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Exploring the influence of citizen involvement on the assimilation of crowdsourced observations: a modelling study based on the 2013 flood event in the Bacchiglione catchment (Italy)

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Abstract. To improve hydrological predictions, real-time measurements derived from traditional physical sensors are integrated within mathematic models. Recently, traditional sensors are being complemented with crowdsourced data (social sensors). Although measurements from social sensors can be low cost and more spatially distributed, other factors like spatial variability of citizen involvement, decreasing involvement over time, variable observations accuracy and feasibility for model assimilation play an important role in accurate flood predictions. Only a few studies have investigated the benefit of assimilating uncertain crowdsourced data in hydrological and hydraulic models. In this study, we investigate the usefulness of assimilating crowdsourced observations from a heterogeneous network of static physical, static social and dynamic social sensors. We assess improvements in the model prediction performance for different spatial–temporal scenarios of citizen involvement levels. To that end, we simulate an extreme flood event that occurred in the Bacchiglione catchment (Italy) in May 2013 using a semi-distributed hydrological model with the station at Ponte degli Angeli (Vicenza) as the prediction–validation point. A conceptual hydrological model is implemented by the Alto Adriatico Water Authority and it is used to estimate runoff from the different sub-catchments, while a hydraulic model is implemented to propagate the flow along the river reach. In both models, a Kalman filter is implemented to assimilate the crowdsourced observations. Synthetic crowdsourced observations are generated for either static social or dynamic social sensors because these measures were not available at the time of the study. We consider two sets of experiments: (i) assuming random probability of receiving crowdsourced observations and (ii) using theoretical scenarios of citizen motivations, and consequent involvement levels, based on population distribution. The results demonstrate the usefulness of integrating crowdsourced observations. First, the assimilation of crowdsourced observations located at upstream points of the Bacchiglione catchment ensure high model performance for high lead-time values, whereas observations at the outlet of the catchments provide good results for short lead times. Second, biased and inaccurate crowdsourced observations can significantly affect model results. Third, the theoretical scenario of citizens motivated by their feeling of belonging to a "community of friends" has the best effect in the model performance. However, flood prediction only improved when such small communities are located in the upstream portion of the Bacchiglione catchment. Finally, decreasing involvement over time leads to a reduction in model performance and consequently inaccurate flood forecasts.

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1 Introduction

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 structures and to regulate water levels. Reliable and accurate streamflow simulation and water level prediction by means of hydrological and hydraulic models are therefore of utmost importance. However, model performance and related predictions are inherently uncertain due to the lack of reliable and sufficient observational data, lack of understanding of the natural hydrological and hydraulic processes, and the limitations and assumptions of the modelling system (Merz et al., 2010, p. 514).

Various attempts have been made to improve the accuracy of flood model predictions for operational early warning. In particular, data assimilation techniques have been used extensively (Liu et al., 2012). Data assimilation is a common method for updating model input, parameters, states or outputs. It is used to integrate real-time observations of hydrological variables (WMO, 1992; Refsgaard, 1997) while accounting for the uncertainties in both model and observed data (McLaughlin, 1995; Robinson et al., 1998; McLaughlin, 2002; Madsen and Skotner, 2005; Lahoz et al., 2010; Liu et al., 2012). In operational early-warning systems, only observed data derived by static physical (StPh) sensors are used, as described in Liu et al. (2012). However, recent studies have demonstrated that water system models could improve their performances with the assimilation of observations from multiple sources, such as in situ and remote sensors, and other hydrologic variables such as soil moisture and streamflow (Aubert et al., 2003; McCabe et al., 2008; Pan et al., 2008; Lee et al., 2011; Montzka et al., 2012; Pipunic et al., 2013; López López et al., 2016; Rasmussen et al., 2015). Those studies have also shown that data assimilation applications require specific, frequent and high-quality measurements.

In parallel, the availability of recent technological advances to the public has strengthened the idea of involving people in data collection. This idea is not limited to the data collection of flood or real-time information, and various terms have been used in scientific literature (Wehn and Evers, 2015). In natural sciences this idea is known as "citizen science" (Silvertown, 2009), in geography as "volunteer geographic information, VGI" (Goodchild, 2007) and "crowdsourcing geospatial data" (Heipke, 2010), and in computer science as "people-centric sensing" (Campbell et al., 2006) and "participatory sensing" (Höller et al., 2014). Other terms explicitly emphasize the involvement of the public, for instance the "value of information and public participation" (Alfonso, 2010), "public computing" (Anderson, 2003) and "community data collection" (Aanensen et al., 2009).

Crowdsourcing particularly refers to the involvement of a large, often undefined and diverse group of people in data collection and/or data analysis and can be mediated via information technologies and online tools or platforms (Xintong et al., 2014). In this study, we refer to crowdsourced (CS) citizen-based observations as the involvement of citizens in general (whether experts or not) in collecting water level observations at a particular location via a smartphone application upon request of water authorities.

Several previous studies have attempted to use CS citizens-based observations in water system models since more spatially distributed coverage can be achieved (Alfonso, 2010; Fava et al., 2014; Smith et al., 2015; Fohringer et al., 2015; Gaitan et al., 2016; Giuliani et al., 2016; de Vos et al., 2017; Rosser et al., 2017; Schneider et al., 2017; Starkey et al., 2017; Yu et al., 2016). In Fava et al. (2014), a methodology for flood forecasting integrating VGI and wireless sensor networks is proposed. Smith et al. (2017) and Fohringer et al. (2015) proposed frameworks for real-time flood monitoring using information retrieved from social media. In both studies, the observation filtering process was one of the main challenges. Rosser et al. (2017) proposed a data fusion method to rapidly estimate flood inundation extent using observations from remote sensing, social media and high-resolution terrain mapping. Yu et al. (2017) validated the results of an urban hydro-inundation model (surface-water-related flooding) with a crowdsourced dataset of flood incidents. In a similar fashion, Starkey et al. (2017) demonstrated the value of community-based observations for modelling and understanding the catchment response. In particular, they showed significant improvement in the spatial and temporal characterization of the catchment response by integrating a local network of community-based observations together with a traditional network rather than using traditional observations only. Recently, Herman Assumpção et al. (2017) have provided a detailed review of studies in which citizen observations are used for flood modelling applications.

However, none of the previous studies assessed the usefulness of CS observations in improving flood predictions, nor have they taken into account the variable distribution, intermittency and, potentially, lower quality of citizen-based data (Shanley et al., 2013; Buytaert et al., 2014; Lahoz and Schneider, 2017). The first attempts are reported in Mazzoleni et al. (2015, 2017a, b) and Mazzoleni (2017). In those studies, the authors investigated the effects on flood prediction in assimilating real-time (synthetic) CS observations in hydrological models. However, in the former studies the authors did not investigate the effects of assimilating (synthetic) CS observations in hydraulic models. Furthermore, the authors did not consider (theoretical) scenarios of citizen involvement, nor the simultaneous assimilation of CS observations from static and dynamic social sensors. For this reason, the main objective of this study is to assess the usefulness of assimilating CS observations in model-based predictions of flood events. We analyse a flood event which occurred in May 2013 in the Bacchiglione catchment (Italy). Static physical, static social (StSc) and dynamic social (DySc) sensors are considered in this study. Synthetic CS observations

of water level are assimilated in a cascade of hydrological and hydraulic models since real CS measurement are not yet available for this particular study site. Two sets of experiments of theoretical scenarios are analysed. Citizen involvement level (CIL) is further defined as the probability of receiving a CS observation based on the citizen's own interest or intention in collecting water levels. We assume that CILs mainly limit the intermittency or timely availability of observations. The achievement of the paper's objective is a step forward in understanding the effect of public involvement on the possible improvement of hydrological and hydraulic models, with methods that can be replicated in other fields.

2 Case study

2.1 The Bacchiglione catchment

The Bacchiglione catchment (north-eastern Italy, see Fig. 1) is one of the case studies in which the WeSenseIt (WSI) Citizen Observatory of Water project (http://wesenseit.com) developed and tested innovative static and low-cost mobile sensors (Ciravegna et al., 2013). The main goal of the WSI project was to allow active citizens to support the work of water authorities by providing CS observations. Innovative static sensors were strategically integrated into the existing monitoring networks for collecting physical and CS data. Low-cost mobile sensors were developed such as a mobile phone application, which uses a quick response (QR) code for geographical referencing and allows to send, among others, flood reports and water level (W_L) observations. In addition, the WSI project set up a pilot platform in which CS observations collected with this application can be sent. However, this pilot is not yet operational and CS observations are not yet available (see details of the testing of this pilot in Sect. 2.3). In this research, only W_L data are assimilated.

This research focuses on the upper part of the Bacchiglione catchment which flows into the Adriatic Sea in the south of the Venetian Lagoon. The case study has an overall extent of about 450 km^2 with a river length of approximately 50 km. The three main tributaries are the Timonchio River on the east side and Leogra and Orolo rivers on the west side. The main urban areas are located close to the outlet section of the case study area, the city of Vicenza. 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., 2017a). Forecasted and measured precipitation time series are available for a flood event that occurred in May 2013. The forecasted precipitation time series are provided by the COSMO-LAMI model, a regional model that provides numerical prediction over the national territory at 7 km resolution and 3-day time interval. Currently, AAWA is performing quality control on the forecasted data before using them in the Bacchiglione flood early-warning system. The measured precipitations are supplied and validated by Veneto Regional Agency of Environmental Prevention and Protection (ARPAV). The event of May 2013 is considered to be significant due to its high intensity, which resulted in several traffic disruptions at various locations upstream of Vicenza. In this study, we assess the usefulness of assimilating CS W_L (synthetic) observations in the hydrological and hydraulic models to improve model performance and consequently flood prediction.

2.2 Sensor classification

Although CS observations were neither operational nor available in the case study, we analysed the characteristics of each sensor to generate the synthetic W_L observations that we assimilated for the flood event of 2013. We considered three types of sensors to measure W_L, static physical, static social and dynamic social sensors. Currently, only StPh sensors are used by AAWA to provide daily flood forecasts in the Bacchiglione catchment. This section of the paper aims to describe the characteristics of these sensors in terms of spatial coverage and accuracies.

The StPh sensors are traditional physical sensors such as water level ultrasonic sensors. StPh have a fixed location and a regular measurement interval. Data from StPh sensors are validated by ARPAV. Observational error depends on how well the cross section where the StPh sensor is located is documented and on random and bias errors due to sensor characteristics. Despite the potential observational error, we assume a high accuracy level as the observation is automatically generated by the sensor and therefore not affected by the variability of CS data.

StSc sensors have a higher spatial distribution than StPh sensors along the river reach but are characterized by intermittent CS observations. The StSc sensors are staff gauges at safe, strategic and accessible locations along the river reaches. Citizens can report observations using these static sensors to estimate W_L values. According to the data collection tool, CS observations can come in a variety of formats either quantitative or qualitative, which is often one of the biggest challenges when involving citizens. Automatic mechanisms for data processing can be implemented. For example, whenever photos are collected, these can be automatically analysed using image recognition methods as proposed by van Overloop and Vierstra (2013) and Le Boursicaud et al. (2016). In this case, a reference gauge must be available. The WSI mobile phone application will be used to send quantitative measurements (water level) observed at a specific staff gauge. Photos and videos are not supported by the WSI application. The geographical referencing will be provided by means of QR codes together with associated date and time. The WSI mobile application is equipped with a filter that automatically discards those water level measurements that fall outside the range associated with the staff gauge.

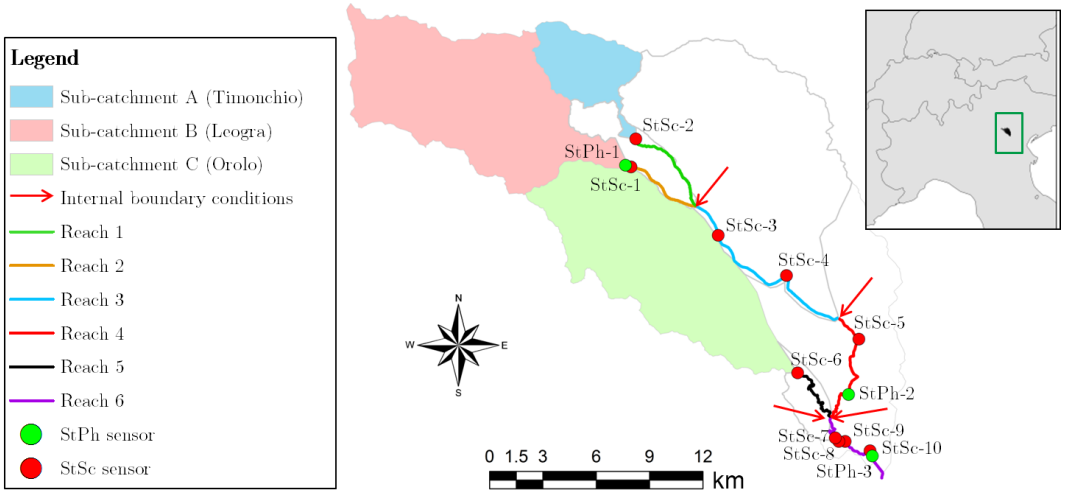

Figure 1. Spatial distribution of the sub–catchments, river reaches, and StPh and StSc sensors implemented in the catchment by AAWA. The prediction point of Ponte degli Angeli (PA) corresponds to the StPh-3 sensor.

DySc sensors do not have fixed locations. Water level observations at a particular location via a smartphone application can be requested by water authorities according to the accessibility of the location. A possible method for measuring flow using DySc sensors is described in Lüthi et al. (2014). The authors proposed an approach based on particle image velocimetry to estimate with acceptable accuracy water level, surface velocity and runoff in open channels. However, this approach requires a priori knowledge of the channel geometry at the location of the measurement, which is one of the main sources of uncertainty. For this reason, in this paper it is assumed that DySc sensors have lower accuracy than StSc sensors. Another example of DySc sensors is reported in Michelsen et al. (2016) where water level time series are derived from the analysis of YouTube videos. It is worth noting that the WSI mobile application does not allow for automatic retrieval of flow information from photos and video as proposed in Lüthi et al. (2014).

As reported in Table 1, W_L observations have different characteristics of temporal availability and accuracy based on the adopted sensor and changes in the cross section. Regardless of the type of social sensor, whether expert or amateur, we acknowledge that the data accuracy and intermittency of CS observations can be affected by various factors. Source of errors in observations include but are not limited to the following (Cortes Arevalo, 2016; Kerle and Hoffman, 2013; Le Coz et al., 2016): (i) the expertise level (training and experience is required to read a gauge, take a picture and use the mobile application), (ii) type and format of CS observation based on sensor classification and data collection procedure (W_L measurement and photo with reference to a staff gauge vs. a photo with reference to a neighbouring object), and (iii) the specific conditions at the reporting location (accessibility, visibility and environmental conditions). Intermittency (temporal availability) of the CS observations is directly related to CIL, i.e. the probability of receiving a CS observation. In addition, CS observations imply the filtering and integration of a variety of formats and information types, which are required to develop suitable tools for data collection and processing (Kosmala et al., 2016).

2.3 Citizen involvement in the Bacchiglione catchment

Gharesifard and Wehn (2016) categorized participants into "netizens", citizen scientists and volunteers to accordingly distinguish: (i) unawareness about their implicit involvement and contribution to monitoring networks (netizens); (ii) explicit and intentional involvement in data provision (citizen scientists) and (iii) the involvement of individuals or groups that are systematically targeted and recruited to participate in data provision with predefined goal(s) (volunteers).

In the framework of the WeSenseIt project, an exercise was carried out with volunteers who were providing water level observations via the smartphone application, from a limited number of locations to test the pilot set up. However, due to the limited number of participants, duration and testing goal of the exercise, no formal assessment of citizen involvement could be undertaken. For this reason, we propose theoretical involvement scenarios to represent the hypothetical situations according to which citizens are fully or partially involved in the Bacchiglione catchment. In the numerical simulations performed in this study, we did not make a distinction between citizen expertise (expert or amateur) and involvement type (citizen scientists or volunteers). We do not refer to the engagement process (how to get citizens involved) but rather to the involvement level (probability of receiving a CS observation based on the citizen's own interest or intention in collecting water levels). In fact, motivations and involvement levels are the only variables that differentiate the citizens, as described in the next sections.

Table 1. General characteristics of the type of observations based on sensor classification.

Sensor type	Type of observation	Location	Time of availability	Observational error	Example reference	Assumed accuracy level
Static physical (StPh)	Water level time series	Fixed, generally in key inlet or outlets	Each model time step	Missing data due to, for example, unexpected damage or lack of maintenance; Observational noise due to flow conditions and water level below or above the optimum range; Missing or non-representative rating curve due to changes in the cross section.	Irrigation Training and Research Center, 1998, p. 58	High
Static social (StSc)	Water level and photo of the river gauge	Fixed but distributed at strategic points along the river reach	Intermittent, according to CIL	Same as StPh; Inaccurate reading of the river gauge; Inaccurate photo limiting validation; Unknown expertise level of the citizen reporting.	Le Boursicaud et al. (2016), 95–99; Le Coz et al. (2016), p. 770	Medium
Dynamic social (DySc)	Photo and water level estimation by means of mobile application	Variable	Intermittent, according to CIL and accessibility level to the river reach	Same as StPh; Same as StSc but inaccurate estimation of the flow using mobile application; Unknown (irregular) cross section and river bank conditions at the reported location.	Le Boursicaud et al. (2016), 95–99; Le Coz et al. (2016), p. 770	Low

3 Modelling tools

3.1 Semi-distributed hydrological model

In order to implement the semi-distributed model, the Bacchiglione catchment is divided into different sub-catchments and the so-called inter-catchments which contribute streamflow to the main river channel up to the urbanized area of Vicenza. In the schematic representation of the Bacchiglione catchment (see Fig. 1), the location of the StPh and StSc sensors corresponds to the outlet section of the three main sub-basins, Timonchio, Leogra and Orolo. The remaining sub-basins are considered as inter-catchments. The rainfall–runoff processes within each sub-catchment and inter-catchment are represented by the conceptual hydrological model developed by AAWA. In the case of the main river channel, a hydraulic model is used to propagate the flow down to the gauge station of PA in Vicenza. The river reach is divided into several reaches according to the location of the internal boundary conditions. We use hydrological outputs as upstream (from sub-catchments) and internal boundary conditions (from inter-catchments). Figure 1 shows that the output of the hydrological model (red arrows) are boundary conditions for the proposed hydraulic model.

3.1.1 Hydrological modelling

The hydrological model used in this study is a part of the early-warning system implemented and used by AAWA. We briefly relate to the model equation here, as a detailed description is available in Ferri et al. (2012) and Mazzoleni et al. (2017a). Precipitation time series is the only input. The water balance is applied to a generic control volume of active soil, on the sub-basin scale, to mathematically represent the processes related to runoff generation processes such as surface, subsurface and deep flow.

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

where $S_{W,t}$ is the water content at time t, P is the precipitation component, E_T is the evapotranspiration, R_{sur} is the surface runoff, R_{sub} is the subsurface runoff and L is the deep percolation. Temperature is used for the estimation of the real evapotranspiration, which is calculated using the formulation of Hargreaves and Samani (1985). The routed contributions of the surface flow Q_{sur}, subsurface flow 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.

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 (PA) for a period between 2000 and 2010 (Ferri et al., 2012). 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:

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

$$z_t = H(\boldsymbol{x}_t, \vartheta) + v_t, \tag{3}$$

where $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-1}$ are the model state vectors at time t and $t-1$, respectively; M is the model operator; $\boldsymbol{I}_t$ is the vector of the model inputs; and H is the operator which maps the model states into the model output z_t. The terms w_t and v_t indicate the system and measurements errors, respectively, which are assumed to be normally distributed with zero mean and covariance $\mathbf{S}$ and R. In the case of the hydrological model used in this study, the states are identified as 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. (2017a), sensitivity analysis is carried out by perturbing the model states $\pm 20\,\%$ around the true state at every time step in order to find out to which model states the output is more sensitive. The study shows that model output is most sensitive to x_{sur}. For this reason, we decide to update only the model state x_{sur}, which is related to the linear reservoir, so the state-space form can be expressed as follows:

$$\boldsymbol{x}_t = \boldsymbol{\Phi}\boldsymbol{x}_{t-1} + \boldsymbol{\Gamma}\boldsymbol{I}_t + w_t, \tag{4}$$

$$z_t = \mathbf{H}\boldsymbol{x}_t + v_t, \tag{5}$$

where $\boldsymbol{x}$ is the vector of the model states (stored water volume, m^3), $\boldsymbol{\Phi}$ is the state-transition matrix, $\boldsymbol{\Gamma}$ is the input-transition matrix and $\mathbf{H}$ is the output matrix. In this case, the model output $\boldsymbol{z}$ is expressed as streamflow Q at the outlet section of the sub-catchment or inter-catchment. The detailed description of data assimilation in linear systems and the ways the matrices $\boldsymbol{\Phi}$, $\boldsymbol{\Gamma}$ and $\mathbf{H}$ are built can be found in, for example, Szilagyi and Szollosi-Nagi (2010).

3.1.2 Hydraulic modelling

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); it is based on the mass balance equation applied over a prismatic section delimited by the upstream and downstream river sections. As described in Cunge (1969) and Todini (2007), a four-point time-centred scheme can be applied to numerically solve the kinematic routing equation, and to derive a first-order approximation of a kinematic wave model and express the MC model as follows:

$$Q_{t+1}^{j+1} = C_1 Q_t^j + C_2 Q_t^{j+1} + C_3 Q_{t+1}^j, \tag{6}$$

where t and j are the temporal and spatial discretization and Q is the streamflow; C_1, C_2 and C_3 are the routing coefficients, which are a 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 reported in detail by Mazzoleni (2017). It is worth noting that in this formulation of the MC model, the only model parameter is the Manning coefficient of the river channel considered in the estimation of the wave celerity. In addition, MC model is implemented, independently, along each of the six river reaches represented in Fig. 1.

As in the case of a hydrological model, to apply the data assimilation method, the state-space form of the hydraulic model is used as well. The state and observation process equations are similar to those described in Eqs. (4) and (5). In the case of the hydraulic model, the model state vector is defined as $\boldsymbol{x}_t = (Q_t^1, Q_t^2, \ldots Q_t^j, \ldots, Q_t^N)$, where Q is the discharge along the river in cubic metres per second, while the input matrix is $\boldsymbol{I}_t = (Q_t^1, Q_{t+1}^1)Q^1$, being the discharge at the upstream boundary condition. The state-transition $\boldsymbol{\Phi}$ and input-transition $\boldsymbol{\Gamma}$ matrixes are calculated following the approach derived by Georgakakos et al. (1990). In the observation process of the hydraulic model, $\boldsymbol{z}$ represents the flow along the river channel, while $\mathbf{H}$ is output matrix equal to $[0\ 0 \ldots 1]^T$ in the case of flow measurements at the outlet section of the river reach. In this study, due to the varying position of social sensors, the matrix $\mathbf{H}$ changes accordingly at 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 step, considered 1000 m in order to guarantee the numerical stability of the MC model scheme.

3.2 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) algorithm, within a dynamic linear system resulting in the best state estimate with minimum variance of the model error. In Liu et al. (2012), a detailed review of KF and other types 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 the covariance matrix is expressed as follows:

$$\mathbf{P}_t^- = \boldsymbol{\Phi}\mathbf{P}_{t-1}^+\boldsymbol{\Phi}^T + \mathbf{S}_t, \tag{7}$$

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. When an observation z^{o} becomes available, the second (update) step of the KF is executed, in which the forecasted model states $\boldsymbol{x}$ and covariance $\mathbf{P}$ are updated as follows:

$$\boldsymbol{x}_t^+ = \boldsymbol{x}_t^- + \mathbf{K}_t \left(z_t^{\mathrm{o}} - \mathbf{H}_t z_t^{\mathrm{o}}\right), \tag{8}$$

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

$$\mathbf{K}_t = \mathbf{P}_t^- \mathbf{H}_t^T \left(\mathbf{H}_t \mathbf{P}_t^- \mathbf{H}_t^T + \mathbf{R}_t\right)^{-1}, \tag{10}$$

where $\mathbf{K}$ is the Kalman gain matrix (the higher its values, 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^0 as streamflow based on the river cross-sectional geometry.

In this study, CS 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. (2015) is adopted. According to this approach, when no observation is available, the model state vector $\boldsymbol{x}$ is estimated using Eq. (4), while the model error covariance $\mathbf{P}$ is left unchanged:

$$\mathbf{P}_t^+ = \mathbf{P}_t^-. \tag{11}$$

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

3.3 Synthetic observations

In operational practice, W_{L} values are converted into streamflow values to be then assimilated within hydrological models. This is usually done using the available rating curves at the sub-catchment outlets. However, W_{L} data can usually be directly assimilated in hydraulic models, but the problem is that the MC model used in this study requires flow information rather than W_{L}. For this reason, the synthetic W_{L} observation at a certain random location (DySc sensor) is converted into streamflow by means of the Manning equation if no rating curve information is available. In fact, it is quite unlikely to have the information of the rating curve at a random location provided by DySc sensors in real-world applications. When there are no data regarding the cross section, assumptions should be made about a rectangular cross section with a given width and depth. However, this approach will introduce significant uncertainty in river flow estimation. A possible solution is the use of mobile applications able to automatically retrieve flow information from photos and video as proposed in Lüthi et al. (2014), Overloop and Vierstra (2015) and Le Boursicaud et al. (2015). We believe that these types of mobile applications will become increasingly available (at reasonably low costs) to citizens in order to easily measure river flow.

Due to the lack of distributed CS observations at the time the considered flood event occurred, synthetic W_{L} observations are used (Mazzoleni et al., 2017a). In order to generate these synthetic observations, the observed time series of precipitation during the considered flood event are used as input for the hydrological models of the sub-catchments and inter-catchments to generate synthetic discharges and then propagate them with the hydraulic model down to the prediction point of PA (corresponding to the sensor StPh-3 in Fig. 1). In this way, the synthetic W_{L} values at the outlet of the sub-catchments or 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 an "observing system simulation experiment" (OSSE), as described for example by Arnold and Dey (1986), Errico et al. (2013) and Errico and Privé (2014).

Regarding the observation error, as described in Weerts and El Serafy (2006), Rakovec et al. (2012), and Mazzoleni (2017), the covariance matrix R is assumed to be as follows:

$$R_t = \left(\alpha_t \cdot Q_t^{\mathrm{synth}}\right)^2, \tag{12}$$

where α is a variable related to the accuracy level of the measurement. The accuracy (i.e. degree to which the measurement is correct overall) is subjected to random error and bias or systematic errors (Bird et al., 2014). Moreover, for W_{L} observations, accuracy levels vary temporally, spatially, and for each physical or social sensor. Table 2 summarizes the distribution of the coefficient α of the observational error of Eq. (12). The distribution of the coefficient α does not pretend to be exhaustive in accounting for the different accuracies between observations coming from physical and social sensors, but a first and simplified approximation that is a possible aspect for further research (see details in Sect. 2.2 and Table 1).

Although there are many sources of uncertainty in the indirect estimation of streamflow, for StPh sensors it is assumed that the rating curve estimation is the main source of uncertainty to properly estimate the streamflow given a certain W_{L} value. In fact, for the StPh sensors used in this study the instrument precision is about 0.01 m. As described in Weerts and El Serafy (2006) and Rakovec et al. (2012), the coefficient α is assumed equal to 0.1, constantly in time and space.

However, due to the unpredictable accuracy of the CS observations coming from the StSc and DySc sensors, the coefficient α is assumed to be random stochastic, variable in time and space within a minimum ($\alpha_{\min}$) and maximum ($\alpha_{\max}$) value, and based on the type of sensor and citizen accuracy. Table 2 summarizes the values for the accuracy levels that are used in this study and are assumed under the following considerations:

- For both StSc and DySc, sensor α values are higher than those of StPh sensors due to the additional sources of

Table 2. Assumptions behind the observational errors (based on Weerts and El Serafy, 2006, Rakovec et al., 2012, and Mazzoleni et al., 2017a) according to the sensor types used in this study.

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	$\alpha = U(0.2, 0.5)$	Variable location Intermittent arrival

uncertainty introduced with the CS W_L estimation and the consequent conversion to discharge. Moreover, the coefficient α for both StSc and DySc sensors is considered to be a random stochastic variable uniformly distributed in time and space (see Table 2).

- For CS observations derived from StSc sensors, α_{min} and α_{max} are assumed to be equal to 0.1 and 0.3, respectively (Mazzoleni et al., 2017a). Accurate α values mainly account for the uncertainty introduced in the streamflow estimation from W_L by means of the available rating curve derived during the installation of the sensor–staff gauge. The minimum value of α equal to 0.1 assumes a low observational error similar to that of StPh sensors. The maximum value of α, equal to 0.3, assumes high observational errors consistent with values used in previous studies (Mazzoleni et al., 2015, 2017a).

- In the case of DySc sensors, the minimum and maximum values are set to 0.2 and 0.5, respectively, i.e. 2 and 5 times higher than the uncertainty coming from the StPh sensors. The minimum α, equal to 0.2, assumes that W_L can be better estimated from StSc (i.e. by citizens using a reference staff gauge) compared to the DySc sensors. As described in Lüthi et al. (2014), flow in open channels can be estimated using mobile application only if the channel geometry in known. The maximum α, equal to 0.5, is almost double that for StSc, considering that the increasing uncertainty on the assessment of the W_L is due to the limited knowledge of the cross-sectional geometry at any location.

Unfortunately, we do not have any real CS observations to test the appropriateness of choosing these coefficients' values. A statistical model of systematic error against series of CS observations is proposed by Bird et al. (2014). Walker et al. (2016) propose correlations for consistency of CS with W_L values and rainfall series from nearby hydrologically similar catchments. In addition, to maintain accuracy levels within assumed ranges, Kosmala et al. (2016) suggest developing methods and tools to boost data accuracy and account for bias and to include iterative evaluation of CS observations, volunteer training and testing, expert validation, and replication across volunteers.

4 Experimental setup

In this section, we report two sets of experiments that are performed to test the benefits of assimilation of real-time CS observations, from a network of heterogeneous static and dynamic social sensors, under different assumptions of CIL.

A 3-day rainfall forecast is used to assess the simulated W_L values along the Bacchiglione River and at the prediction 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. The observed and forecasted W_L values are compared at the outlet section of PA.

The number of observations used in each experiment varies based on CIL. Considering a 48 h flood event and hourly model time step, an involvement equal to 1 corresponds to 48 available observations, while with involvement of 0.5 only 24 observations (randomly distributed in time and space) are assimilated.

In addition, several model runs (100) are performed to account for random accuracy and involvement level in time and space of the citizen providing CS observations. In each run, a specific α value and arrival moment for each observation are considered and the corresponding NSE value is estimated. From the 100 samples of these NSE values, the corresponding mean μ (NSE) and standard deviation σ (NSE) are calculated.

The widely used measure in hydrology, the Nash–Sutcliffe efficiency (NSE) index (Nash and Sutcliffe, 1970), is used to compare simulated and observed quantities:

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T}\left(W_{L,t}^{m} - W_{L,t}^{o}\right)^2}{\sum_{t=1}^{T}\left(W_{L,t}^{m} - \overline{W_{L,i}^{o}}\right)^2}, \tag{13}$$

where the superscripts m and o indicate the simulated and observed values of W_L, while $\overline{W_L}$ is the average observed water level. An NSE of 1 represents a perfect model simulation whereas an NSE smaller than zero indicates that the model simulating streamflow is only as skilful as the mean observed water level. NSE values between 0.0 and 1.0 are

generally considered as acceptable levels of model performance (Moriasi et al., 2007).

4.1 Experiment 1: Random citizen involvement levels

In the first experiment, CS observations are taken from StSc (experiment 1.1) and DySc (experiment 1.2) sensors according to random CILs. Such involvement, closely related to the intermittent nature of the W_L observations, can be considered as the probability of receiving an observation at a given model time step. This means that in the case of $CIL = 0.4$ there is 40 % of probability of obtaining an observation at a given model time step. In fact, in the case of $CIL = 0$, no observation is assimilated and the semi-distributed model is run without any update, whereas if $CIL = 1$, observations are available at every time step and this situation is analogous to the observation from StPh sensors, which are assumed to be regular in time.

4.1.1 Experiment 1.1: Assimilation of data from static social (StSc) sensors

Experiment 1.1 considers only the assimilation of W_L observations from StSc sensors. The sensors StSc-1, -2 and -6 are located in sub-catchments A, B and C, respectively, while the other sensors are located along the river reaches of the Bacchiglione catchment (see Fig. 1). In contrast to the observations from StPh sensors, those from StSc are not regular in time since they are strictly related to the citizen involvement level.

Observation error is defined as in Sect. 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 for different combinations of sensor availability in the different sub-catchments and river reaches is performed.

4.1.2 Experiment 1.2: Assimilation of data from dynamic social (DySc) sensors

In experiment 1.2, the assimilation of W_L observations coming only from DySc sensors is considered. The two main differences between StSc and DySc sensors are as follows: (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 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 person, it might be difficult to estimate the W_L in a river without any reference device, as in the case of StSc sensors.

Analysis on the effect of biased CS observations from DySc sensors is carried out within this experiment. In fact, due to the Bacchiglione catchment complexity and the low quantity of available data, the semi-distributed model used in this study may not properly represent internal states away from the calibration point. Consequently, synthetic CS observations may not fully mimic real CS observations, as underlined in Viero (2017). This means that real CS observations may be likely biased with respect to the synthetic CS observations generated in this study. For this reason, in the case of CS observations derived using DySc sensors, a systematic error is also accounted for by means of different values of observation bias:

$$W_{L,t}^{synth} = W_{L,t}^{true} + \gamma_t = W_{L,t}^{true} + W_{L,t}^{true} \cdot U(\gamma_{min}, \gamma_{max}), \quad (14)$$

where γ is a random stochastic variable function of time, having minimum and maximum values γ_{min} and γ_{max}. In the case of no bias $\gamma_{min} = \gamma_{max} = 0$, if W_L is underestimated $\gamma < 0$ and if W_L is overestimated then $\gamma_{max} > 0$. Bias in CS observations from StSc sensors is not considered in this study.

Table 3. Minimum and maximum values γ_{min} and γ_{max} in 4 different cases of observation bias used in experiment 1.2 and 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

The coefficients γ are subjectively assumed. In fact, we do not want to argue that a particular value (e.g. 0.3 as in this experiment) should be considered as the default value to estimate bias in real-life crowdsourced observations. Such bias has to be defined based on field experiments with volunteers proving water level observations during real flood conditions. The main point of this analysis is to assess the model sensitivity for different subjective values of γ. The value of γ should be also defined based on field experiments with volunteers.

4.2 Experiment 2: Theoretical scenarios of citizen involvement levels

In this experiment, all the StPh, StSc and DySc sensors are considered. One main problem in citizen science is understanding the motivations that drive citizens to be involved in such activities (Gharesifard and Wehn, 2016). For this reason, a theoretical assumption about citizen involvement based on their motivations, varying in time and space, is introduced. In the previous experiments, involvement is considered to be random varying from 0 to 1. In this experiment, involvement level is assumed to be a function of the spatial distribution of the population within the Bacchiglione catchment.

As stated by Gharesifard and Wehn (2016), we acknowledge that stronger motivations or intentions are not only driven by a combination of more positive and favourable attitudes. The motivations also rely on stronger positive social

Table 4. Estimate of the active population that potentially can provide CS observations of W_L with StSc sensors.

Sensor	Municipality	Active area (m^2)	Density (inhab km^{-2})	Population (inhab)	Active citizens (inhab)
StSc–1	Schio	206 828	597	124	51
StSc–2	Schio	71 293	597	43	18
StSc–3	Malo	100 734	491	50	21
StSc–4	Villaverla	359 744	400	144	59
StSc–5	Caldogno	67 311	720	49	20
StSc–6	Costabissara	421 778	563	238	98
StSc–7	Vicenza	86 544	1400	122	50
StSc–8	Vicenza	241 451	1400	339	139
StSc–9	Vicenza	415 513	1400	583	239
StSc–10	Vicenza	500 000	1400	700	287

pressure and greater perceived control or self-sufficiency regarding the means to provide CS observations. In this paper, the distinction between favourable attitudes are treated from a theoretical point of view since during the WSI project, no consistent analysis of motivational structures was undertaken for the Bacchiglione case study. Based on Batson et al. (2002), we assume the three main motivations for citizens involvement in collecting data: (1) for their own personal purposes (usefulness of the collected data for personal interest or direct flood risk management impact), (2) belonging to a community of peers with shared interests and (3) altruism (benefiting society at large). In order to assess citizen involvement, we propose a three-step procedure consisting of (1) estimation of the active-citizen area; (2) estimation of the number of active citizens and (3) estimation of the citizen involvement curve.

Step 1 involves the estimation of the "active-citizen area". A hypothetical 500 m buffer around each sub-river reach of 1000 m (spatial discretization of the MC model) is used to identify the area in which the active population might provide CS observations using DySc sensors (see Fig. 2). It is assumed that the citizens located further than 500 m from the river are not contributing to the collection of CS observations. In the case of the StSc sensor, we assume the active area to be a circle with a 500 m radius with the sensor at the centre. Different extents of the buffer will lead to different coverages of the active area, with significant effects on the simulated number of hypothetically involved citizens. However, analysing the implications of different buffer extents on the number of active citizens and subsequent flood predictions is out of the scope of this research. 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 Fig. 2).

Step 2 involves the estimation 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 500 m buffer of each sub-river reach in which the urban areas are located. In the case of agricultural areas, an involvement value equal to zero is considered. In addition, not all citizens would be able to provide CS observations because only a certain proportion of them use mobile phones. According to Statistica (2016), the mobile phone market penetration in Italy in 2013, the year of the flood event analysed in this study, was about 41 %, which means that about 41 % of the population was potentially able to submit data. In view of the lack of a better source, we assume that this proportion is also valid for the regional scope. Therefore, to estimate the potential number of active citizens that could submit data close to the river reach, we first estimate the total population enclosed in a cell of 1 km long by 1 km wide (a buffer of 500 m from each side of the river) and then estimate 41 % of this. Table 4 summarizes the results for the case of the StSc sensors and Table 5 those 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 (at kilometers 3, 4, and 5), the main urban areas are contained in more than one sub-reach. Naturally, for a better estimation of these values, a more exhaustive social–economic analysis should be performed.

Step 3 involves the estimation of the theoretical citizen involvement curve. It is now necessary to estimate the level of citizen involvement based on the hypothetical number of active citizens and their motivation for sharing data. For this reason, three different involvement curves, each representing a scenario and corresponding number of active citizens, providing the maximum citizen involvement level (MCIL), are proposed. These scenarios are based on Batson et al. (2002), whose aggregated categories of citizen's motivations are still in agreement with more comprehensive and detailed analyses such those recently reported in Geoghegan et al. (2016) and Gharesifard and Wehn (2016).

In scenario 1, we assume that citizens collect data mainly for their own personal use. In this case, the MCIL is low for a low number of citizens, while it grows following a logistic

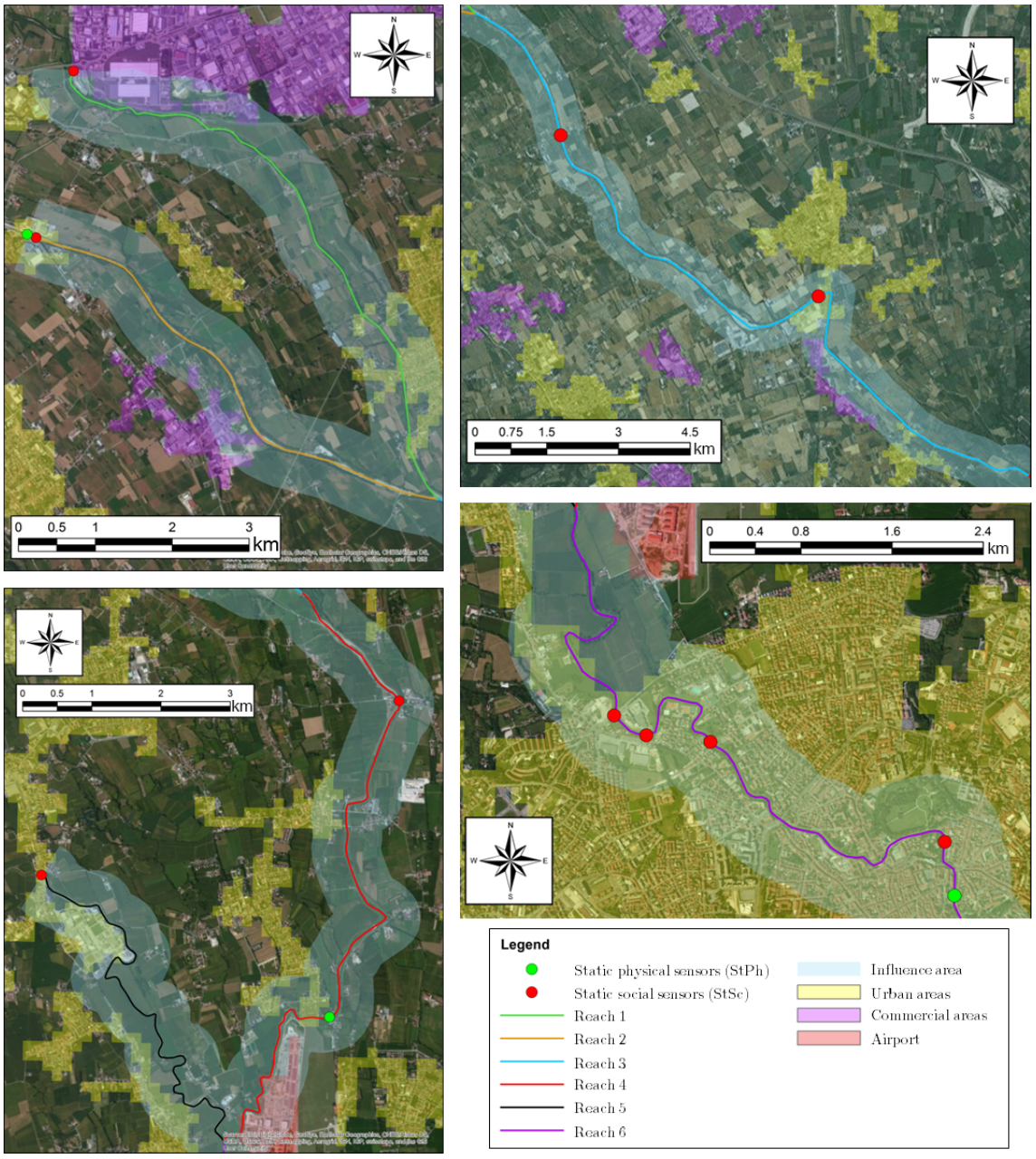

Figure 2. Representation of the different Bacchiglione river reaches, land use (Corine Land Cover, 2006), location of the StSc and StSc sensors and the 500 m buffer.

function, Eq. (15), for increasing numbers of people.

$$\mathrm{MCIL} = \frac{K \cdot P_o \cdot e^{r \cdot P_{\mathrm{op}}}}{K + P_o \cdot \left(e^{r \cdot P_{\mathrm{op}}} - 1\right)} + w, \tag{15}$$

where P_{op} is the population; r is the growth rate (we assumed two different values of r, 0.04 and 0.08); K is the carrying capacity, i.e. the maximum value of MCIL, assumed to be equal to 1; w is a coefficient related to the additional CS observations received from enthusiastic individuals (third citizen scenario explained below); and P_o is the minimum value of MCIL assumed equal to 0.01.

In scenario 2, 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 MCIL is achieved for small population values while for increasing population this value is decreasing. This scenario follows an inverse logistic function as shown in the graphical representation of scenario 2 in Fig. 3.

Table 5. Estimate of the active population that potentially can provide CS observations of W_L with DySc sensors.

Reach	Municipality	Active area (m^2)	Density (inhab km^{-2})	Population (inhab)	Active citizens (inhab)
1 (km 6–7–8)	Marano Vicentino	608 985	800	487	200
2 (km 2)	Schio	39 536	597	24	10
3 (km 8)	Villaverla	359 744	400	144	59
3 (km 11)	Caldogno	232 474.1	720	167	69
4 (km 2)	Dueville	30 692	701	22	9
4 (km 3)	Caldogno	191 988	720	138	57
4 (km 5)	Caldogno	292 519.8	720	211	86
5 (km 1)	Costabissara	351 921	562	198	81
5 (km 2)	Costabissara	119 898	562	67	28
5 (km 3–4–5)	Vicenza	212 453	1400	100	41
6 (km 1–2)	Vicenza	129 816	1400	90	37
6 (km 3–4–5)	Vicenza	1 156 964	1400	539	221

Table 6. Involvement curves based on different citizen motivations.

Involvement scenario	Citizen motivation	Growth rate (Factor r in Eq. 15)	Additional CS observations (Factor w in Eq. 15)*
1	Own purposes (1)	0.035	0
2	Shared or community interests (2)	0.060	0
3	Societal benefits (3)	0.035	0.10

* Increment applies when CS observations are also driven by societal benefits (third citizen motivation).

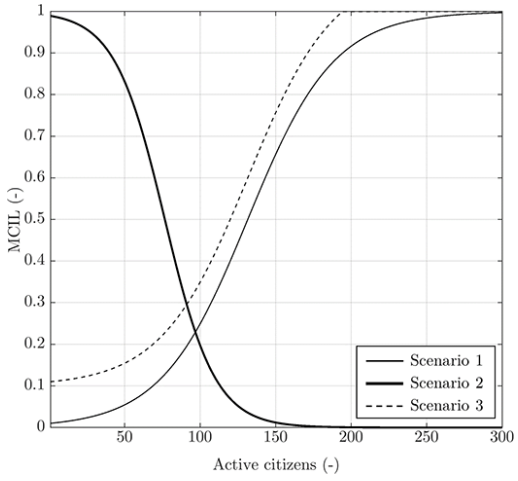

Figure 3. Representation of the theoretical MCIL scenarios based on the number of active citizens.

In scenario 3, enthusiastic individuals might provide additional information driven by moral norms and the wish to create knowledge about the hydrological status of the river, benefiting society at large. This is potentially a much smaller subset of the population. The added value of this information is accounted for in Eq. (15) by means of a coefficient w. Table 6 summarizes the different involvement curves based on the previous scenarios and different values of the coefficients r and w.

In the next phase of analysis, a number of model runs (100) are carried out, considering the random values of citizen involvement from 0 to the MCIL according to the given involvement scenarios and the population. For example, considering scenario 1 and 150 inhabitants enclosed in a given river sub-reach, several model runs are performed for involvement values varying from 0 to 0.65 based on Fig. 3. In case different CS observations are coming in at the same time from different sensors, only the most accurate observation, i.e. that having the lower value of the coefficient α in Eq. (12), is assimilated in the hydrological and/or hydraulic model. Another approach could be to assimilate all measurements instead of only the most accurate ones. In this case, each observation is used within the assimilation scheme with the account of its error: less weight would be given to the more uncertain observations.

Finally, this experiment also investigated the effect of the spatial variability of smartphone market penetration and decrease in citizen involvement levels over time. For this reason, a higher (double) percentage of active citizens in Vicenza is assumed (smartphone market penetration of 80 %),

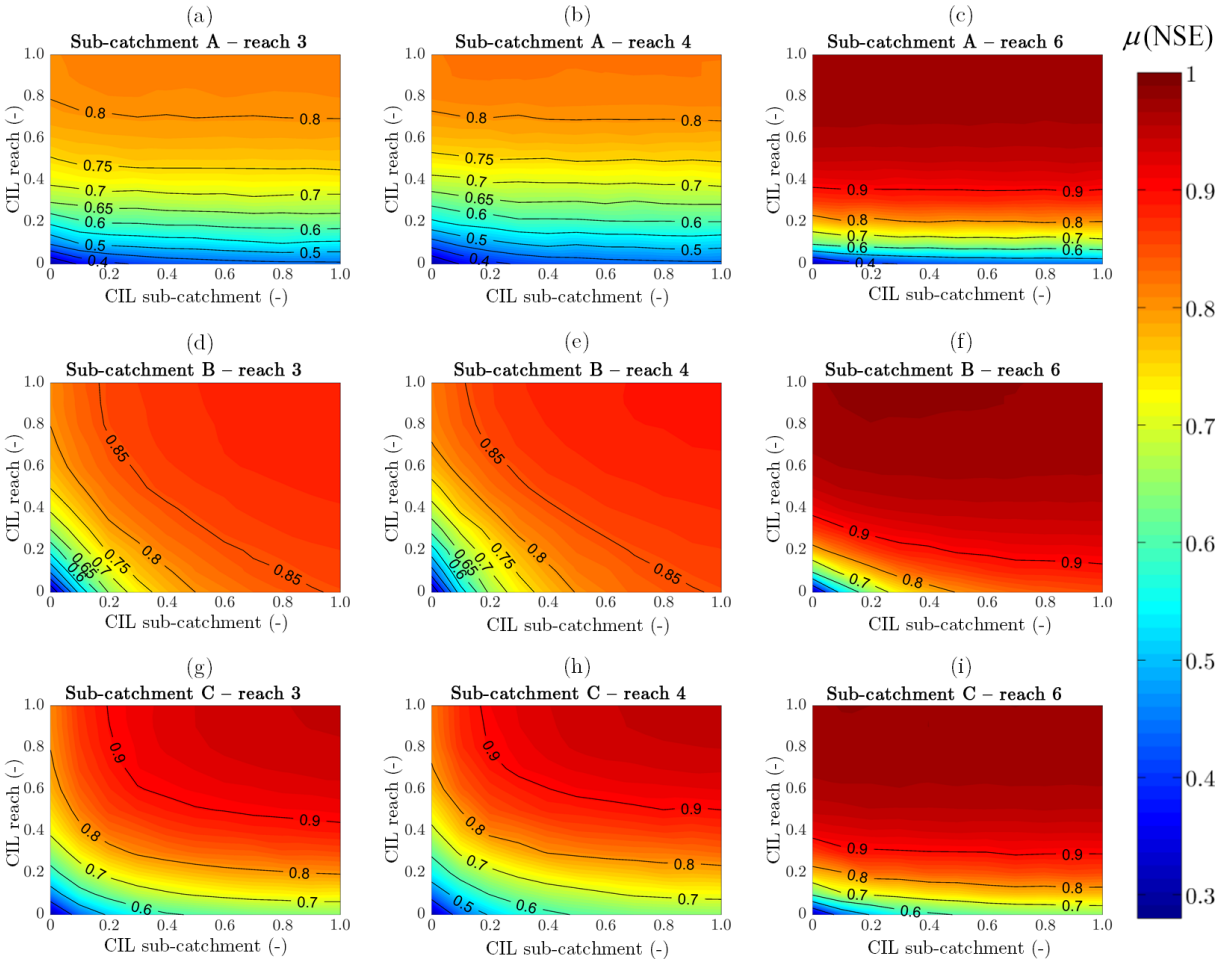

Figure 4. The μ (NSE) values obtained by assimilating CS observations from a combination of StSc sensors located in different sub-catchments and river reaches with 1 h lead time in the case of different CIL values.

while random values of the coefficient r are considered to represent lower involvement levels over time.

5 Results

5.1 Experiment 1

5.1.1 Experiment 1.1

In experiment 1.1, the effect of different CILs on the assimilation of CS observations from StSc sensors is analysed. Figure 4 aims to represent the μ (NSE) values obtained when assimilating CS observations from StSc sensors located in different sub-catchments (hydrological model) and river reaches (hydraulic model) for a 1 h lead time. For example, in Fig. 4a, the NSE values obtained by assimilating CS observations from sub-catchments A and river reach 3 are shown for different involvement values.

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

In the case of assimilation in sub-catchment B, Fig. 4d, e and f, higher NSE values are achieved if compared to those for the sub-catchment A (first row of the same figure). In particular, NSE values are mainly influenced by different involvement levels of CS observations from sub-catchment B than from river reach 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 involvement 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 Fig. 4).

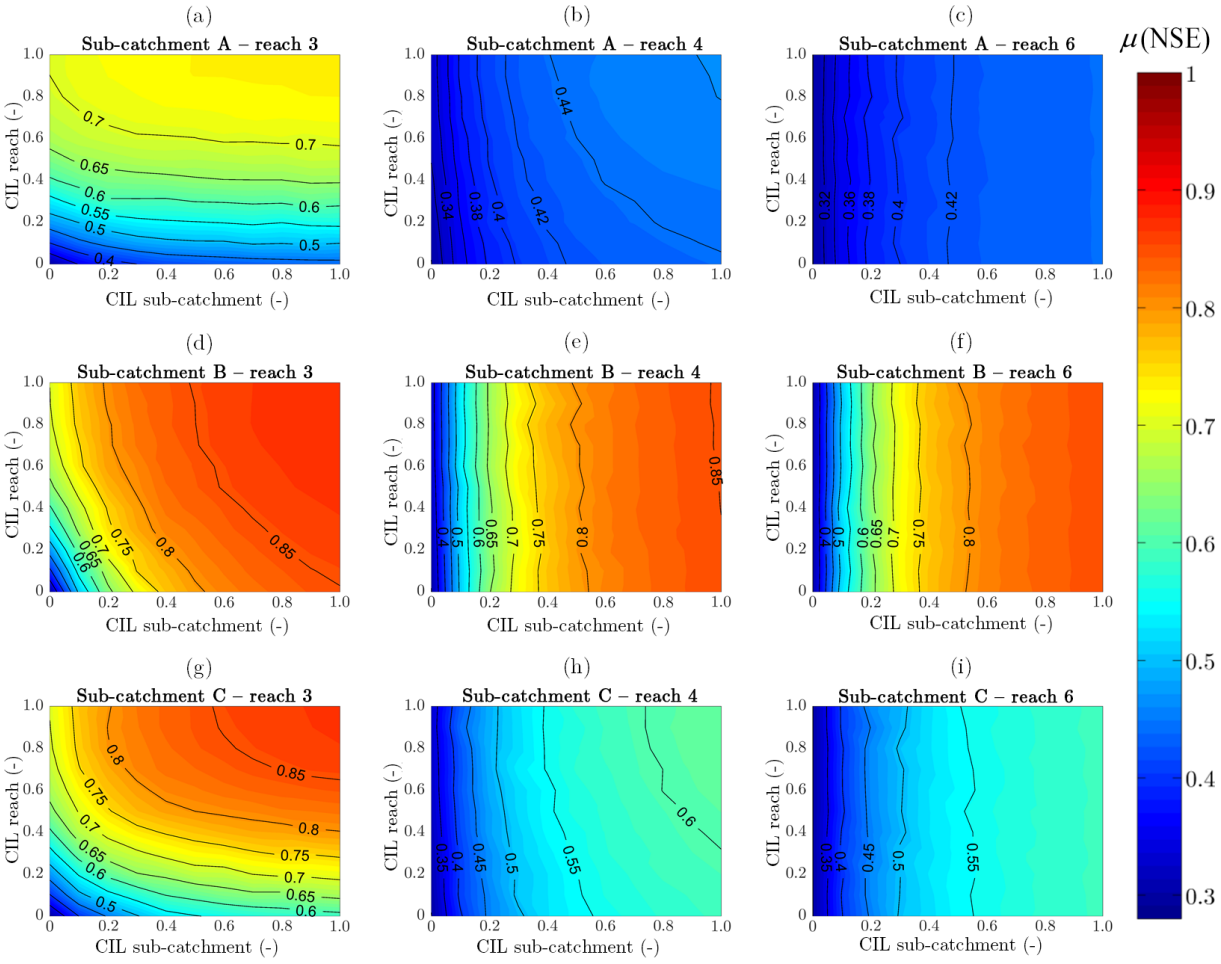

Figure 5. The $\mu(N_{SE})$ values obtained by assimilating CS observations from a combination of StSc sensors located in different sub-catchments and river reaches with 4 h lead time in the case of different CIL values.

Similar results are shown for StSc sensors located in sub-catchment C and different river reaches (Fig. 4g, h and i). However, involvement levels in upstream river reaches affect the NSE values more than the involvement of StSc sensors in sub-catchment C. The same behaviour is manifested considering StSc sensors located from the upstream river reach to downstream. The third row of Fig. 4 can be considered as an average situation between the first (sub-catchment A) and the second (sub-catchment B) row of the same figure.

Figure 5 is analogous to Fig. 4, but with a lead time of 4 h. Overall, as expected, the NSE values are lower for a lead time of 4 h, if compared to that of 1 h. Model results are dominated by the assimilation in the sub-catchments A, B and C if compared to the involvement in reaches 4 and 6. This is due to the fact that assimilation from the hydrological model allows good model predictions to be achieved in the case of high lead values. An intermediate situation is achieved for reach 3. It can be seen that assimilation of CS observations in this upstream river reach allows higher NSE values to be obtained in the case of high lead times due to the longer travel time than those of StSc sensors located closer to PA (e.g. reach 6). Citizen involvement in reach 3 affects the NSE values more than the involvement levels in sub-catchment A and C. Moreover, as in the case of Fig. 4 for 1 h lead time, involvement in sub-catchment B has a higher impact on NSE values than involvement in reach 3. A more detailed analysis of the effect of sensor location and lead time is provided in Mazzoleni et al. (2017a).

5.1.2 Experiment 1.2

In experiment 1.2, the effect of CIL in assimilating CS observations only from DySc sensors is analysed. In this case, the DySc sensors are assumed to be located only along river reaches 3, 4 and 6, so only the hydraulic model is used in this experiment. Also, in this experiment, 100 runs are carried out to account for the random accuracy and location of the CS observations.

In Fig. 6, DySc sensors are assumed to be present every 1000 m, while CIL changes in each model run. This means

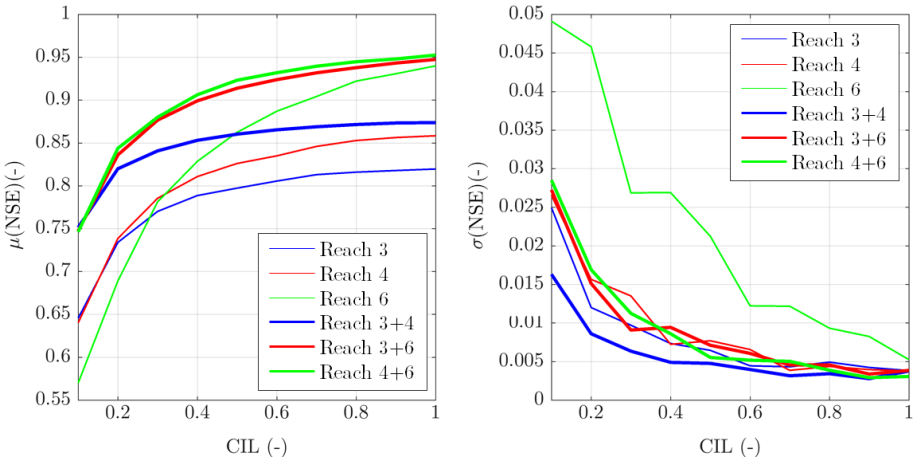

Figure 6. Effect of different levels of involvement, in terms of μ (NSE) and σ (NSE), on the assimilation of CS observations from DySc sensors for different CIL values.

that CS observations that are available at one time step at one specific location may not be available at the same location for the next time steps. It can be observed that in most of the cases μ (NSE) values converge asymptotically to some threshold, as the involvement level increases. Among the three river reaches, 3 and 4 are the ones providing higher NSE values for low involvement levels. This can be related to the high number of DySc sensors located in reach 3 (13 sensors) and 4 (8 sensors). Although reach 6 is performs better in the case of high involvement levels, high σ (NSE) values are obtained for this reach, showing a significant sensitivity of model performance in the case of different CILs in the hydraulic model. Assimilating CS observations from DySc sensors at different reaches induces an overall improvement of μ (NSE) and reduction in σ (NSE). The lowest σ (NSE) values are obtained including DySc sensors from reaches 3 and 4. However, this reduction in the σ (NSE) values does not correspond to a higher improvement in μ (NSE). In fact, the highest μ (NSE) values are achieved by joining sensors from reach 4 and 6, i.e. the closest river reaches to the PA station. Similar results in terms of μ (NSE) and σ (NSE) are obtained by joining reaches 3 and 6. It is worth noting that in Fig. 6, no bias in the observations from DySc sensors is considered.

Figure 7 presents the μ (NSE) values obtained considering random locations of DySc sensors along the river reaches 3, 4 and 6 in four different cases of CS observation bias for 1 h lead time. As reach 6 has five different sub-reaches of 1000 m, CS observations from only five sensors can be assimilated. However, in Fig. 7 a total number of 13 DySc sensors is considered. In these experiments, location of DySc sensors are randomly generated. It might happen that two sensors are located, say, at distances of 2600 and 2900 m from the upstream boundary condition. Because of the small spatial discretization of the hydraulic model (1000 m), it is assumed that the difference between the hydrographs estimated between the two different model discretization is negligible. For this reason, the two CS observations from the DySc sensors at 2600 and 2900 m 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 points.

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 in the μ (NSE) values due to the underestimated forecasted precipitation. 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 involvement levels. In the case of γ_2 the behaviour in between γ_3 and γ_4 can be observed.

5.2 Experiment 2

Experiment 2 focuses on the assimilation of CS observations from a distributed network of heterogeneous StPh, StSc and DySc sensors. In particular, the involvement level is calculated in a more realistic way, accounting for the population living in the range of 500 m from the river. Based on Fig. 3, different MCIL values are calculated for the three scenarios in collecting and sharing W_L observations. It is worth noting that bias 2 is considered in the CS observations from DySc sensors.

Figure 8 shows μ (NSE) values in the case of different involvement scenarios and MCIL according to the different types of sensors. A random value of involvement level between 0 and MCIL is considered for a given river subreach and model run. In particular, in Fig. 8, smaller values of MCIL such as MCIL1, MCIL2, MCIL3, MCIL4 and MCIL5 are estimated as 0.2 MCIL, 0.4 MCIL, 0.6 MCIL, 0.8 MCIL and MCIL, respectively. Note that scenario 2 is the one providing the best model improvements, followed by scenario 3.

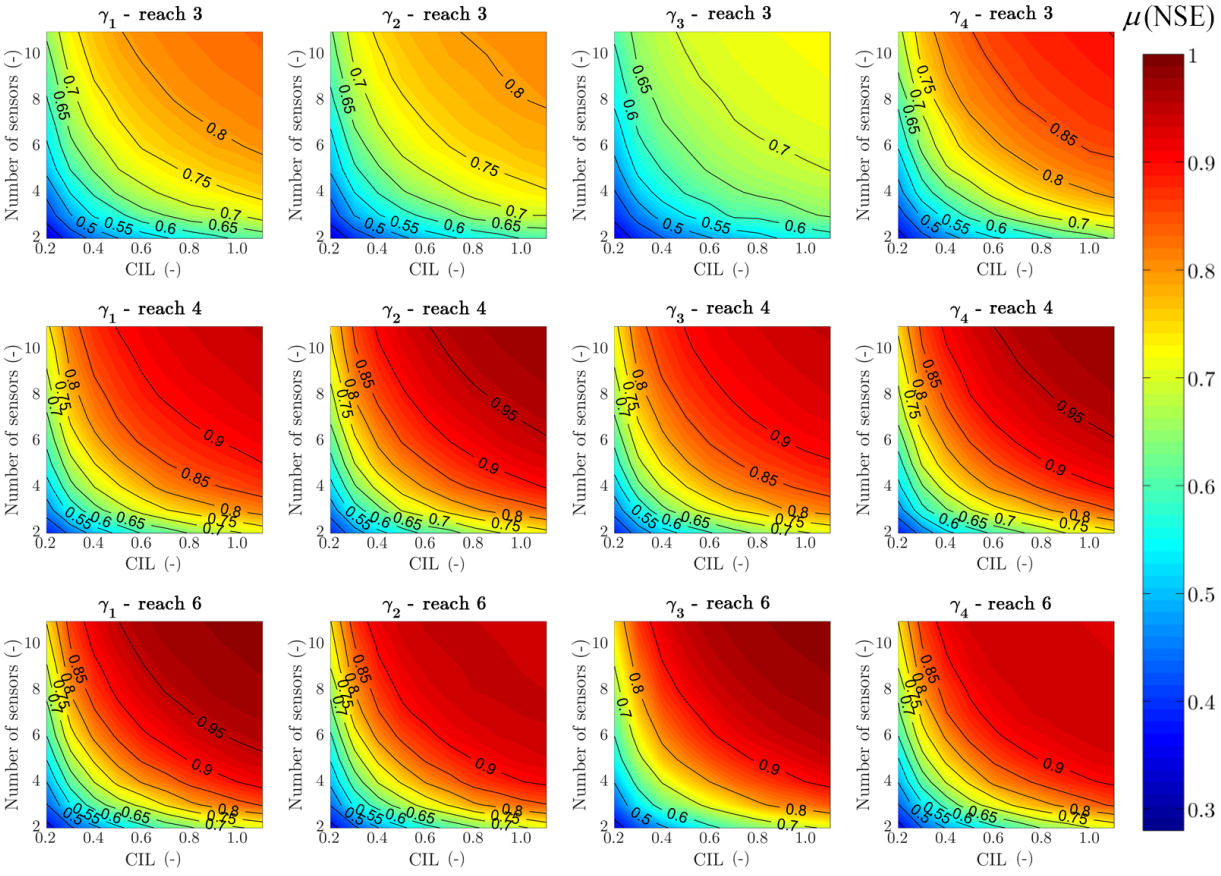

Figure 7. The μ (NSE) values obtained considering random location of dynamic social (DySc) sensors along river reaches 3, 4 and 6 in four different cases of CS observation bias for 1 h lead time and citizen involvement level (CIL) values.

Involving the enthusiastic people (scenario 3) helps to improve μ (NSE), especially for low involvement values. Scenario 1 is the one that gives the lowest μ (NSE) values due to the lowest growth rate of the involvement curve and consequent lower involvement of citizens.

In scenarios 1 and 3, the steepest vertical gradient of the contour plot can be observed, leading to the conclusion that model results seem to be more sensitive to the change in MCIL values in StSc sensors rather than DySc sensors. However, the gradient reduces with scenario 2.

In the previous analysis, NSE is used as the only performance indicator without considering improvement in the prediction of the peak and rising limb of the hydrograph, which are extremely important in operational flood management. For this reason, the relative error between the observed streamflow peak and simulated peak (see Eq. 16) is included to better assess the assimilation of crowdsourced observations from an operational point of view.

$$E_{RR} = \frac{\left(W^{O}_{L,P} - W^{S}_{L,P}\right)}{W^{O}_{L,P}}, \tag{16}$$

where $W^{O}_{L,P}$ and $W^{S}_{L,P}$ are the observed and simulated streamflow ($m^3\ s^{-1}$). The results reported in Fig. 8 show comparable results to those achieved using NSE. Including CS observations from enthusiastic citizens seems not to lead to a more accurate representation of the peak discharge. In fact, similar μ (NSE) values are achieved between scenarios 1 and 3. However, error in peak prediction is lower in scenario 1 than in scenario 2. It can be observed that E_{RR} values are clearly more sensitive to the different involvement values in StSc sensors than DySc sensors (vertical gradient).

In the previous analysis, unrealistically high citizen involvement (up to 80 %) is considered. For this reason, the following analysis focuses more on the lower part of the theoretical involvement curve, assuming more realistic CIL. In particular, the maximum carrying capacity of the logistic curve (K) is changed from 0.01 up to 1. In the case of K equal to 1, the values of μ (NSE) related to the different scenarios are estimated as mean average of the contour plot shown in Fig. 8. The same analysis is performed for the vector of different values of K.

The results of this analysis show an expected reduction in the model performances for low values of the parameter K (which indicates the maximum possible level of involve-

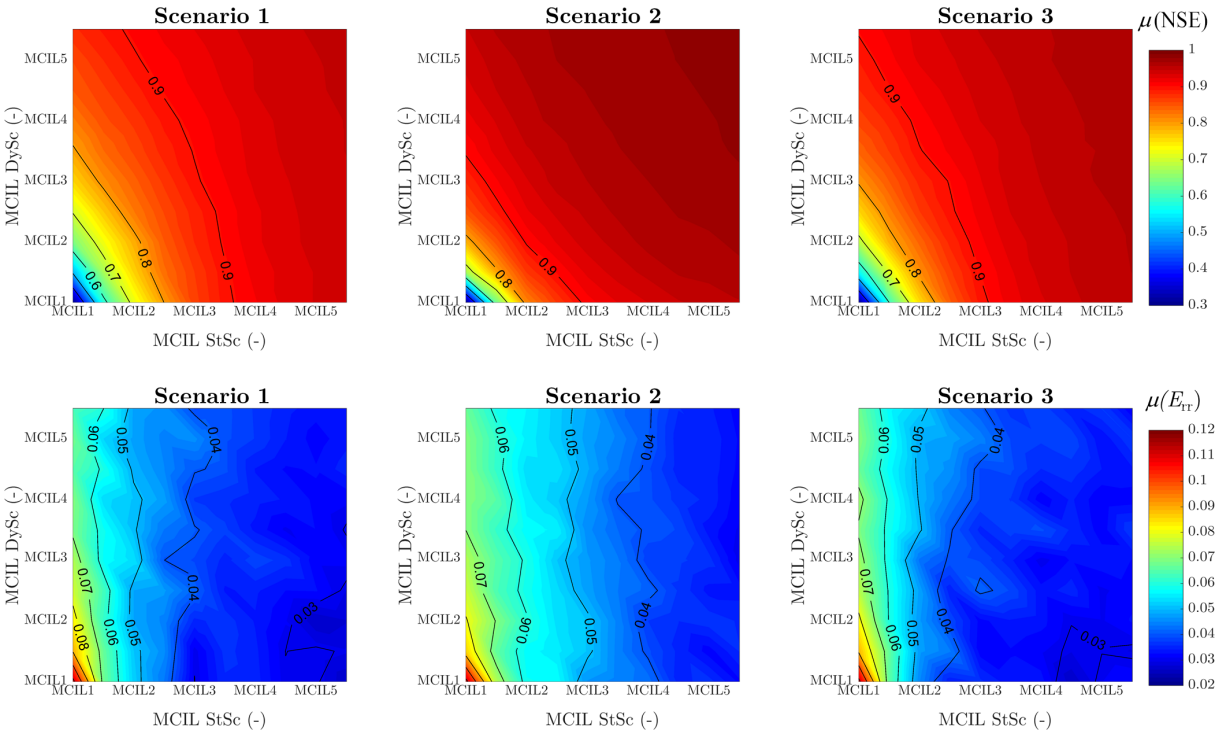

Figure 8. The μ (NSE) and μ (E_{rr}) values obtained in the case of different maximum citizen involvement level (MCIL) scenarios comparing involvement level from StSc and DySc sensors.

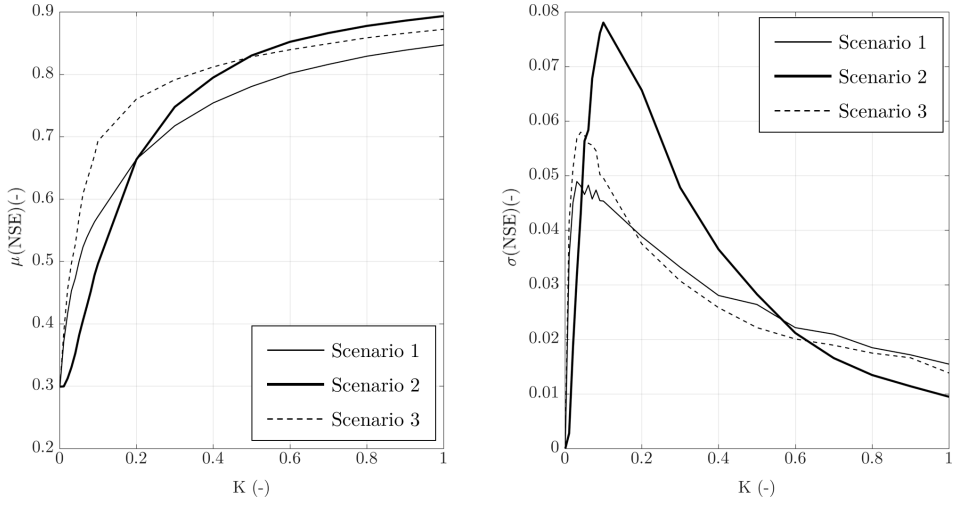

Figure 9. μ (NSE) and σ (NSE) values obtained considering varying values of K for different involvement scenarios.

ment). It can be noted that if K is equal to 0.5, assimilation of crowdsourced observations still provide significant model improvement for all the different scenarios even though the involvement is halved. As expected, σ (NSE) values tend to increase for low involvement of citizens. From Fig. 9, it can be seen that μ (NSE) values do not follow a linear trend as expected. On the contrary, it tends to drop for values of K between 0 and 0.2 (for example in scenario 3), while for higher K values μ (NSE) does not grow significantly. In particular, for K values higher than 0.5, scenario 2 provides the highest μ (NSE) values. Besides, for K values lower than 0.5, scenario 3 is the one leading to better model performances. This is because the presence of enthusiastic individuals keeps high involvement values even for low values of K. Regarding the variability of NSE, i.e. σ (NSE), for values of K lower than 0.4, high σ (NSE) can be observed in scenario 1.

Additional analysis considering negative and positive bias (bias 3 and 4 in Table 3) in the CS observations are

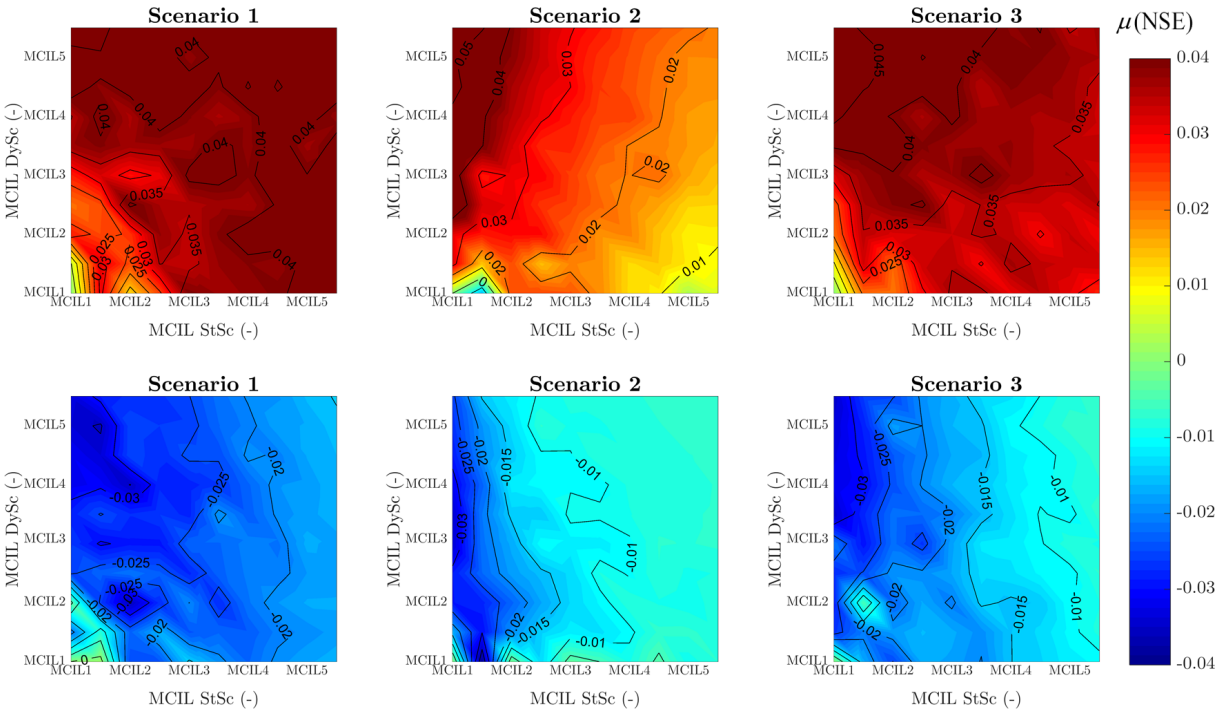

Figure 10. Difference between μ (NSE) values obtained considering bias 2 with bias 3 (first row) and bias 2 with bias 4 (second row) for different involvement levels for StSc and DySc sensors.

considered (see Fig. 10). As expected, it can be observed that bias 4 provides higher NSE values than bias 2 since the model without update underestimate observed streamflow or water level. Moreover, results obtained using observations with bias 3 have lower NSE than the results with bias 2. However, in both bias 3 and 4, such changes in NSE are very small, leading to the conclusion that assimilation of biased W_L observations during the May 2013 flood event in the Bacchiglione River do not reduce model performances.

5.2.1 Effect of spatial variability of smartphone market penetration

The value of smartphone market penetration depends mainly on the geographic area and on the characteristic of the population. We assume that not everyone is prone to use smartphones to collect and share water level data due to their age and habits. However, smartphone market penetration and consequent percentage of active citizens may change spatially. In the following simulations, a higher percentage of smartphone users (80 %) is assumed in the urbanized area of the municipality of Vicenza. From Fig. 11 it can be seen that increasing the smartphone market penetration in Vicenza does not affect model results in the case of scenario 2.

For this scenario, no involvement is assumed in highly urbanized areas such as the municipality of Vicenza. The higher number of smartphones in Vicenza partially affects only scenarios 1 and 3. In these scenarios, an expected increment in the model performance (due to the higher involvement in Vicenza), can be observed. However, small increments in the NSE values are reported in Fig. 11, with a maximum difference of 0.04 between normal and higher smartphone market penetration.

5.2.2 Effect of temporal variability of citizen involvement

In the previous analyses, CIL is considered constant in time. However, in practice, involvement may decrease if citizens are not properly engaged in a water observatory (Geoghegan et al., 2016; Gharesifard and Wehn, 2016), so for the assimilation of CS observations it is also important to consider this situation. A possible idea to represent the decrease in the involvement level over time could be to assume varying values of growth rate r of the logistics curve over time.

In Fig. 12, results of sensitivity analysis on model results with respect to the varying values of the coefficient r of Eq. (15) are presented. Only scenario 3 and three different values of w are considered. The results demonstrate that decreasing involvement over time (low values of r) leads to a reduction in the model performance and consequently inaccurate flood forecasts. This is an expected result that demonstrates again the importance of keeping citizens continuously engaged. However, this reduction in model performance is significant only for values of r lower than 0.3, leading to the

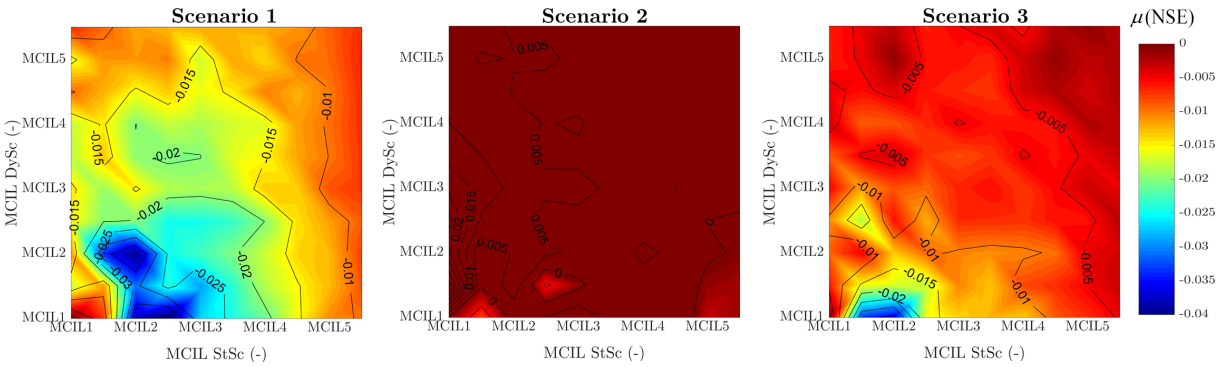

Figure 11. Difference between μ (NSE) values obtained considering standard and higher active citizen percentage in the municipality of Vicenza for different involvement levels from StSc and DySc.

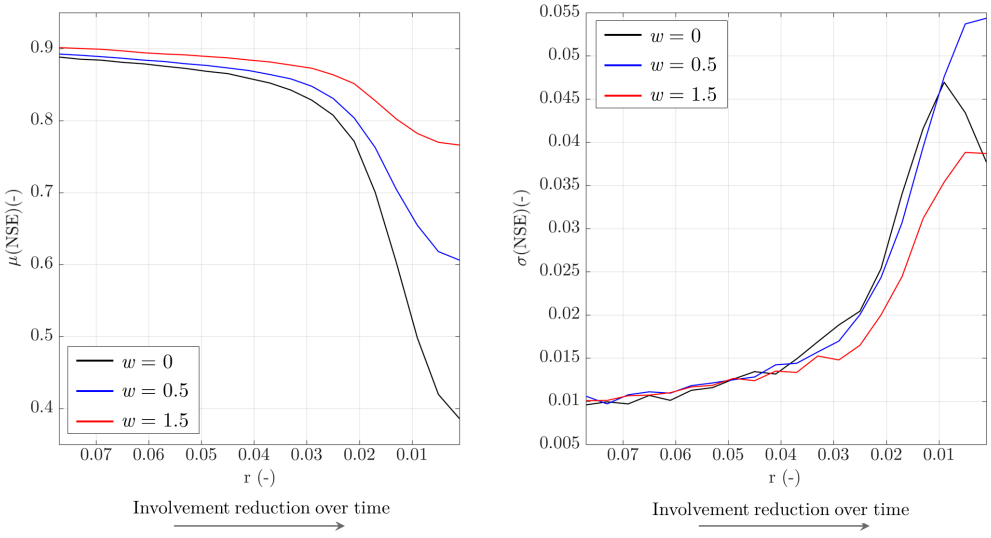

Figure 12. The μ (NSE) and σ (NSE) values obtained considering varying values of the coefficient r for scenarios 1 and 3 with three different values of w.

conclusion that model performances can still be high even if involvement decreases over time.

6 Discussion

In flood risk management, CS observations of hydrological variables can potentially contribute to the situational awareness of citizens and to decision-making (Howe, 2008; Alfonso, 2010; Rotman et al., 2012; Gura, 2013; Bonney et al., 2014; Buytaert et al., 2014, Wehn and Evers, 2016). Citizen observatories enabled with information and communications technology become possible via, for example, mobile and web-based easy-to-use sensors and low-cost monitoring technologies (Jonoski et al., 2012; Ciravegna et al., 2013). However, the fact that information and communications technology tools and citizen observatories initiatives are in place does not automatically imply a higher level of citizen involvement – due to the intermittency and timely availability of CS observations (Degrossi et al., 2013; Wehn et al., 2015). This section aims to summarize the main findings of our study and to analyse the pros and cons of using CS observations for improving flood predictions. It is worth noting that in this study we do not refer to how to get the citizens involved, but rather to the probability of receiving a CS observation based on the citizen's own interest in collecting water level observations. Engagement and involvement levels are related and represent a huge barrier for collecting CS observations (Gharesifard and Wehn, 2016; Starkey et al., 2017).

Overall, the results we have obtained are in accordance with the recent studies on the use of (real) crowdsourced observations in the area of water resource management (Gaitan et al., 2016; Giuliani et al., 2016; de Vos et al., 2017; Rosser et al., 2017; Schneider et al., 2017; Starkey et al., 2017; Yu et al., 2017). In particular, any improvement of model performance, with respect to the current practice for flood forecasting in the catchment used by the Alto Adri-

atico Water Authority with no model update, provides additional useful information for flood risk management. The results from experiment 1.1 (assimilation only from StSc) show that model outputs depend on the particular sub-catchment and river reach in which the observations are assimilated. In fact, we also found that accuracy of the assimilation process is highly dependent on different factors, including the total number of observations, their spatial distribution and their accuracy, as demonstrated by Schneider et al. (2017) and Starkey et al. (2017) by using real CS observations. In addition, assimilation of CS observations into the hydrological model tends to provide lower improvement than the assimilation in the hydraulic model. However, assimilation in hydrological models ensures better model prediction for high lead-time values than the assimilation in the hydraulic model. This is due to the high travel time needed to reach the prediction point of PA (around 22 h from the outlet of sub-catchment B). For operational flood management it is advisable to consider model results in which observations at upstream locations of the catchment are assimilated in both hydrological and hydraulic models. In experiment 1.2, assimilation of CS observations from DySc sensors produced an overall improvement of model performances in terms of μ (NSE) increase and σ (NSE) reduction. Higher values of μ (NSE) are achieved by assimilating CS observations coming from multiple river reaches, in particular for those reaches close to PA. Due to the fact that the model without assimilation underestimates the observed water level, overestimated biased CS observations tends to increase model performances. Comparable results were obtained in Rakovec et al. (2012) and Mazzoleni et al. (2015, 2017a) in the case of assimilation of distributed sensors in hydrological modelling.

The aim of experiment 2 was to investigate the effects of different, theoretical, levels of involvement in the assimilation of CS observations coming from heterogeneous sensors (StPh, StSc and DySc). Our findings demonstrate that sharing CS observations driven by a feeling of belonging to a community of peers (scenario 2 in the proposed theoretical social model) can help improve flood prediction if such a small community is located upstream of a particular interest point. The results achieved for scenario 1 point out that a growing participation of citizens motivated by personal interests, sharing hydrological observations in big cities, can help improve model performance. In particular, the model results can benefit from the additional observations provided by enthusiastic citizens (scenario 3). Similar conclusions are reported in Starkey et al. (2017), who demonstrate the importance of proper engagement for providing additional sources of catchment information.

Finally, it is important to investigate the effect of varying percentages of smartphone usage in space and the decrease in citizen involvement over time. The percentage of active citizens may change spatially in densely populated areas such as the municipality of Vicenza. Increasing the smartphone market penetration in Vicenza would not affect model results in the case of scenario 2, because no involvement is assumed in densely urbanized areas. A high percentage of active citizens in Vicenza affects only scenarios 1 and 3. However, because the number of active citizens in Vicenza is already high for a smartphone usage of 41 %, the model improvement is not significant for a higher percentage of active citizens. This means that in the proposed theoretical involvement model more active citizens (i.e. more mobile phones available) will not significantly improve involvement and affect the model performance. It is worth noting that a more exhaustive social–economic analysis should be performed in order to better define the smartphone market penetration and consequent percentage of active citizens.

In this study, we assume intrinsic motivation, constant in time, differentiated according to the level of involvement. However, a main challenge in citizen science is to keep this involvement high in the long term. In the case of flood events, citizen involvement tends to disappear if no other event occurs in a short time (Wehn et al., 2015). In fact, depending on the memory of the community, the awareness of flood risk decreases over time (Raaijmakers et al., 2008), and, therefore, the tendency to be engaged in data collection will also reduce or even disappear. For this reason it is important to keep citizens engaged using, for example, gamification approaches or periodic meetings or seminars with interested participants. However, the main goal of this paper is not to review or propose approaches to engage and keep citizen involved over a long time. For this purpose, a comprehensive and detailed analysis of citizen motivations and engagement mechanisms is reported in Geoghegan et al. (2016), Gharesifard and Wehn (2016) and Rutten et al. (2017) and these aspects are being studied in detail in the H2020 GroundTruth 2.0 Project (www.gt20.eu). A possible solution for collecting water level data over time could be the involvement of the civil protection volunteers. This approach is currently being used in the Bacchiglione catchment by the Alto Adriatico Water Authority which requests the water level data at particular locations and moments from the Civil Protection volunteers to validate model results in near-real time.

This study demonstrates that a high-performance model can still be achieved even for decreasing citizen involvement over time. Moreover, crowdsourced observations of either experts or citizens will not necessarily have the quality high enough to support decision-making (Cortes Arevalo et al., 2014). In addition, real-time observations require safe conditions, good internet connections and trusted observers by water authorities. Therefore, it is of utmost importance to understand limitations and to develop quality control mechanisms for CS observations (Tulloch and Szabo, 2012; Vandecasteele and Devillers, 2013; Bordogna et al., 2014; Bird et al., 2014; Cortes Arevalo, 2016).

7 Conclusions

This study assesses the usefulness of assimilating crowdsourced observations coming from a network of distributed static physical, static social and dynamic social sensors, installed within the WeSenseIt Project in the Bacchiglione catchment, with the aim of advancing the understanding of the effect of public involvement on the improvements of flood models. In the complex process of assimilating of CS observations into water system models, many factors play an important role for correct flood estimation: types of social sensors, citizen involvement, decrease in involvement over time, types of hydrological and hydraulic models, spatial variability of citizen involvement, etc. In this study, we focus on the type of social sensor, the citizen involvement level, and its variability in time and space. 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 only one case study. Since CS observations of water levels are not available at the time of this study, we use synthetic observations with intermittent measurement intervals and random accuracy in time and space. Two different sets of experiments are carried out. In experiment 1, the crowdsourced observations from StSc and DySc are assimilated with the hydrological and hydraulic model considering the random levels of citizen involvement. However, in experiment 2, three hypothetical citizen involvement level scenarios are introduced to provide a more realistic representation of the availability of CS observations for the model. Scenarios are based on the combination of population distribution and three types of citizens' motivations to collect data based on Batson et al. (2002): (1) own personal purposes, (2) shared or community interests and (3) societal benefits. We further assume that CIL affects only observation intermittency, not accuracy.

Overall, we demonstrate that the assimilation of CS observations provided by citizens improves model performance. Experiment 1.1 shows that the assimilation of CS observations in the hydrological model tends to lead to a lower improvement than the assimilation in the hydraulic model, in the case of low lead-time values. In the case of high lead-time values, assimilation in the hydrological model allows better model predictions to be achieved than with the assimilation in the hydraulic model. In experiment 1.2, high values of NSE are achieved for DySc sensors located close to the boundary conditions, while moving these sensors to downstream locations reduces NSE values. These results are due to the higher error of the boundary conditions if compared to the model error of the hydraulic model itself. Systematic (bias) and random errors in water level observations play an important role. Finally, experiment 2 demonstrates that crowdsourced observations provided by citizens driven by a feeling of belonging to a community of peers (motivation 2) can help to improve flood prediction if such small communities are located in the upstream part of the catchment. However, increasing participation of citizens motivated by their own purposes, sharing hydrological observations in big cities, can help improve model performance. In particular, the model results can benefit from the additional observations provided by enthusiastic citizens. In this study, the higher smartphone market penetration in the urbanized area of Vicenza compared to the upstream towns tends to not significantly affect model results. High model performance can still be achieved even for decreasing involvement over time.

A number of limitations of this study have to be addressed as well. Firstly, in order to generalize the findings of this research, the proposed methodology has to be applied in more case studies and flood events. Secondly, real CS observations should be used to properly assess the observational error and accuracy level which vary according to the sensor type (static or dynamic). Thirdly, 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 citizen behaviour during 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 involvement in monitoring river water level in the case study. Finally, in real-life conditions, it may occur that active citizens might not be available at the right time, i.e. during a flood event. In our study, we do not distinguish between observations provided during day-time or night-time (as addressed by Mazzoleni et al., 2015).

For future studies it is recommended to (a) introduce better characterization of the CS observations accuracy level, (b) propose an involvement model based on social analysis of citizen motivations and engagement, (c) use agent-based models to simulate and represent the interactions between autonomous agents (citizens) based on their motivations, and (d) test the proposed method using real CS observations during other flood events.

Data availability. The DEM data were downloaded from the SRTM database (http://srtm.csi.cgiar.org, USGS, 2004). The rainfall and river discharge data were provided by the Alto Adriatico Water Authority. The CORINE Land Cover dataset of the European Environment Agency was used.

Appendix A: List of acronyms used in this study.

Acronyms	Meaning
AAWA	Alto Adriatico Water Authority
CIL	Citizen involvement level
CS	Crowdsourced
DySc	Dynamic social
KF	Kalman filter
MCIL	Maximum citizen involvement level
PA	Ponte degli Angeli
StPh	Static physical
StSc	Static social
W_L	Water level
WSI	WeSenseIt

Appendix B: Response times for the sub-catchment and the reaches of the Bacchiglione catchment.

Location	Time (hours)
Sub-catchment A	1.5
Sub-catchment B	3.5
Sub-catchment C	6.0
Reach 1	2.2
Reach 2	2.0
Reach 3	7.2
Reach 4	9.5
Reach 5	3.4
Reach 6	5.2

Competing interests. The authors declare that they have no conflict of interest.

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