models of the sub-catchments and inter-catchments to generate synthetic discharge and then propagate it with the hydraulic model up to the target point of PA. The hydrological model for each sub-catchment uses as input data spatial interpolation of meteorological variables (using Kriging methods). In this way, both the synthetic streamflow and W_L values at the outlet of the sub-catchments/inter-catchments and at each spatial discretization of the six reaches of the Bacchiglione River are estimated and assumed as observed variables in the assimilation process. In meteorology, this kind of approach is often called “observing system simulation experiment” (OSSE), as described for example by Arnold and Dey (1986), Errico et al. (2013) and Errico and Privé (2014).

In case of observations derived using DySc sensors, a systematic error is also accounted by means of different values of observations bias estimated as:

$$W_{L,t}^{synth} = W_{L,t}^{true} + \gamma_t = W_{L,t}^{true} + W_{L,t}^{true} \cdot U(\gamma_{min}, \gamma_{max}) \quad (11)$$

where γ is a random stochastic variable function of the time, having minimum and maximum values γ_{min} and γ_{max} reported in Table 2 in case of the experiment 2.2 reported in the next section. For example, Bias 1 represent the case of no bias, bias 3 of underestimation and bias 4 overestimation of the real W_L value.

Table 2. Minimum and maximum values γ_{min} and γ_{max} in case of 4 different cases of observation bias used in experiment 2.2

	γ_{min}	γ_{max}
Bias 1 (γ_1)	0	0
Bias 2 (γ_2)	-0.3	0.3
Bias 3 (γ_3)	-0.3	0
Bias 4 (γ_4)	0	0.3

As described in Weerts and El Serafy (2006), Rakovec et al. (2012), and Mazzoleni et al. (2015a, 2016b), the covariance matrix R is assumed to be:

$$R_t = (\alpha_t \cdot Q_t^{synth})^2 \quad (12)$$

where α is a variable related to the degree of uncertainty of the measurement. To account for the differing accuracy between the users of physical and social sensors (see details in section 2.2 and

Table 1), Table 3 summarises the distribution of the coefficient α of the observational error (i.e. bias) of Eq.(12). As described in Weerts and El Serafy (2006) and Rakovec et al. (2012), in order to account for the rating curve uncertainty in the estimation of streamflow from W_L , the coefficient α is assumed equal to 0.1, constantly in time and space.

On the other hand, due to the unpredictable accuracy of the CS observations coming from the sensors StSc and DySc sensors, the coefficient α is assumed as a random stochastic variable within a minimum (α_{min}) and maximum (α_{max}) value. In fact, the accuracy of CS observations relies on, but is not limited to, the expertise level of participants (Section 2.2). The uncertainty of



a measurement provided by neophyte volunteer or interested volunteer is generally larger than that of an experienced volunteer or technician. Specifically, based this assumption on the consideration that expert volunteers or technicians may have submitted a large number of observations, have enough training or received sufficient background expertise to provide reliable water level reports. Regardless of the expertise level, basin authorities should establish quality control procedures of CS before, during and after the submission of reports to set these minimum and maximum accuracy values.

In case of observations derived from StSc sensors, α_{min} and α_{max} are assumed equal to 0.1 and 0.3, while for DySc sensors, the minimum and maximum values are set to 0.2 and 0.5, i.e. two and five times higher than the uncertainty coming from the physical sensors (StPh).

Table 3. Assumptions behind the observational errors according to the sensor type

Sensor type	Assumed accuracy level	Coefficient α	Temporal and spatial variability
Static Physical (StPh)	High	$\alpha = 0.1$	Fixed location Constant in time
Static Social (StSc)	Medium	$\alpha = U(0.1, 0.3)$	Fixed location Intermittent arrival
Dynamic Social (DySc)	Low	$\alpha = U(0.2, 0.5)$ Systematic bias	Variable location Intermittent arrival

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4.4 Performance measures

Two different performance measures are used in order to assess the effect of assimilating CS observations within the models previously described. The widely used measure in hydrology, the Nash-Sutcliffe Efficiency (N_{SE}) index (Nash 1970), is used to compare simulated and observed quantities:

$$N_{SE} = 1 - \frac{\sum_{t=1}^T (W_{L,t}^m - W_{L,t}^o)^2}{\sum_{t=1}^T (W_{L,t}^m - \overline{W_D})^2} \quad (13)$$

where the superscripts m and o indicate the simulated and observed values of W_D , while $\overline{W_D}$ is the average observed water level. An N_{SE} of 1 represents a perfect model simulation whereas an N_{SE} of zero indicates that the simulated streamflow is only as skilful as the mean of observed water level.

The Bias index (B_I) measures the tendency, on average, of a given simulated variable to be bigger or smaller than its observed value. Values of B_I bigger than 1 indicate overestimation of such variable, and vice versa, for B_I lower than 1, an overall underestimation is present.

$$B_I = \frac{\sum_{t=1}^T W_{L,t}^m}{\sum_{t=1}^T W_{L,t}^o} \quad (14)$$



5 Experimental setup

In this section, three sets of experiments are performed to test the benefits of real-time assimilation of CS from a network of heterogeneous static and dynamic sensors. A 3-day rainfall forecast is used to assess the simulated streamflow and W_L values along the Bacchiglione River and at the target point of PA. W_L observations from StPh sensors are assimilated at an hourly frequency, while CS observations from StSc and DySc sensors are assimilated at different intermittent moments to account for the random temporal nature of such observations. In addition, different model runs are performed to consider the random accuracy and engagement level of the citizen providing CS observations.

Three sets of experiments are carried out as described in the following subsections. Experiment 1 considers only the assimilation of observations from StPh sensors. Experiment 2 considers that CS observations become available from StSc (Experiment 2.1) and DySc (Experiment 2.2) according to random CEL. In this study, we assumed that CEL do not affect observations accuracy but just their intermittency nature. Instead, Experiment 3 consists of a unique experiment where the assimilation of CS observations from all sensors is carried out. This experiment considers a more realistic assumption of engagement based on citizen's engagement and the spatial distribution. Observed and forecasted W_L values are compared, for different lead times, at the outlet section of PA to evaluate the assimilation of CS observation within the semi-distributed model.

5.1 Experiment 1: Assimilation of data from static physical (StPh) sensors

In this experiment, CS observations coming from sensor StPh1 are assimilated within the hydrological model, being located at the outlet section of a sub-catchment. Instead, observations from sensors StPh2 and StPh3, which are installed along the main river reach, are assimilated into the hydraulic model of the Bacchiglione catchment. The observations are assumed to be regular in time. In particular, because of the high accuracy of these sensors compared to dynamic sensors (DySc), the coefficient α of Eq.(12) is considered equal to 0.1 as described in Section 3.3. The assimilation of W_L observations is firstly performed considering a single sensor at a time and then all StPh sensors together. Model performances, expressed in terms of N_{SE} , are calculated for different lead time values, up to 24 hours.

5.2 Experiment 2: Engagement scenarios of social sensors

Different values of CEL are considered. Such engagement, closely related to the intermittent nature of the W_L observations, can be considered as the probability to receive an observation at a given model time step. This means that in the case of CEL=0.4 there is 40% of probability to obtain an observation at a given model time step. In fact, in the case of CEL=0, no observation is assimilated and the semi-distributed model is run without any update. On the other hand, for CEL=1, observations are available at every time step and this situation is analogous to the observation from StPh sensors, which are regular in time.



5.2.1 Experiment 2.1: Assimilation of data from static social (StSc) sensors

In Experiment 2, only assimilation of W_L observations from StSc sensors is considered. Besides StSc1, 2 and 6, located in sub-catchment A, B and C respectively, the other sensors are located along the river reaches of the Bacchiglione catchment. On contrast to the observations from StPh, the ones from StSc are not regular in time since they are strictly related to the citizen engagement level.

Observation error is defined as in section 3.3 using Eq.(12). The value of α for each StSc sensor is only a function of time t since the location of the sensor is assigned and fixed. Assimilation of W_L observations in case of different combinations of sensor availability in the different sub-catchments and river reaches is performed.

5.2.2 Experiment 2.2: Assimilation of data from dynamic social (DySc) sensors

In the Experiment 2.2, the assimilation of W_L observations coming only from DySc sensors is considered. In this case, the CS observations can be sent without the use of the static reference tool as in case of the StSc sensors but only with the dynamic device (e.g. smart phone). The two main differences between StSc and DySc sensors are that: 1) DySc sensor locations vary every time step along the river reaches in contrast to StSc sensors whose locations are considered constant in time. In fact, in the case of the DySc sensors, the mobile sensor might provide observations in different random places due to the fact that there is no need for a static reference tool to measure the W_L ; 2) uncertainty in the observations provided by DySc sensors is higher than for those from StSc sensors. This is because, for a non-expert, it might be difficult to estimate the W_L in a river without any reference device as in the case of StSc sensors. For this reason, citizens might provide observations of the distance between the water profile and the river bank. This information is then used by the modeller to calculate the W_L knowing the distance from river bank and thalweg (from available natural section). This procedure introduces high uncertainty in the estimation of the W_L .

A synthetic W_L value is considered instead of the distance between water profile and river bank. Synthetic W_L observations are then assimilated only in the hydraulic model of the Bacchiglione River. That is because W_L observations are easier to be integrated within the hydraulic than the hydrological model. In fact, W_L observations should be converted into streamflow values, for example by means of a rating curve, in order to be assimilated within the hydrological model. It would be very difficult to assess the rating curve for a random point, as the information about the geometry of the river cross-sections is not available within each sub-catchment. Also in this experiment, different random values of engagement are accounted for.

5.3 Experiment 3: Realistic scenarios of engagements

In this experiment, all the StPh, StSc and DySc sensors are considered. However, the engagement level is estimated in a more realistic and complex way. In fact, in the previous experiments, engagement was considered as random values varying from 0 to 1. In this experiment, engagement level is considered as a function of the population distribution within the Bacchiglione



catchment. We proposed 3-steps procedure including: 1) estimation of citizen active area; 2) number of active citizens and; 3) citizen engagement curve.

Step1: Estimate of the citizen “active area”. A 500m buffer around each sub-river reach of 1000m (spatial discretization of the MC model) is used to identify the area in which the active population is which might provide CS observations using DySc sensors (see Figure 3). It is in fact assumed that citizens located more than 500m from the river are not contributing to the collection of CS observations. In the case of the StSc sensor, we assume the active area as a circle with 500m radius with the sensor at the centre. Land cover maps are used to identify the main urban area from which citizens might provide CS observations of W_L within the buffer previously estimated (see Figure 3).

Step 2: Estimate of the number of active citizens. The population density for the different municipalities along the different river reaches is used to estimate the number of citizens within the 500m buffer of each sub-river reach in which the urban areas are located. In the case of agricultural areas, an engagement value equal to zero is considered. In addition, not all citizens would be able to provide CS observations because only proportion of them uses mobile phones. According to Statistica (2016), the mobile phone penetration in Italy in 2013, the year of the flood event analysed in this study, was about 41%. For this reason, in order to estimate the active population, the number of citizens enclosed between the 500m buffer and 1000m of river sub-reaches is multiplied by this percentage. Table 4 summarizes the results for the case of the StSc sensors and in Table 5 for the DySc sensors. In Table 5, the active citizens are divided by the number of sub-reaches (3 for reach 6). For reach 6 (km 3-4-5), main urban areas are contained in more than one sub-reach.

Table 4. Estimate of the active population which can provide CS observation of W_L from StSc sensors

Sensor	Municipality	Active area (m ²)	Density (inhab/km ²)	Population (inhab)	Active citizens (inhab)
StSc-1	Schio	206828.3	597	124	51
StSc-2		71292.5		43	18
StSc-3	Malo	100733.8	491.39	50	21
StSc-4	Villaverla	359743.8	400	144	59
StSc-5	Caldogno	67310.9	720	49	20
StSc-6	Costabissara	421777.7	562.53	238	98
StSc-7	Vicenza	86543.9	319.49	28	11
StSc-8		241.450.9		77	32
StSc-9		415513.4		133	55
StSc-10		500000.0		160	66

Table 5. Estimate of the active population which can provide CS observation of W_L from DySc sensors

Reach	Municipality	Active area (m ²)	Density (inhab/km ²)	Population (inhab)	Active citizens (inhab)
1 (km6-7-8)	Marano Vicentino	608985.2	800	487	200
2 (km2)	Schio	39536.4	597	24	10
3(km8)	Villaverla	359743.8	400	144	59



3(km11)	Caldogno	232474.1	720	167	69
4(km2)	Dueville	30692.3	700.85	22	9
4(km3)	Caldogno	191987.6	720	138	57
4(km5)	Caldogno	292519.8		211	86
5(km1)	Costabissara	351920.7	562.53	198	81
5(km2)		119897.9		67	28
5(km3-4-5)		212452.9		68	28
6(km1-2)	Vicenza	129815.9	319.49	41	17
6(km3-4-5)		1156964.3		370	152

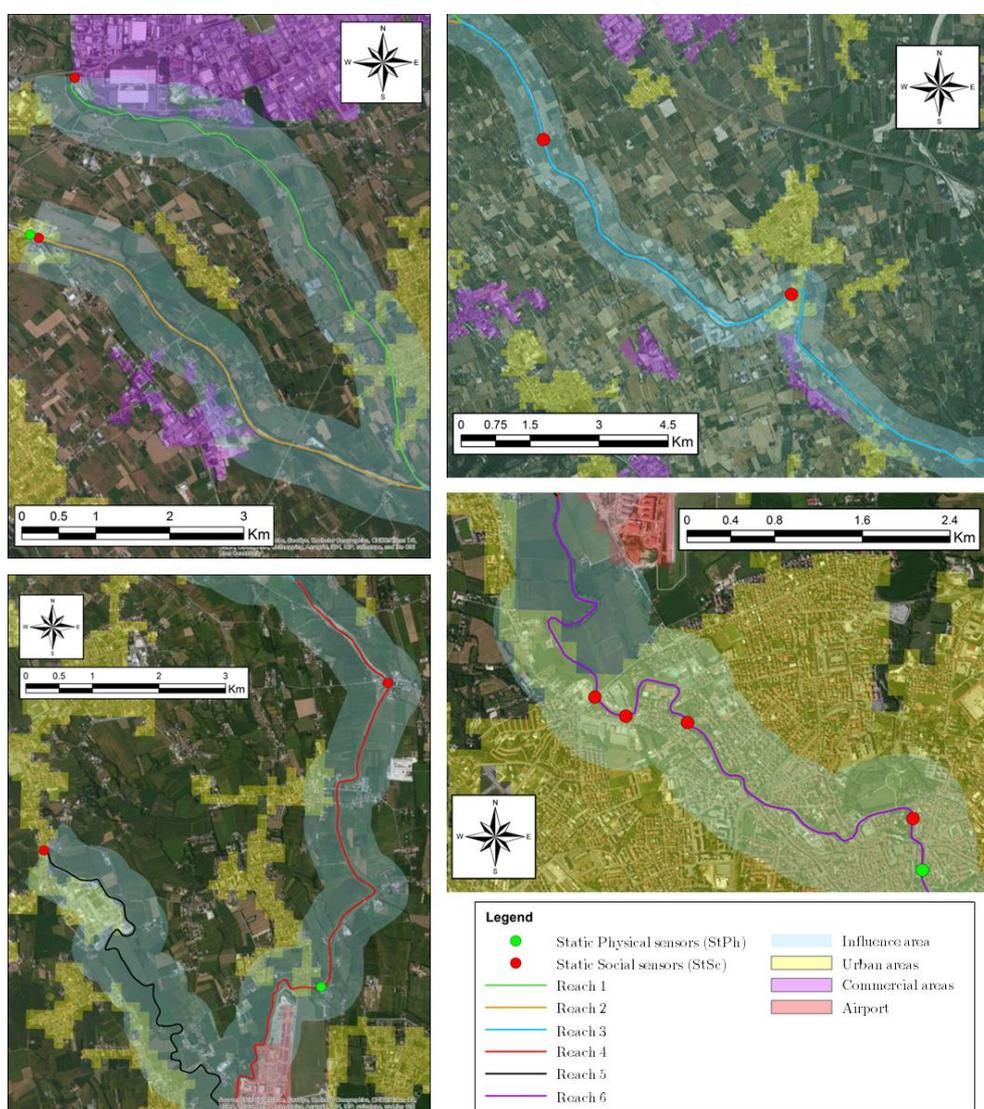


Figure 3. Representation of the different Bacchiglione river reaches, land use (Corine Land Cover, 2006), location of the StSc and StSc sensors and the 500m buffer



Step 3: Estimate of the citizen engagement curve. It is now necessary to estimate the citizen' level of engagement based on the hypothetical number of active citizens. For this reason, six different scenarios of Maximum Citizen Engagement Level (*MCEL*), function of three diverse citizen behaviours (Ghahesifard and Wehn, 2016a) and the number of active citizens, are proposed.

- 5 In the behaviour 1 (*own personal purposes*), we assume that citizens collect data mainly for their own personal purposes. In this case, the *MCEL* is low for low number of citizens, while it grows following a logistic function, Eq.(15), for increasing numbers of people.

$$MCEL = \frac{K \cdot P_o \cdot e^{r \cdot P_{op}}}{K + P_o \cdot (e^{r \cdot P_{op}} - 1)} + w \quad (15)$$

Where:

- 10 P_{op} is the population number;
 r is the growth rate, we assumed two different values of r are (0.04 and 0.08);
 K is the carrying capacity, i.e. maximum value of *MCEL*, assumed equal to 1;
 w is a coefficient related to the additional CS observations are also driven by societal benefits (third citizen behaviours explained below);
- 15 P_o is the minimum value of *MCEL* assumed equal to 0.01.

In the behaviour 2 (*shared or community interests*), citizens might decide to collect and share CS observations driven by a feeling of belonging to a community of peers with shared interests and vision. In this case, it is assumed that a maximum value of *MCEL* is achieved for small population values while for increasing population this value is reducing. This behaviour follows an inverse logistic function as shown in the graphical representation of Figure 4.

- 20 In the behaviour 3 (*social benefits*), weather enthusiast individuals, weather networks and related hobby-clubs might provide additional information driven by moral norms and the wish to create knowledge about the weather, benefiting society at large. This is potentially a much smaller subset of the population than those practicing. The added value of this information is accounted for in Eq.(15) by means of a coefficient w . Table 6 summarizes the different engagement scenarios, based on different values of the coefficient r and w related to citizen behaviours.
- 25 In the next analysis, different model runs (100) are performed considering random values of citizen engagement from 0 to the *MCEL* according to the given engagement scenario and population. For example, considering scenario 5 and 60 inhabitants enclosed in a given river sub-reach, different model runs are performed for engagement values varying from 0 to 0.6 based on Figure 4. In case different CS observations coming at the same time from different sensors, only the most accurate observation, i.e. having the lower value of observational noise, is assimilated in the hydrological and/or hydraulic model.

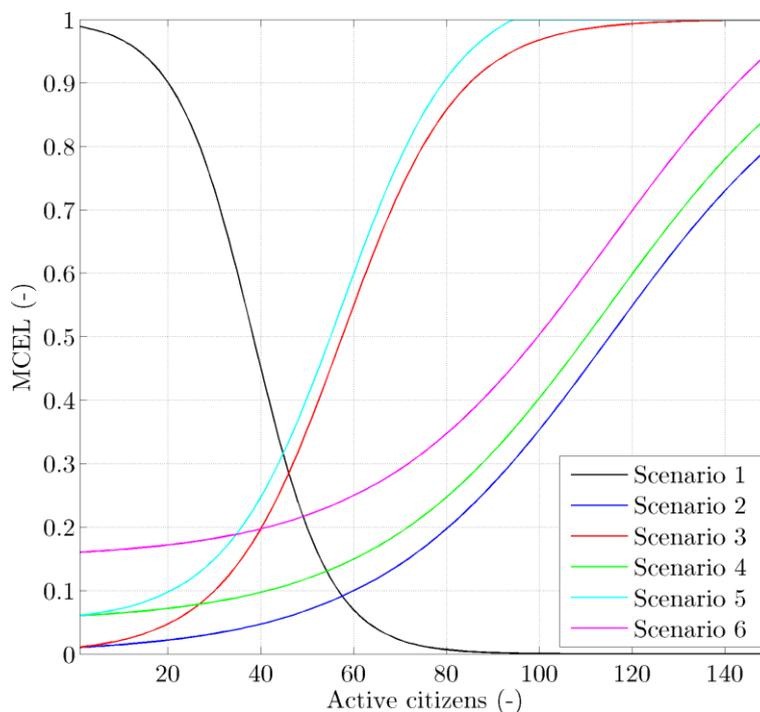


Figure 4. Maximum Citizen Engagement Level (MCEL) scenarios based on number of active citizens.

Table 6. Engagement scenarios based on different citizen behaviours

Engagement scenario	Citizen behaviour	<i>Logistic function Growth rate (Factor r in Eq 15)</i>	<i>Additional CS observations (Factor w in Eq. 15)*</i>
1	Shared or community interests (2)	0.12	0
2	Own purposes (1)	0.04	0
3	Own purposes (1)	0.08	0
4	Own purposes (1)+Social benefits(3)	0.04	0.05
5	Own purposes (1))+Social benefits(3)	0.08	0.05
6	Own purposes (1)+Social benefits(3)	0.04	0.15

*Increment applies when CS are also driven by societal benefits (third citizen behaviours)



6 Results and discussions

6.1 Experiment 1

Experiment 1 deals with the assimilation of streamflow and W_L observations from StPh sensors located in the hydrological (StPh1) and hydraulic (StPh2 and StPh3) models of the Bacchiglione catchment. As it can be seen from Figure 5, assimilation in hydrological model (StPh1) provides the best model improvement, in terms of W_L hydrograph at PA (Vicenza), if compared to the other StPh sensors. In particular, both flood peaks are well represented with assimilation from StPh1 sensor, while, with observations from the other two StPh sensors, only the second simulated peak fits the observed values. Assimilation of W_L observations from StPh2 gives lower improvement than the assimilation from the StPh3 sensor, located close to the PA station. However, assimilation from StPh2 insures a better model prediction than StPh3, expressed as N_{SE} values, in case of high lead time value. This is due to the location of the StPh2 sensor, upstream StPh3, and the consequent high travel time (around 6 hours) required reaching the target point of PA. As can be seen from Figure 5, travel time from StPh3 to PA is around 2 hours, after that, N_{SE} drops to the value achieved in case of no model update. Assimilation in hydrological model provides best model improvement also in case of high lead value. As expected, good fit of the simulated hydrographs and high N_{SE} values are achieved from the assimilation from all the distributed StPh sensors. In particular, up to 6 hours lead time N_{SE} values are affected by the assimilation of streamflow and W_L observations from all StPh sensors, while after that, only StPh1 influences the model performance.

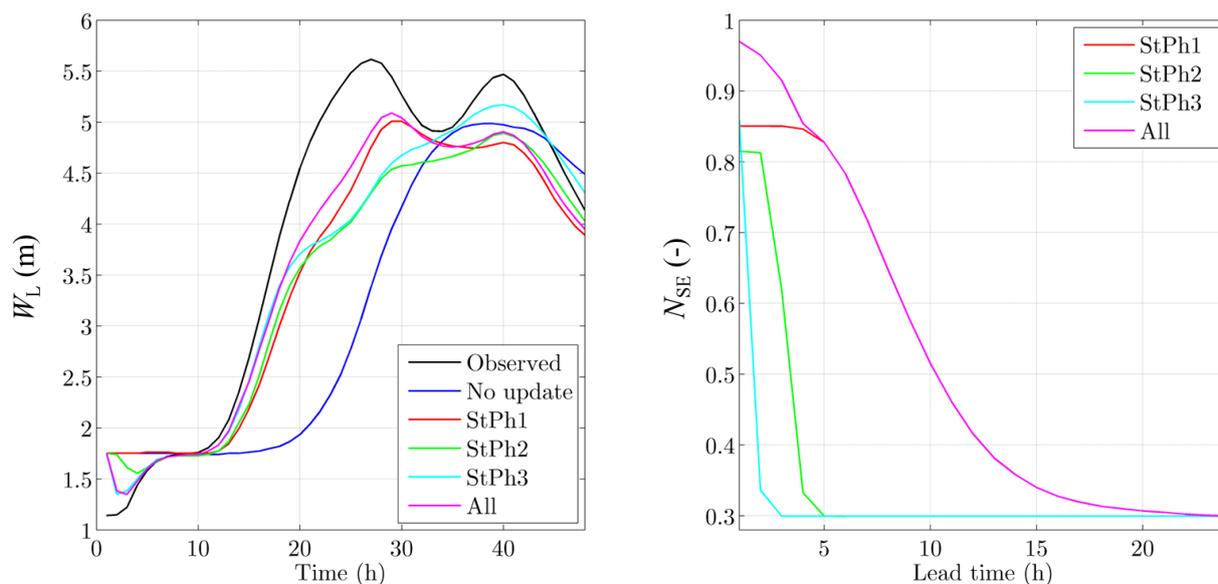


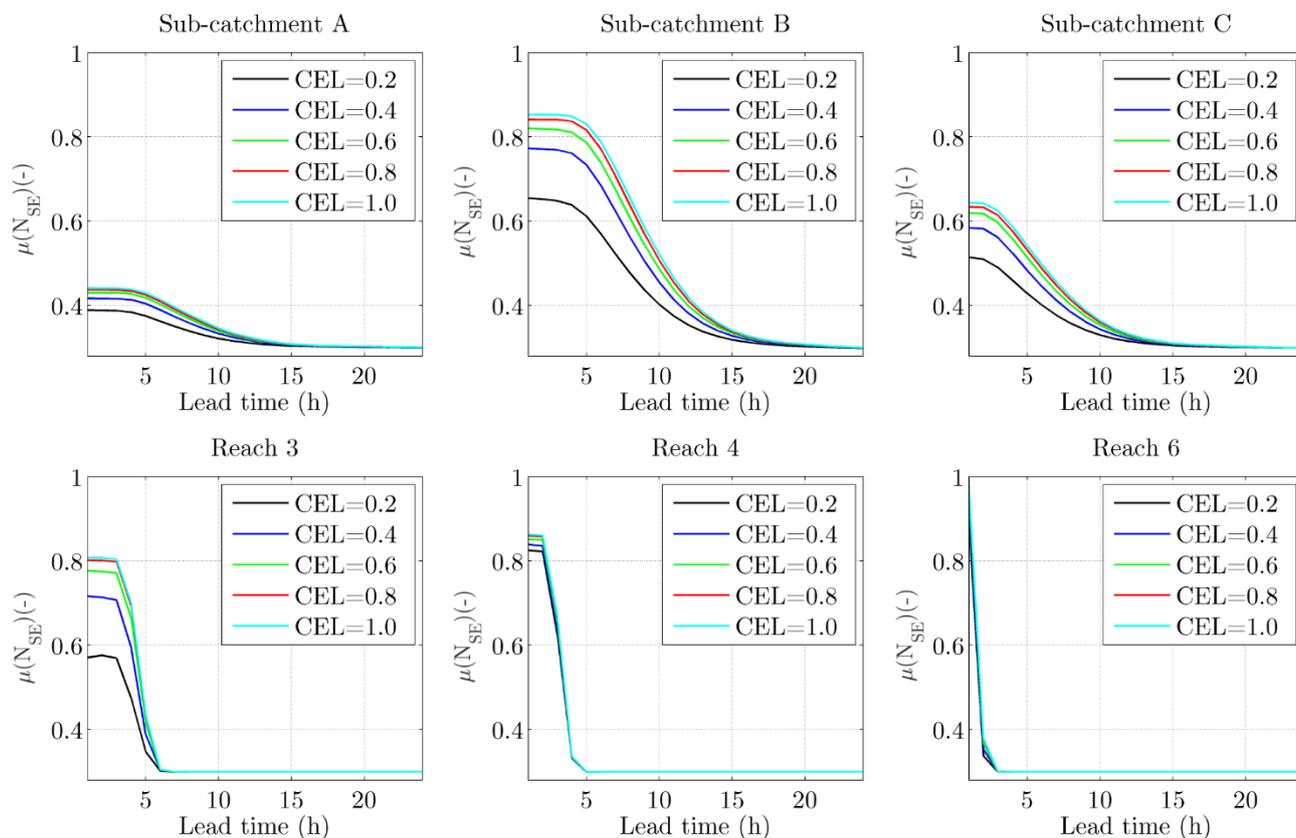
Figure 5. Hydrograph and N_{se} with assimilation of Q and W_L observations from StPh sensors in hydrological (StPh1) and hydraulic models (StPh2 and StPh3)



6.2 Experiment 2

6.2.1 Experiment 2.1

In Experiment 2.1, only the assimilation of CS observations from StSc sensors is considered. Because CS observations are not regular in time and they have variable accuracy, five engagement levels and random uniform values of the coefficient α are considered. Several model runs (100) are performed to account for such random behaviour of CS observations. In each run, a specific α value and arrival moment for each observation is considered and for this run a N_{SE} value is estimated. From the sampling of these 100 N_{SE} values, the corresponding mean $\mu(N_{SE})$ is calculated and shown in Figure 6 in case of assimilation from StSc sensors located at the outlet of the sub-catchment (hydrological model) or main river reaches (hydraulic models) where the sensors are located. As in case of Experiment 1, different lead time values of up to 24 hours are considered. From the results represented in Figure 6, it can be pointed out that assimilation from the hydrological model allows achieving good model predictions in case of high lead values. On the other hand, for short lead times, assimilation from StSc located in the river reaches (hydraulic model) induced high N_{SE} values if the sensors are located close to the PA station (reach 6 in Figure 6).



15 **Figure 6.** $\mu(N_{SE})$ obtained assimilating CS observations from different sub-catchments (first row) and river reaches (second row) in case of different Citizen Engagement Level (CEL) values.



However, this improvement is not guaranteed for high lead time values due to the short travel time as shown in the previous section. In fact, in case of assimilation in upstream reaches (as reach 3), N_{SE} is higher for high lead time values due to the system memory and higher travel time. As expected, for increasing engagement values, N_{SE} tends to increase as well. In case of engagement equal to 1, CS observations are received continuously at each time step, while for engagement equal to 0.6 the CS observations have a 60% random probability to be received and then assimilated into the hydrological and/or hydraulic models.

In Figure 7, the $\mu(N_{SE})$ values obtained assimilating CS observations derived from a combination of StSc sensors located in different sub-catchments and river reaches are represented for a lead time of 1 hour. For example, in the contour map located in the first row and first column, the N_{SE} values obtained assimilating CS observations from sub-catchments A and river reach 3 are shown for different engagement values.

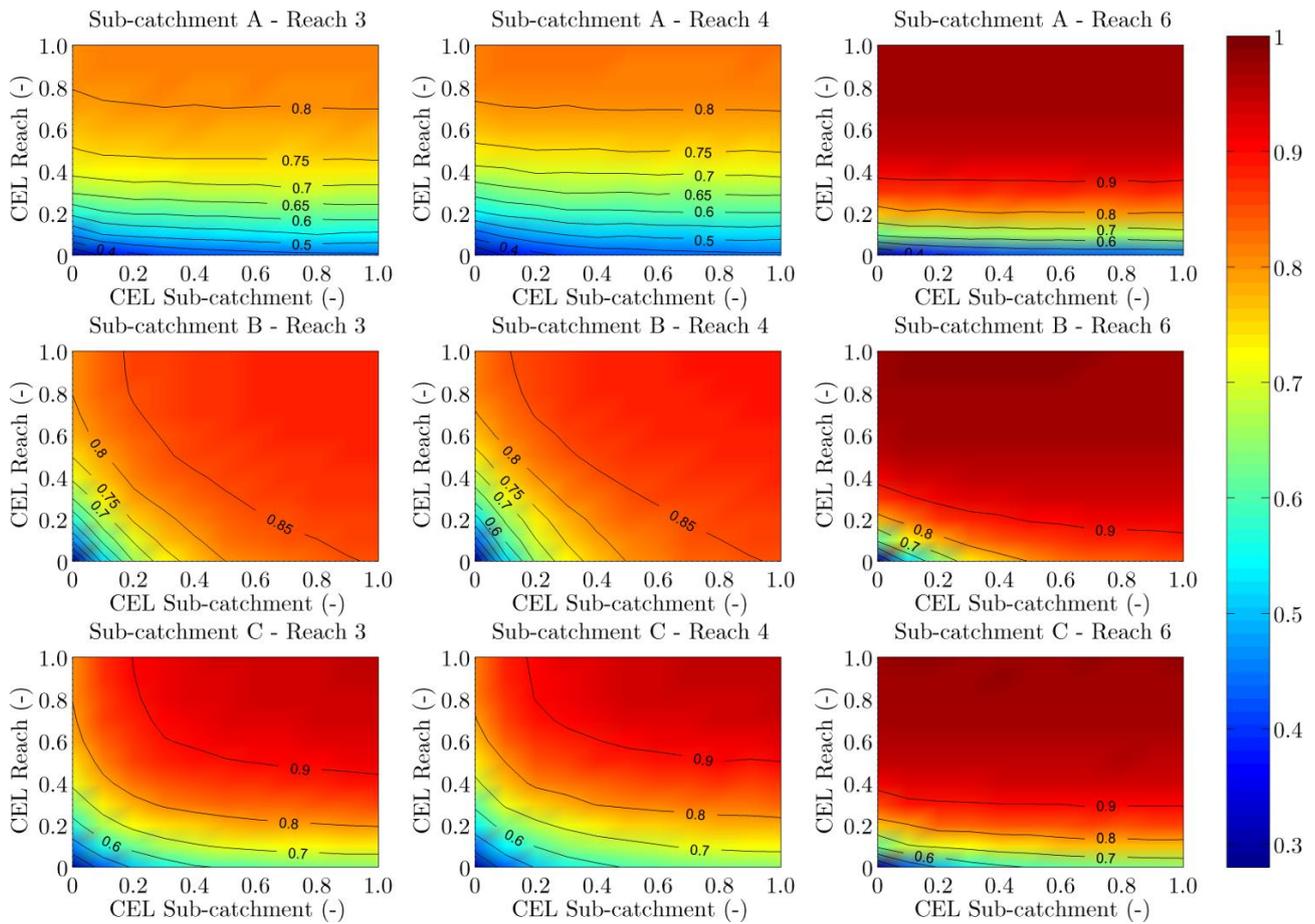


Figure 7. $\mu(N_{SE})$ values obtained assimilating CS observations from a combination of static social (StSc) sensors located in different sub-catchments and river reaches with 1-hour lead time in case of different Citizen Engagement Level (CEL) values.



Figure 7 shows that N_{SE} values are less affected by the assimilation of CS observations located in the sub-catchment A than in the other reaches. In fact, from the first row of Figure 7, it is clear that N_{SE} values change only for different engagement values of StSc sensors along reach 3, 4 and 6, while constant N_{SE} values are achieved for varying engagement values of the StSc2 (sub-catchment A). As previously shown, for a low lead time value, N_{SE} is higher in case of StSc sensors located in reach 6 rather than in the other river reaches 3 and 4.

In case of assimilation in sub-catchment B, second row of Figure 7, higher N_{SE} values are achieved if compared to the ones of the sub-catchment A (first row of the same figure). In particular, N_{SE} values are mainly influenced by different engagement levels of CS observations from sub-catchment B than from river reaches 3. However, moving from upstream (reach 3) to downstream (reach 6) a switch in the model behaviour can be observed, with an increasing influence of engagement in StSc sensors located in the river reach close to the PA station, as previously demonstrated (see contour map of sub-catchment B and reach 6 in Figure 7).

Similar results are shown for StSc sensors located in sub-catchment C and different river reaches (third row of Figure 7). However, engagement levels in upstream river reaches affect the N_{SE} values more than the engagement of StSc sensors in sub-catchment C. The same behaviour is manifested considering StSc sensors located from upstream river reach to downstream. The third row of Figure 7 can be considered as an average situation between the first (sub-catchment A) and second (sub-catchment B) row of the same figure.

Figure 8 is analogous to Figure 7, with the only difference that in this case the lead time is equal to 4 hours. Overall, N_{SE} values are lower for lead time equal to 4 hours than 1 hour, as expected. As previously discussed, assimilation of CS observations in river reaches located upstream the PA station allows to achieve higher N_{SE} values in case of high lead time than StSc located downstream. Model results are dominated by the assimilation in the sub-catchments A, B and C if compared to the engagement in reach 4 and 6. An intermediate situation is achieved for reach 3. In fact, engagement in reach 3 affects the N_{SE} values more than engagement levels in sub-catchment A and C. On the other hand, as in case of Figure 7 for 1-hour lead time, engagements in sub-catchment B has higher impact on N_{SE} values than engagement in reach 3.

In Figure 9, StSc sensors located in different sub-catchments and river reaches are assimilated at the same time considering three different lead time values. For lead time of 1 hour, high N_{SE} values are achieved even for small engagement values due to the high number of StSc sensors considered in the assimilation process (3 in the sub-catchments and 7 in river reaches). The higher the lead time value, the lower the model performance and the higher the influence of engagement of the StSc sensors located at the sub-catchment outlet over the sensors located at the river reaches.

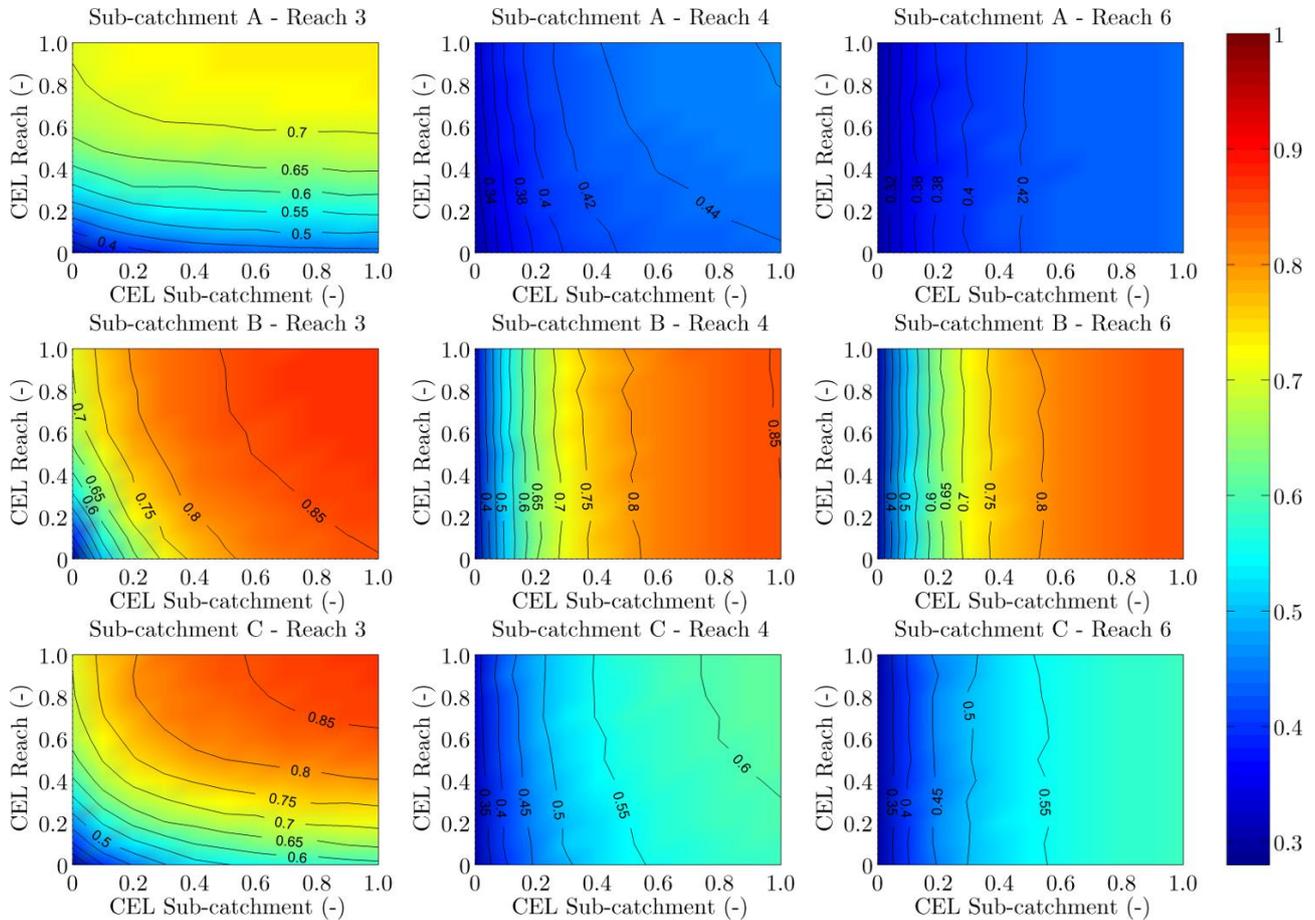
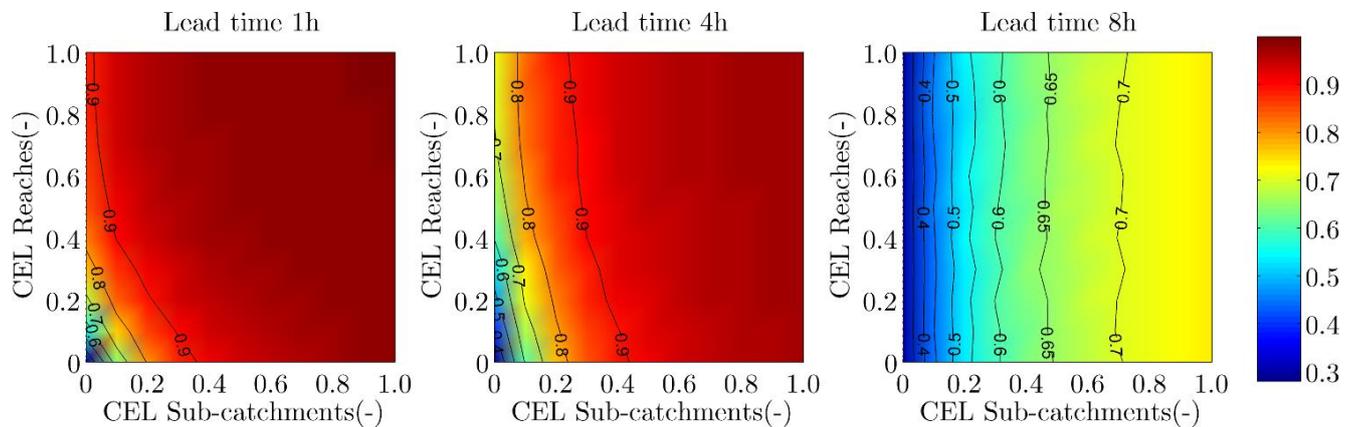


Figure 8. $\mu(NSE)$ values obtained assimilating CS observations from a combination of static social (StSc) sensors located in different sub-catchments and river reaches with 4-hours lead time in case of different Citizen Engagement Level (CEL) values.



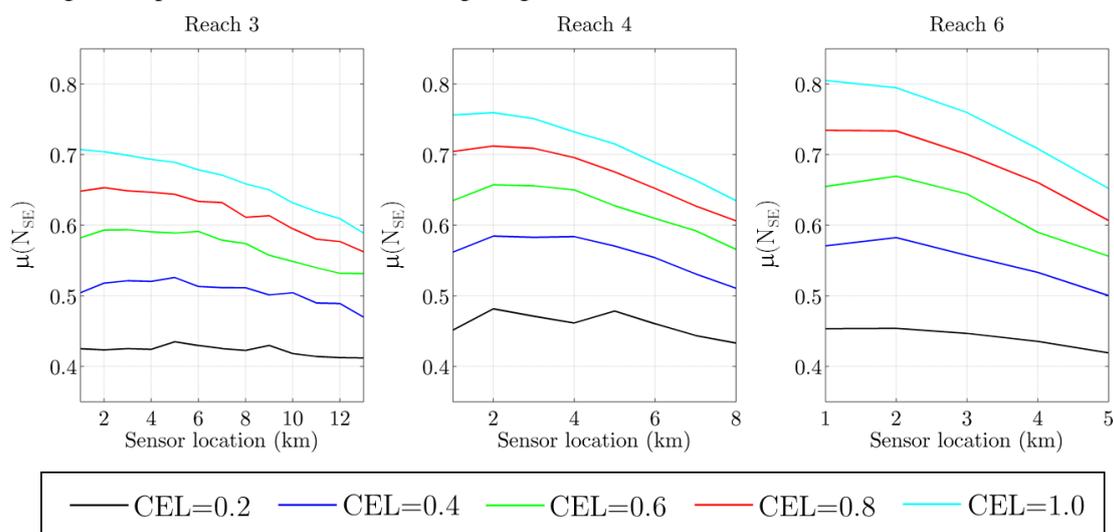
5 Figure 9. $\mu(NSE)$ values obtained assimilating CS observations from static social (StSc) sensors located in all sub-catchments and river reaches in case of 3 different lead time values and Citizen Engagement Level (CEL)



6.2.2 Experiment 2.2

In Experiment 2.2, the effect of assimilating CS observations from DySc sensors is analysed. In this case, the DySc sensors are assumed to be located only along the river reach 3, 4 and 6 so only the hydraulic model is used in this experiment. Moreover, 100 runs are carried out to account for the random accuracy and location of the CS observations.

- 5 Figure 10 shows the $\mu(N_{SE})$ values assimilating CS observations from DySc sensors at different locations along the three river reaches. In Figure 10, for each model run, the DySc sensor location is assumed fixed in time. Assimilation from DySc located close to the outlet of the Bacchiglione catchment provides the best N_{SE} values for engagement equal to one. As expected, N_{SE} values drop for reducing engagement values. Because boundary conditions have a higher error than the model error, N_{SE} tends to reduce moving from upstream to downstream along the given river reach.



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Figure 10. Effects of different dynamic social (DySc) sensor locations on the model performances in case of five values of Citizen Engagement Level (CEL)

- For both Figure 10 and Figure 11, the sensor location is assumed fixed in time, while both CS observation accuracy and engagement level are variable in time for a given river reach or combination of the two. However, in this case, DySc sensors are assumed located at all the river reach spatial discretization, i.e. at each 1000m, and not at one specific point as in Figure 10. In most of the cases, $\mu(N_{SE})$ values converge to an asymptotic threshold for increasing engagement levels. Among the three river reaches, 3 and 4 are the ones providing higher N_{SE} values for low engagement levels. This can be related to the high number of DySc sensors located in reach 3 (13 sensors) and 4 (8 sensors). On the other hand, reach 6 is better performing in case of high engagement levels. However, high $\sigma(N_{SE})$ values are obtained for reach 6 showing a significant sensitivity of model performance in case of different engagement levels. Assimilating DySc sensors from different reaches at the same time induces an overall improvement of $\mu(N_{SE})$ and $\sigma(N_{SE})$ reduction. Lowest $\sigma(N_{SE})$ values are obtained including DySc from reaches 3 and 4. However, this reduction in the $\sigma(N_{SE})$ values does not correspond to a relative high improvement in $\mu(N_{SE})$. In fact, the highest $\mu(N_{SE})$ are achieved joining sensors from reach 4 and 6, i.e. the closest river reaches to the PA station.

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Similar results in terms of $\mu(N_{SE})$ and $\sigma(N_{SE})$ are obtained joining reaches 3 and 6. It is worth noting that in both, Figure 10 and Figure 11, no bias in the observations from DySc sensors is considered.

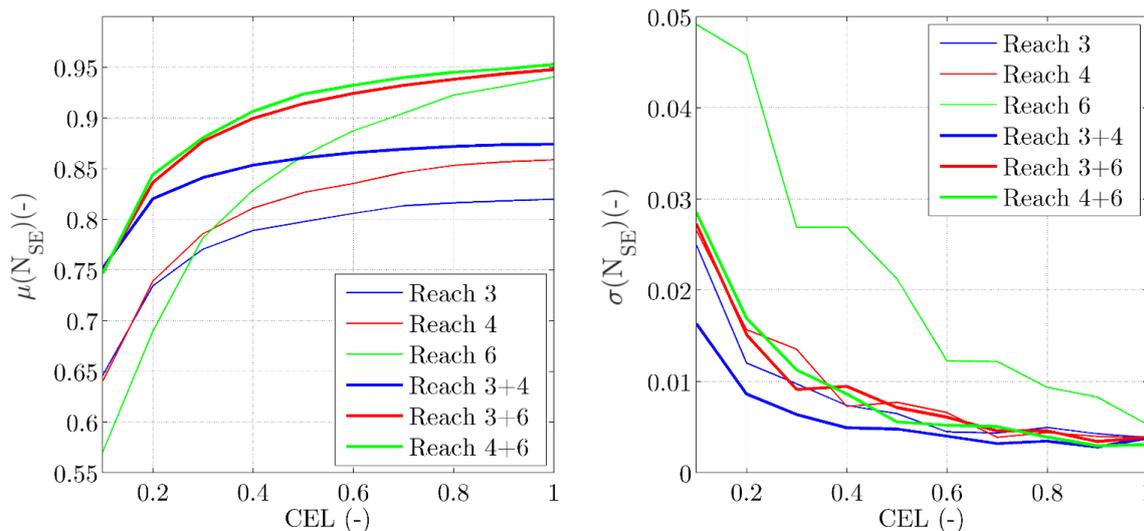


Figure 11. Effects of different level of engagement, in terms of $\mu(N_{SE})$ and $\sigma(N_{SE})$ in the assimilation of CS observations from dynamic social (DySc) sensors for different Citizen Engagement Level (CEL) values

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Figure 12 represents the $\mu(N_{SE})$ values obtained considering random locations of DySc sensors along the river reaches 3, 4 and 6 in 4 different cases of CS observation bias for 1 hour lead time. It is worth noting that reach 6 has five different sub-reaches of 1000m. This means that CS observations from only five sensors can be assimilated. However, in Figure 12 a total number of 13 DySc sensors is considered. In these experiments, the location of DySc sensors it is randomly generated. It might in fact happen that two sensors are located at distances of 2600m and 2900m from the upstream boundary condition. Because of the small spatial discretization of the hydraulic model (1000m), it is assumed that the difference between the hydrographs estimated between two different model discretization is negligible. For this reason, the two CS observations from the DySc sensors at 2600m and 2900m are simultaneously assimilated at the third sub-reach. In this way, it is possible to assimilate CS observations from a number of DySc sensors higher than the number of model spatial discretization.

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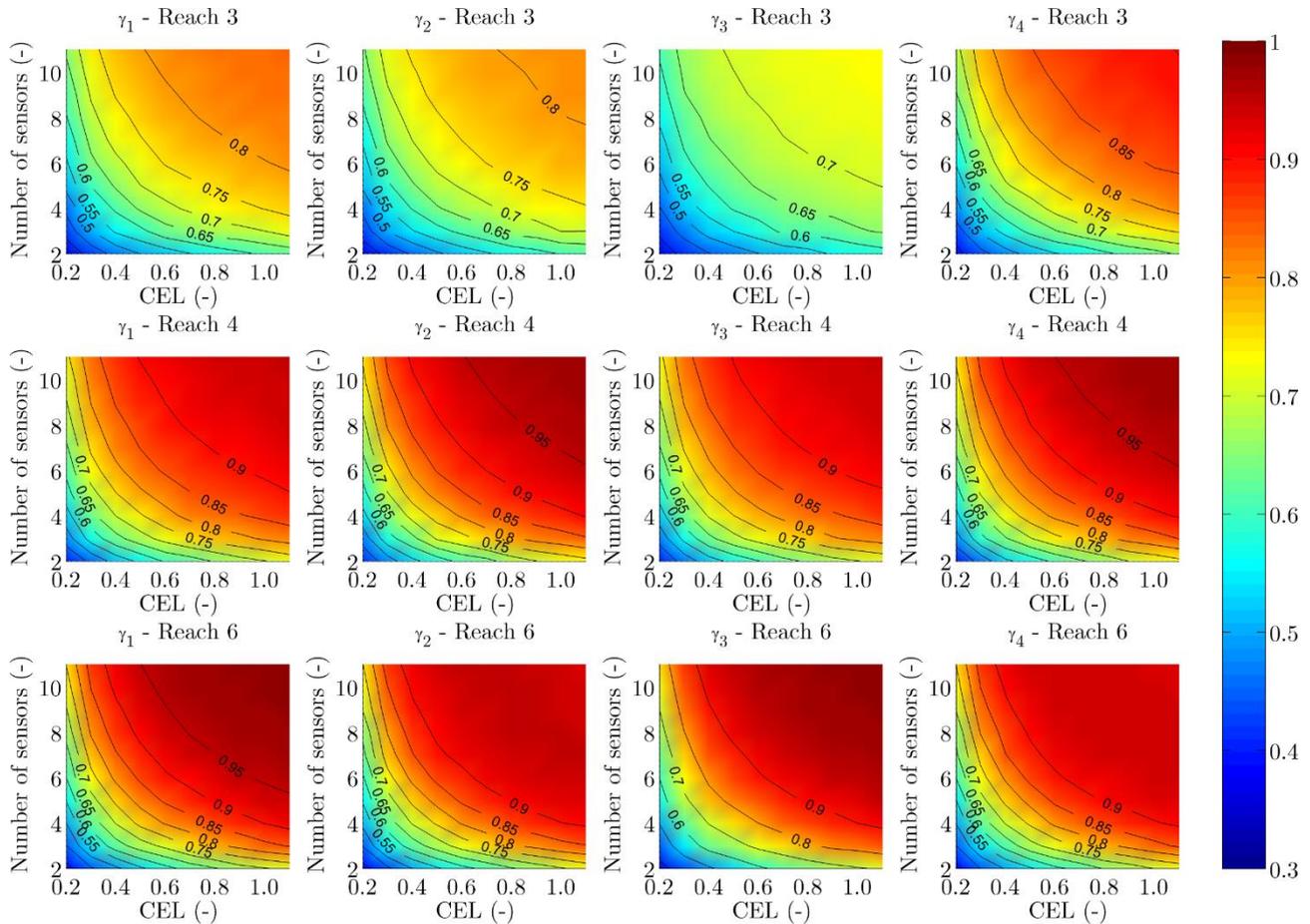


Figure 12. $\mu(N_{SE})$ values obtained considering random location of dynamic social (DySc) sensors along the river reaches 3, 4 and 6 in 4 different cases of CS observation bias for 1hour lead time and Citizen Engagement Level (CEL) values

As it can be observed, different γ values (bias assumptions) affect the model performance in different ways. Underestimation of the CS observations (γ_3) induces a reduction of the $\mu(N_{SE})$ values due to the underestimated forecasted precipitation which generated a consequent underestimated simulated water level hydrograph at PA in case of no model update. For the same reason, overestimation of CS observations (γ_4) causes an increase in model performance especially for a low number of DySc sensors and engagement levels. An intermediate behaviour between γ_3 and γ_4 is obtained in case of γ_2 . However, the indication of the N_{SE} alone is not enough to evaluate the obtained results in case of biased observations.

For this reason, the estimation of the B_1 metric, Eq.(14), is used in Figure 13 to provide additional evidence of the results just obtained. The highest B_1 values are obtained with DySc located in reach 6 in case of γ_4 , while the lowest are achieved in reach 3 with γ_3 . Reach 4 insures a compromise between high N_{SE} values and B_1 close to one.

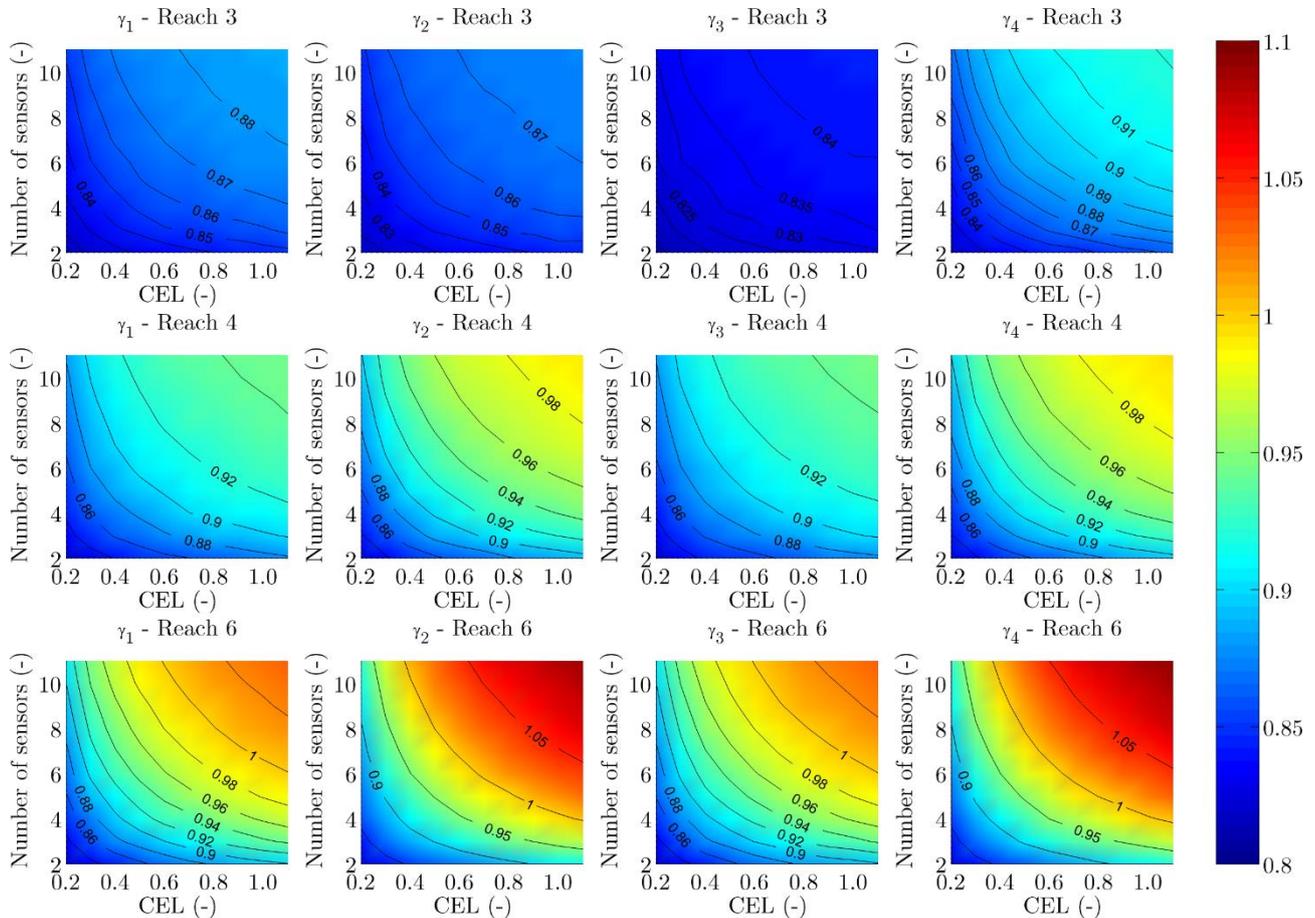


Figure 13. B_1 values obtained considering random location of dynamic social (DySc) sensors along the river reaches 3, 4 and 6 in 4 different cases of CS observation bias for 1hour lead time and Citizen Engagement Level (CEL) values

6.3 Experiment 3

5 Experiment 3 focuses on the assimilation of CS observations from a distributed network of heterogeneous StPh, StSc and DySc sensors. In particular, the engagement level is calculated in a more realistic way accounting for the population living in the surrounding 500m of the river. Six different engagement scenarios are introduced based on three citizen behaviours in collecting and sharing W_L observations. Based on Figure 4, different MCEL values are calculated.

Figure 14 shows $\mu(N_{SE})$ values in case of different engagement scenarios and MCEL according to the different type of sensors.

10 In fact, a random value of engagement level between 0 and MCEL for the fixed river sub-reach of 1000m is considered for a given model run. In particular, in Figure 14, smaller values of MCEL such as MCEL1, MCEL2, MCEL3, MCEL4 and MCEL5 are estimated as to MCEL/5, 2MCEL/5, 3MCEL/5, 4MCEL/5 and MCEL, respectively. It can be noticed that scenario 1 is the one providing the best model improvements, followed by scenarios 3 and 5. These results demonstrated that sharing CS observations driven by feeling of belonging to a community of friends (behaviour 2) can help improve flood prediction if such



a small community is located upstream of a particular target point. The results achieved in case of scenario 3 pointed out that a growing participation, of individualist citizens (behaviour 1), towards sharing hydrological observations in big cities can help to improve model performance. In particular, the model results can benefit from the additional observations provided by weather enthusiasts (behaviour 3). The difference between results obtained with scenarios 2 and 3 shows the influence of the growth rate parameter in the calculation of the MCEL curve for the same citizen behaviour.

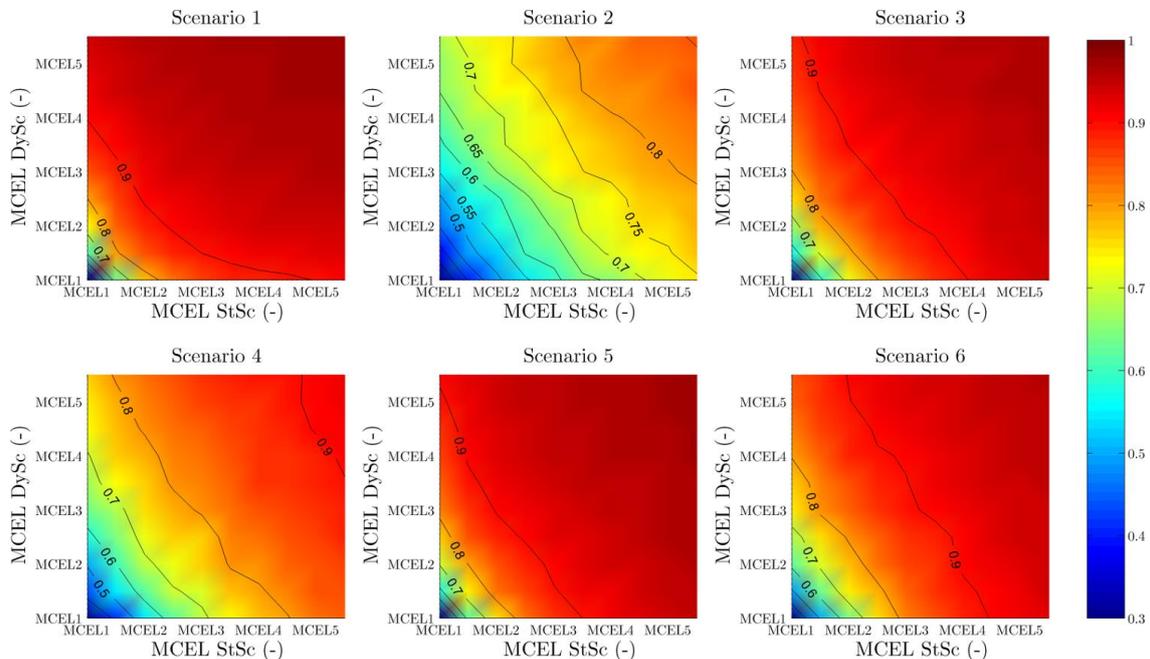


Figure 14. $\mu(N_{SE})$ values obtained in case of different Maximum Citizen Engagement Level (MCEL) scenarios comparing engagement level from static social (StSc) and dynamic social (DySc) sensors

Overall, the model results are more sensitive to the change of MCEL values in StSc sensors rather than DySc sensors. However, opposite results are shown in scenario 1. It is worth noting that no bias in the CS observations is assumed for DySc sensors. Low values of $\sigma(N_{SE})$, shown in Figure 15, are achieved in scenario 1, 3 and 5. Including weather-enthusiastic people (scenarios 4 and 5 if compared to 2 and 3) helps to reduce $\sigma(N_{SE})$, especially for low engagement values. Also in this case, $\sigma(N_{SE})$ values are more sensitive to the different engagement levels for the StSc sensors than DySc sensors. In particular, the highest values of $\sigma(N_{SE})$ are located for the value of MCEL equal to MCEL1 (for DySc sensors) and MCEL2 (for StSc sensors).

Analogous results are represented in Figure 16 and Figure 17 where a comparison between $\mu(N_{SE})$ and $\sigma(N_{SE})$ calculated for different engagement levels in the hydrological and hydraulic model is performed. Also in this case, good model improvement is achieved in scenarios 1, 3 and 5. In particular, $\mu(N_{SE})$ values are more sensitive to the assimilation of CS observations from random points in river reaches than from the outlet of the hydrological models. This effect is visible for engagement levels higher than MCEL3, i.e. 3MCEL/5. Figure 16 shows additional evidence on how CS observations provided by weather



enthusiasts are useful in order to increase $\mu(N_{SE})$ values passing from scenario 2 to 4 and from scenario 3 to 5. In the same way, the beneficial effect of a high growth rate in the citizen engagement can be observed moving from scenario 2 to 3 and from scenario 4 to 5.

The same results can be observed for $\sigma(N_{SE})$, Figure 17. Low $\sigma(N_{SE})$ values are achieved in scenarios 1, 3, and 5, as previously shown in Figure 15. In addition, variable values of $\sigma(N_{SE})$ are obtained for different engagement levels along the river reaches, while no changes in $\sigma(N_{SE})$ are visible for varying engagement levels in the sub-catchments.

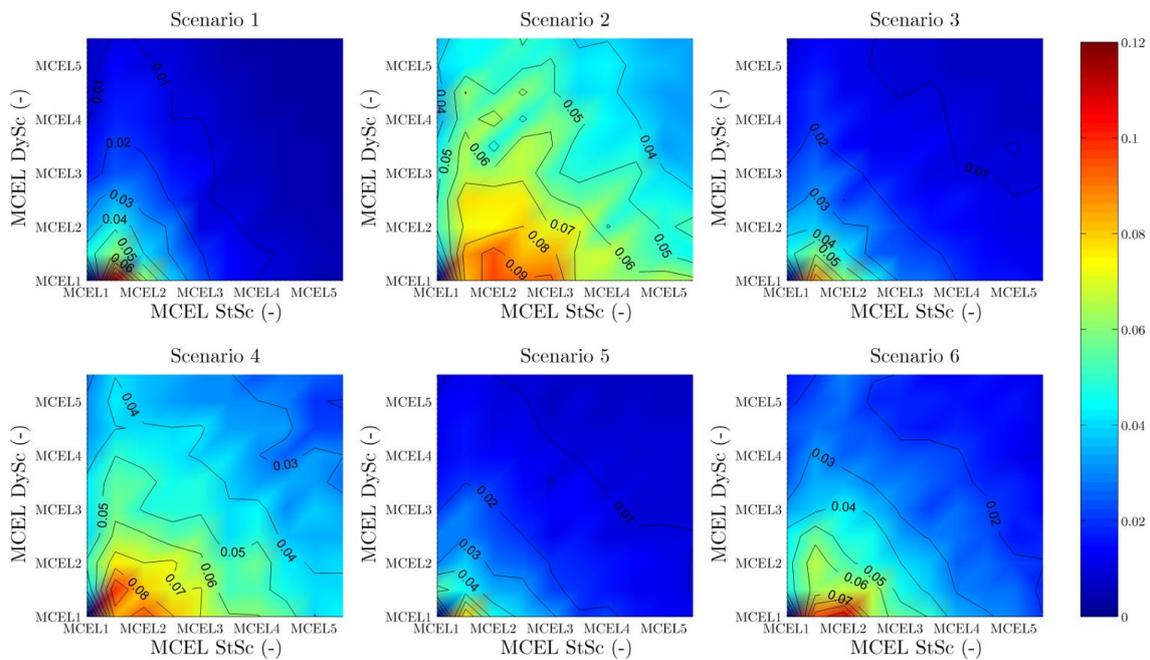


Figure 15. $\sigma(N_{SE})$ values obtained in case of different Maximum Citizen Engagement Level (MCEL) scenarios comparing engagement level from static social (StSc) and dynamic social (DySc) sensors

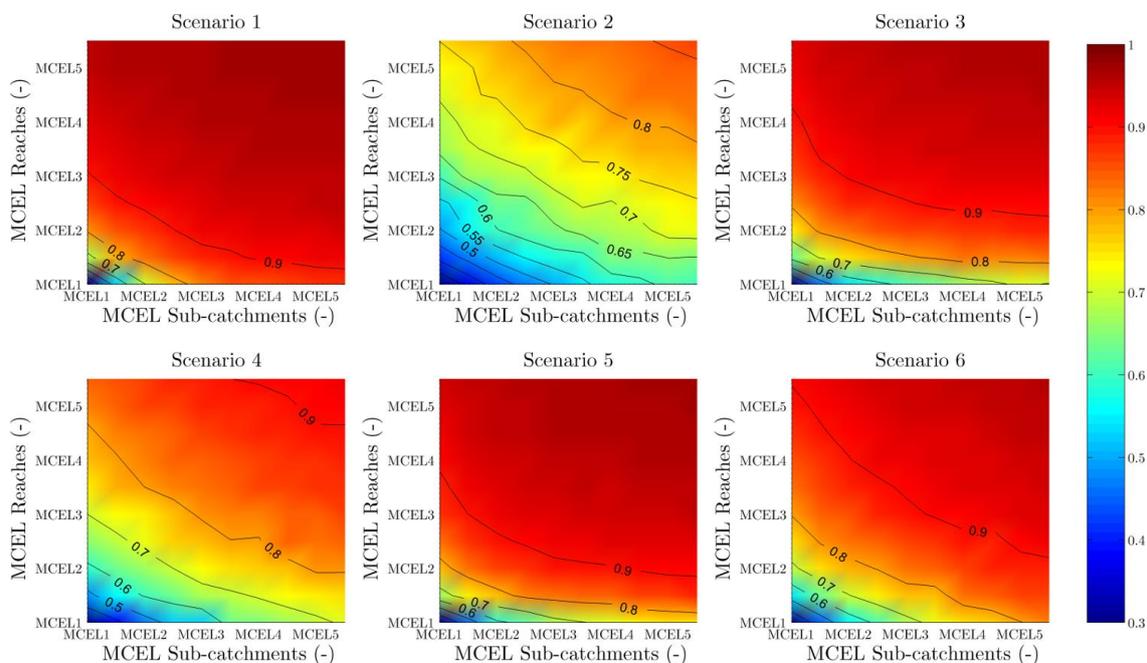
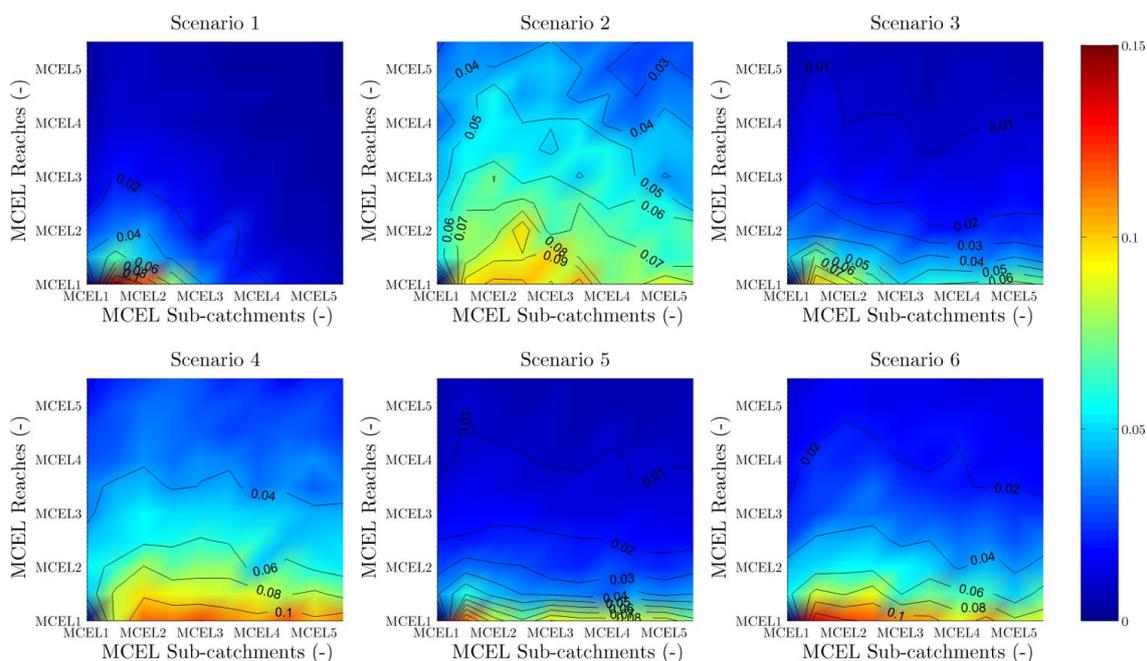


Figure 16. $\mu(N_{SE})$ values obtained in case of different Maximum Citizen Engagement Level (MCEL) scenarios comparing engagement level from hydrological (sub-catchments) and hydraulic models (reaches)



5 Figure 17. $\sigma(N_{SE})$ values obtained in case of different Maximum Citizen Engagement Level (MCEL) scenarios comparing engagement level from hydrological (sub-catchments) and hydraulic models (reaches)



7 Summary and conclusions

This study assessed the modelling usefulness of assimilating crowdsourced (CS) observations as referred in Section 2.2. A network of distributed heterogeneous sensors is used to assess the potential effects on model performance measures (Section 4.4). The assessment is done for the prediction of the May 2013 flood event in the Bacchiglione catchment, so general conclusions cannot be derived based on this study only. In particular, water level observations from static physical (StPh), static social (StSc) and dynamic social (DySc) sensors, installed within the WeSenseIt Project are assimilated within a semi-distributed hydrological and hydraulic model of the Bacchiglione catchment (Section 3). Because CS observations of water level are not available at the time of this study, we used an experimental setup of synthetic observations with intermittent arrival time and random accuracy in time and space (Section 4). Three different sets of experiments are carried out. In particular, in Experiment 3, six citizen engagement levels scenarios are introduced, in order to provide realistic representation of the arrival moments of CS observations. Scenarios are based on the combination of population distribution and three citizens' behaviours to collect data: 1) own personal purposes; 2) shared or community interests and 3) societal benefits. We summarize the results of these experiments as follows:

- **In Experiment 1, observations from StPh sensors are assimilated:** Assimilation in the hydrological model provides the best model improvement, in terms of water level hydrograph at PA (Vicenza), if compared to the other StPh sensors located along the river reach. Assimilation from StPh2 insures a better model prediction for a high lead time value than the assimilation from the StPh3 sensor, located close to the PA station.
- **In Experiment 2.1, only the assimilation of CS observations from StSc sensors:** In case of high lead values, assimilation from the hydrological model allows to achieve good model predictions, while, for short lead times, assimilation from StSc sensors located in the river reaches close to the target point of PA improves model performance. N_{SE} values are more affected by the assimilation of CS observations from StSc sensors located in sub-catchment B rather than in sub-catchments A and C. For high lead time values, N_{SE} values are dominated by engagement levels in the sub-catchment A, B and C if compared to the engagement in reach 4 and 6. Different engagement levels in reach 3 affects the N_{SE} values more than engagement levels in sub-catchment A and C.
- **In Experiment 2.2, assimilation of CS observations from DySc sensors randomly distributed along the river reaches 3, 4 and 6 is analysed:** High values of N_{SE} are achieved for DySc sensors located at points close to the boundary conditions, while moving the sensor to downstream locations lower N_{SE} values are obtained. This is because boundary conditions, i.e. hydrological model output, have higher error than model error. Different scenarios of observation biases are considered in this experiment.
- **In Experiment 4, a simplified social model is used to propose realistic scenarios of engagement levels:** CS observations driven by feeling of belonging to a community of peers (behaviour 2) can help to improve flood prediction if such small communities are located in the upstream part of the catchment. On the other hand, growing participation of individualist citizens, sharing hydrological observations in big cities can help to improve model



performance. In particular, the model results can benefit from the additional observations provided by weather enthusiasts.

A part from the important results achieved in this study, a number of limitations have to be addressed:

- In order to generalize the findings of this research, the proposed methodology has to be applied in additional case studies and flood events. In fact, the results of this study might be influenced by the particular features of the catchment and the location of the urban areas used in Experiment 3. Additional flood events should be considered as well.
- Real CS observations should be used. In this study, CS observational error and accuracy level vary according to the sensor type static or dynamic. We assumed observational errors (bias) randomly distributed based on accuracy ranges that slightly improve according to the citizens' expertise level. We further assume that CEL affects only observations intermittency rather than accuracy. This study is a first step to assess the effects of CS observations in flood model predictions. In reality, CS observations can be affected by the combination of CEL, the safety of the location and the quality control mechanisms that are in place. For example, mobile applications should include validation procedures upon submission. Effective communication and feedback from water authorities to engaged citizens is further required to minimize intrinsic low-variable accuracy of crowdsourced observations.
- Finally, no specific spatial sensor trajectory of the citizens moving from one StSc sensor to another or using DySc sensors is considered since this would require the introduction of assumptions about citizens' behaviour in the case of a flood event. This component would be extremely important in the case of dynamic sensors but it could not be included in this research due to the lack of information about citizen engagement in monitoring river water level in the case study. Agent Based Models, which simulate the interactions between autonomous agents, could be introduced in future studies and integrated into the presented mathematical modelling framework.

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