1 Point-by-point reply to comments

I'm grateful to the Editor and the Reviewers for their suggestions, which I found insightful and helpful. I'm confident that the revised version of the paper, with respect to the previous version, is more clearly focused, ordered in its structure, and enriched in terms of contents.

According to the Editor's suggestion, I paid particular attention to clarifying that the comment is about the operational aspect of using crowdsourced data.

2 RESPONSE TO THE COMMENTS OF REVIEWER #1

The comment on "Can assimilation of crowdsourced data in hydrological modelling improve flood prediction?" addresses the subtle drawback hidden behind the practice of using traditional and crowdsourced data, recorded at different locations, disjointly. The former are used to calibrate semi-distributed models and to force them in real-time, the latter only to update the model states in operational forecasting.

InMazzoleni et al. (2017), synthetic CSD were generated as model results using observed precipitation, while simulated results were obtained using forecasted precipitation. Since the semi-distributed hydrological model used in Mazzoleni et al. (2017) was calibrated at only one location, Viero (2017) underlined that synthetic CSD at interior points (different from the calibration one) cannot be considered reliable due to equifinality issues. In fact, semi-distributed hydrologic models are commonly over-parametrized and may provide accurate predictions only where the model is calibrated, and it can fail to represent the relative contribution of upstream tributaries. I read the comment with interest and I really appreciate all the author's efforts. However, I have many doubts and considerations that I would like to share with him.

Maurizio Mazzoleni

I thank Maurizio Mazzoleni (Reviewer #1) for his appreciation of the Comment and for his valuable comments and suggestions, which are addressed in the following.

1. *Overall, I found that the main message of the author have been stretched and repeated many times throughout the Comment.*

   I agree. In the revised version of the Comment, the text is substantially reorganized to limit useless repetitions.

2. *It is not clear to me what would the author propose to generate synthetic CSD when only measurements from traditional sensors, located at points different from the ones of CSD, are available. In the summary section, only a pragmatic solution is suggested in case of availability of distributed flow data (not the case in Mazzoleni et al., 2017). This solution involves the collection of CSD for a suitable test period, to verify the model ability in describing the system states correctly at the locations in which CSD are collected. However, this solution will open many other types of questions. For example, how would the author assess the quality of the CSD? Which category of citizen the author would engage in order to collect CSD? For how long will this data collection take place? How can it be insured that CSD quality during data collection will be the same as the CSD quality during real-time modelling updating (no control)? Citizens accuracy is different and data quality assessment is still a burning topic in citizen sciences. In addition, CSD in calibration may be different from the ones in real-time model updating.*

   The work by Mazzoleni et al (2017) is actually a proof-of-concept, which analyses major aspects of the assimilation of crowdsourced data in order to improve flood forecasting. My Comment essentially focuses on what should follow a proof-of-concept, i.e., on the operational use of CSD. Indeed, it is the passage from a proof-of-concept study to a real-world application (i.e., from synthetic CSD to actually measured CSD) that entails additional, significant drawbacks related to equifinality, overparametrization, and deficiency in model structure, which are not discussed in Mazzoleni et al. (2017).

Accordingly, my Comment is not aimed at proposing a different, better way to generate synthetic CSD when measurements from traditional sensors are available only at different locations from the ones of CSD, as this would mainly pertain to a proof-of-concept study.

In the revised version of the Comment, it should be clearer that its main aim is to highlight additional drawbacks inherent the use of CSD in operational flood forecasting, not assessed in Mazzoleni et al. (2017). Possible solutions and additional guidelines are now enhanced (thanks also to suggestions by Reviewer #2) and better explained.

3. *Moreover, I do not understand to which extent the comments of the Author are referred to the paper of Mazzoleni et al. (2017) or to a generic issue on the use of CSD in hydrological modelling.*

   I am aware that it is actually difficult to properly balance comments that must be specific (in that they refer to particular aspects of a given work) and, at the same time, they should be significant in a wider sense. I revised the paper in order to make a better equilibrium by reporting specific comments in Section 2, and by debating them from a more general point of view in Section 3.

4. *The Author mentioned that "Indeed, for synthetic streamflow CSD to be realistic, two specific requirements have to be met: i) a reliable rating curve must be available for the cross sections where hydrometric CSD are recorded, and ii) the model has to be calibrated at these locations". I agree with the author in case of CSD provided by static sensors, like in case of Mazzoleni et al. (2017). However, in a real scenario where CSD are provided by citizens at random moments and locations within the catchment, by means of dynamic sensors, I do not agree with the second point of the comment for two reasons. Firstly, assuming the author is right, it would be extremely difficult to calibrate the model with observed data at unknown locations in which synthetic CSD will be assimilated. Secondly, it is not clear to me why synthetic CSD based on model results should be generated if observed data are already available at the CSD/calibration points. Obviously, such observed data should be directly used to generate synthetic scenarios of CSD, like in case of the first three case studies in Mazzoleni et al. (2017), without using any model result.*

   I thank M. Mazzoleni for this comment, which help me to clarify the focus and the structure of my Comment. The revised version of the Comment more specifically deals with aspects related to operational use of CSD. In the Summary of the Comment, I remarked that locations at which streamflow CSD can be collected are actually always a-priori known because of the need of a rating curve, which must be developed before the assimilation of CSD in real-time operational use. Data collected in order to develop the rating curve should also be used to calibrate or, at least, to verify the model at these sections. Without actual rating curves, assimilation of synthetic CSD remains a theoretical exercise. Accordingly, while synthetic CSD can be certainly useful to carry out proof-of-concept studies and preliminary investigations, operational flood forecasting needs to rely on real data.

5. *Another extremely important point is the assimilation of CSD observations. From Viero's Comment, it is not clear how erroneous synthetic observations can affect assimilation performances. The author briefly mentions this issue referring to Dee (2005) and Liu et al. (2012). Honestly, since the main objective of Mazzoleni et al. (2017) was the assimilation of realistic synthetic CSD, I was expecting a more comprehensive analysis on the effect of assimilating biased/uncertain observations within hydrological model.*

   The issue raised by M. Mazzoleni is undoubtedly interesting and deserves further discussion. The main objective of Mazzoleni et al. (2017) was the assimilation of realistic synthetic CSD. In my Comment, I explain that little can actually be said on the reliability of the synthetic CSD of the Bacchiglione case study. In the revised version, this aspect is better explained through a practical example related to the effects of the "Viale Diaz" floodplain on flood routing. The reader can grasp from this example which are the possible effects of assimilating biased data at location where the model is not verified and when only model states are updated (or in the case of structural deficiencies of the model).

   Importantly, in my Comment I point out that even accurate and unbiased measured data can be "seen" as biased data by a model. This can occur when the model is not properly calibrated at sections where data refer to (and model parameters are not update along with model states), or when the model is unable to reproduce the actual dynamics of the system at those locations due to intrinsic limitations of the model structure. This issue is better explained with practical examples in my answer to the following point #6.

6. *In addition, Viero stated, "In a context of equifinality and of poor identifiability of model parameters, the model internal states can hardly mimic the actual system states away from calibration points, thus reducing the chances of success in assimilating real (i.e. not synthetic) CSD." Why the chances of success in assimilating real CSD is reduced if the model is not calibrated at CSD location? Does this mean that in case of assimilation of distributed soil moisture observations from remote sensing, within a distributed hydrological model, we would need to calibrate the model in each grid cell? I disagree with the author. The main purpose of data assimilation is to use real-time (noisy) observations to update the wrong estimate of the states of a dynamic model (not able to mimic the actual system states away from calibration point). Assimilation of observations at internal points of the catchment is very useful when model states are less accurate than real-time observations.* ***If a model is able to correctly predict actual system states away from calibration points, why should someone bother to add complexity and uncertainty assimilating CSD observations?*** *The literature provides many studies (e.g. Rakovec et al., 2012) in which hydrological models are updated using measurements at internal points, even if such observations are not used during model calibration.*

   Thank you for this comment. I realize that I was not precise enough in that part of my Comment, which was improved in the revised version of the Comment.

   To answer the key question in this Reviewer's comment (which I highlighted above), I remark that a model can predict wrong system states away from calibration points for different reasons (e.g., wrong/insufficient input data and/or poor calibration and/or structural model deficiencies). Assimilation of observations at internal points of the catchment can be extremely useful when model states are less accurate than real-time observations, but not when this lack of accuracy of model states is due to problems with model structure (or due to poor calibration of model parameters if such parameters are not updated through data assimilation along with the model states).

   Therefore, I stress that the statements by M. Mazzoleni are reasonable, but they implicitly assume that the model structure (and the set of model parameter as well, since they were not updated through data assimilation in his work) is (are) able to correctly estimate, at the same time, both the internal states and the model outputs. Although this is a highly desirable feature for physical-based models (see also comment #3 of Reviewer #2), one must admit that it is not true in general and, reasonably, it is not true for the model application of the Bacchiglione River presented in Mazzoleni et al. (2017).

   I try to clarify the question using first a hypothetical example. Consider a hydrological model, not calibrated at internal points, which provides the right prediction at the closing section as the result of wrong predictions at some internal points. The updating of model states at this internal points based on real data (i.e., different to the internal states needed to provide the 'correct' prediction at the outlet) will likely cause this model to produce worse predictions at the closing section with respect to no assimilation at all. This possible occurrence cannot be detected, nor assessed, if data to be assimilated are extracted from the model itself. Indeed, in this case synthetic data represent wrong internal states (with respect to reality), but they represent the best-fit scenario in terms of main model output.

   The problem of assimilating data that are not coherent with internal model states (when this is due to poor estimation/identifiability of model parameters) could be limited by updating the model parameters along with the internal states of the model (as suggested by Reviewer #2), but this strategy could not be sufficient if the model has structural deficiencies.

   As a practical example, consider the "Viale Diaz" floodplain, described in my Comment, which acts as a sort of in-line natural flood control reservoir on flood propagation. Since the attenuation of flood wave exerted by this floodplain can not be properly accounted for by the routing model used in Mazzoleni et al. (2017), the (hypothetical) assimilation of a correct flood hydrograph upstream of the Viale Diaz floodplain leads to incorrect streamflow predictions at Ponte degli Angeli, downstream of the "Viale Diaz" floodplain.

7. *I am puzzled with the sentence "Therefore, beside the key points identified by Mazzoleni et al. (2017), not only data, but also the model has to match specific requirements for data assimilation to be successful". What are these specific requirements that model has to match? Is the Author referring to the reliability of synthetic data at calibration points and to the capability of the model to represent truth states?*

The need to assimilate suitable crowdsourced data was assessed in Mazzoleni et al. (2017). With respect to the specific requirements that the model has to match, its ability of well representing the physics of the hydrological system (i.e., of correctly representing true internal states when forced by correct input data) is actually the key aspect. I tried to make this point clearer in the revised version of the Comment.

3 RESPONSE TO THE COMMENTS OF REVIEWER #2

The author makes some significant critical remarks on the work of Mazzoleni et al. (2017) that are worth to be considered for publication.

I thank Reviewer #2 for his/her appreciation of my Comment and for his/her very useful and precise suggestions, which are addressed in the following

1. *However, I would first advise to mellow the tone of the narrative.*

   Thanks for the suggestion. I revised the text of the paper to smooth the English and to fix many typos.

2. *In addition, I invite the author to make sure that the comments are more general and less focused on the upper Bacchiglione river catchment presented by Mazzoleni et al. (2017). In doing so, Section 2.1 should be reduced considerably, as most of the information and comments seem too specific, and might not be supported for the other test sites.*

   I thank the reviewer for his suggestion. In the revised version of the Comment, Section 2 was shortened and reorganized, trying to separate specific comments that refer to the upper Bacchiglione case study from general comments (Section 3). I agree that Sect. 2.1 is very specific. Nevertheless, I do believe that most part of this specificity is not meaningless for other test sites. Indeed, I remain convinced that much can be learned from in-depth analyses of specific cases. The opposite risk is the (often unperceived) oversimplification of real systems and processes in our schematic representations (i.e., models) of the reality.

   Besides its evident specificity, one of the goals of Sect. 2.1 is to highlight that real-world case studies are often far more complex than what can emerge from most of the applications reported in the literature (this is undoubtedly due to the need of limiting paper length). I am convinced that similarities with many other case studies can easily be found.

   Finally, the Comment is indeed a comment to a specific paper, and only one of the four case studies reported by Mazzoleni et al (2017) is here commented, since the contents of the Comment only apply to (semi-)distributed (and over-parameterized) models and to the assimilation of CSD data at location where the model cannot be calibrated. In the other test cases presented in Mazzoleni et al (2017), the Authors used a lumped model and CSD were assimilated only at calibration sections.

3. *The paper of Mazzoleni et al. (2017) aimed at investigating the value of information retained by crowdsourced data (CSD) when assimilated in surface flow models for flood prediction. Their work is admittedly a proof-of-concept study and the synthetic feature of CSD is quite clear, rather than "briefly mentioned". Their conclusions are correct so long as one assumes the model well represents the physics of the hydrological system, which is a fundamental hypothesis behind observation simulation system experiments. On the other hand, I agree that there seems to be an inherent tendency in Mazzoleni et al. (2017) to present results in a way that somehow overstates the importance of CSD.*

   I agree with the reviewer. The fact that a model well represents the physics of the hydrological system is a fundamental hypothesis for physically-based models, and is tacitly assumed in Mazzoleni et al. (2017). However, it must be stressed that this requirement is not necessarily matched when semi-distributed, physically based models are actually used as lumped models, i.e., they are calibrated only at the closing sections. Given the complexity of the Bacchiglione catchment, the relatively paucity of measured data, and the structure of the model used (see my answer to comment #6 of Reviewer #1 for further details), reasonably it is not true for the model application of the Bacchiglione River presented in Mazzoleni et al. (2017).

4. *There are, in my view, some major points that need to be highlighted: the method chosen for calibrating a model should be consistent regardless of the type of data used. For non-linear models, ensemble based data assimilation methods (e.g the EnKF or the PF) are attractive in that they can be used to update jointly model states and parameters and provide a direct measure of uncertainty. Note that these models cope directly with problems of over parameterization and equifinality since parameter posterior distributions are represented by ensembles. CSD can be instrumental to reduce model uncertainty. Indeed, one can assimilate these data together with traditional hydrologic observations, thereby reducing parameter uncertainty even in those regions where the original reliability of the model is inadequate. In general, the value of information of these data is strictly dependent on their quantity, quality, spatial-temporal distribution. Note that typical data assimilation algorithms are in principle able to screen out noisy data automatically, but need to be modified to tackle possible data bias, which otherwise leads to poorly calibrated models. Thus, it is important, regardless of the nature of the data, to verify if such bias exists before any data assimilation is applied.*

   I thank the Reviewer for these interesting considerations. Ensemble based data assimilation methods are indeed powerful tools. On one hand, their use to jointly update model states and parameters can effectively circumvent the problem of uncertainty in model internal states at crowdsourced data points; on the other hand, such methods can help diagnosing poor identifiability of model parameters.

   However, sophisticated tools to update jointly model parameters and states may fail if assimilating data at locations where the model is unable to correctly reproduce the actual physics of the system due to structural deficiencies. This occurrence is far from being rare in operational flood forecasting frameworks where (over)simplified models are commonly used in order to limit their computational burden.

   While structural deficiencies can be a-priori conjectured through a close inspection of both the physical system and the model characteristics, it can be proved (and quantified) only by comparing model results with measured data (i.e., model validation). The “blind” use of CSD (i.e., its assimilation at locations where the model is neither calibrated nor verified) is at least questionable (see, e.g., the examples reported in the answer to comment #6 of Reviewer #1).

   Finally, in the Reviewer’s comment it is stressed the importance of detecting bias in data to be assimilated. This observation pertains also to the object of my Comment, since assimilating real (i.e., not synthetic) data at locations where the model is unable to reproduce the physic of the system is equivalent to assimilating biased data.

   These considerations have been added to the revised version of the Comment.

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Comment on “Can assimilation of crowdsourced data in hydrological modelling improve flood prediction?” by Mazzoleni et al. (2017)

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Abstract. In their recent contribution, Mazzoleni et al. (2017) investigated the integration of crowdsourced data (CSD) in hydrological models to improve the accuracy of real-time flood forecasts. They showed that assimilation of CSD improves the overall model performance ~~in all the considered case studies. T~~; the impact of irregular frequency of available crowdsourced data, and that of data uncertainty, were also deeply assessed. However, it has to be remarked that, in their work, the Authors used synthetic (i.e., not actually measured) crowdsourced data, because actual crowdsourced data were not available at the moment of the study. ~~This point, briefly mentioned by the authors, deserves further discussion.~~ For this reason, the work by Mazzoleni et al. (2017) is actually a proof-of-concept study. In most real-world applications, ~~rainfall-runoff~~ hydrological models are calibrated using data from traditional sensors; ~~. Typically,~~ CSD are typically collected at different locations, where semi-distributed models are not calibrated. ~~In a context of equifinality and of poor identifiability of model parameters, the model internal states can hardly mimic the actual system states away from calibration points, thus reducing the chances of success in assimilating real (i.e., not synthetic) CSD.~~ As a result of either equifinality, poor model identifiability, and lacks in model structure, internal states of (semi-)distributed models can hardly mimic the actual states of complex systems away from calibration points. Indeed, in operational frameworks, the assimilation of real (rather than synthetic) CSD requires a careful assessment. Additional ~~criteria~~ guidelines are given that are useful for the a-priori evaluation of (assessing the chance of assimilating) crowdsourced data for real-time flood forecasting and, hopefully, to plan apt design strategies for both model calibration and collection of crowdsourced data.

1 Introduction

The availability of hydrometric data, collected by active citizens in the course of severe flood events, offers a new, unexpected chance to improve real-time flood forecasts. In pioneering applications, crowdsourced data (CSD) collected in the upper part of a basin were assimilated into adaptive hydrological models to reduce ~~the~~ uncertainty in forecasting flood hydrographs at downstream sections (Mazzoleni et al., 2015). In a recent work, Mazzoleni et al. (2017) paid particular attention to the issues of ~~data~~ uncertainty and irregular arrival frequency of CSD. Their results showed that assimilation of CSD improves the overall model performance ~~in all the case studies they considered~~. They also showed that the accuracy of CSD is, in general, more important than their arrival frequency.

However, ~~there is a crucial aspect that has to be remarked.~~ in their work, the Authors used synthetic (i.e., not actually measured) CSD, because real streamflow CSD were not available at the moment of the study. ~~The Authors warned about this aspect by stating that~~ Commenting on this aspect, the Authors wrote "*the developed methodology is not tested with data coming from actual social sensors. Therefore, the conclusions need to be confirmed using real crowdsourced observations of water level*". ~~This point deserves further discussion, as the use of synthetic data led them to disregard a subtle, yet significant, limitation inherent in the use of CSD in~~ for ~~real-time flood forecasting. The problem involves equifinality (i.e., uncertainty in model parameters and internal states, Beven, 2006) that characterizes hydrologic, semi-distributed (and over-parametrized) models.~~ A practical verification of the results by Mazzoleni et al. (2017) is indeed necessary; furthermore, particular attention has to be paid to additional drawbacks inherent in the use of CSD in operational flood forecasting, which are not discussed in their proof-of-concept study.

~~After the critical work by Beven (1989), detailed investigations were carried out about the complexity a model needs to simulate rainfall-runoff process. Several studies indicated that the information content in a rainfall-runoff record is sufficient to support models of only very limited complexity (Jakeman and Hornberger, 1993; Refsgaard, 1997). This implies that distributed, or semi-distributed, hydrologic models are seldom calibrated. Rather, they are commonly over-parametrized. As a typical example, a semi-distributed rainfall-runoff model may provide accurate predictions of the outflow discharge at the closing section and, at the same time, it can fail to correctly model the relative contribution of upstream tributaries. To limit problems related to over-parametrization, also the internal states of a distributed model have to be calibrated (Sebben et al., 2012; Viero et al., 2014), and not only the outflow at the closing section.~~

~~Strictly speaking, and bearing in mind that one can get the correct answer for the wrong reason Loague et al. (2010), a semi-distributed model can be said calibrated only at the calibration points. This caveat has important consequences also on data assimilation and models updating.~~

~~In general, data assimilation techniques are used to update model input, states, parameters, or outputs based on new, available observations (Refsgaard, 1997). Assimilation of CSD may improve the performance of a forecasting model inasmuch as assimilated data contribute in updating (i.e., in correcting) the internal states of the model. It must be observed that crowdsourced data typically refers to internal states of the model, since input and output data commonly corresponds to location provided with traditional physical sensors. For updating to be successful, available data must be substantial and accurate (as well debated by Mazzoleni et al., 2017), but further requirements must be met. Indeed, data assimilation is successful if the model can correctly predict, at the same time, both the main output and the internal states of the system. At least, the model have to describe well the real system states (i.e., must be properly calibrated) at every location in which crowdsourced data are collected. Accordingly, crowdsourced data must be collected in correspondence of the control points of the models (i.e., those used to calibrate the model).~~

~~Therefore, beside the key points identified by Mazzoleni et al. (2017), not only data, but also the model has to match specific requirements for data assimilation to be successful. This issue is certainly relevant for the case study of the Bacchiglione River, for the reason reported in the following.~~

The Comment is outlined as follows. Section 2 presents a deep assessment of the Bacchiglione River case study (i.e., the fourth case study presented in Mazzoleni et al., 2017), in order to highlight the actual gap between a proof-of-concept study and a real application for operational flood forecasting. Given the complexity of the basin and the relatively paucity of available data, it is shown that the semi-distributed model used in Mazzoleni et al. (2017) is unable to properly represent the physics of the whole hydrological and hydraulic system, with adverse effects on the assimilation of real CSD. Based on the key features delineated in Sect. 2, a more general assessment of CSD assimilation in (semi-)distributed hydrological models is given in Sect. 3. A brief summary closes the Comment.

2 Specific comments

~~In this Section, the focus is on the fourth case study presented in Mazzoleni et al. (2017), in which synthetic (i.e., not actually recorded) crowdsourced data (CSD) were used to improve the performance of a semi-distributed hydrological model of the Bacchiglione catchment closed at Ponte degli Angeli, Vicenza (Italy).~~

2.1 The Bacchiglione catchment closed at Ponte degli Angeli (Vicenza)

The catchment of the upper Bacchiglione River, closed at Ponte degli Angeli in the historical centre of Vicenza (Fig. 1), is located in the north of the Veneto Region, a plain that is fringed by the Alpine barrier at a distance of less than 100 km to the north of the Adriatic Sea (Barbi et al., 2012).

With regard to the precipitation climatology, the southern part of this plain is the drier, with approximately 700–1000 mm of mean annual rainfall, whereas more than 2000 mm are measured close to the pre-alpine chain due to the interaction ~~with~~ of the southerly warm and humid currents coming from the Mediterranean Sea with the mountain barrier (Smith, 1979). ~~Indeed, the topography of the region rises from the southern plain at about 30 m above sea level (a.s.l.) to about 1500–2200 m a.s.l. in the first orographic barrier, the pre-alpine chain, and then further to the north to the Dolomites, a mountain massive that peaks at over 3000 m a.s.l. In the northern part of the Bacchiglione catchment, the terrain elevations raise from 250 to 1’000 m a.s.l. in less than 1 km, with slopes up to 70%.~~ A significant portion of the annual rainfall often concentrates into very short periods of time in the form of what often turns out to be an extreme event with deep convection playing a central role (Barbi et al., 2012; Rysman et al., 2016). As a consequence, severe flooding event have threatened agricultural and urban areas in the recent years (e.g. Viero et al., 2013; Scorzini and Frank, 2015).

~~A comparison of hourly rainfall rates measured at the four meteorological gauging stations of Valli del Pasubio, Monte Summano, Malo, Montecchio Precalcino, and S.Agostino (Fig. 1) is reported in Fig. 2 for the storm event of 16-18 May 2013 (data provided by the Regional Agency for Flood Protection of the Veneto Region, ARPAV).~~ Due to the spatial and temporal variability of the rainfall fields ~~is apparent. Many~~ meteorological models are often unable to provide accurate and reliable

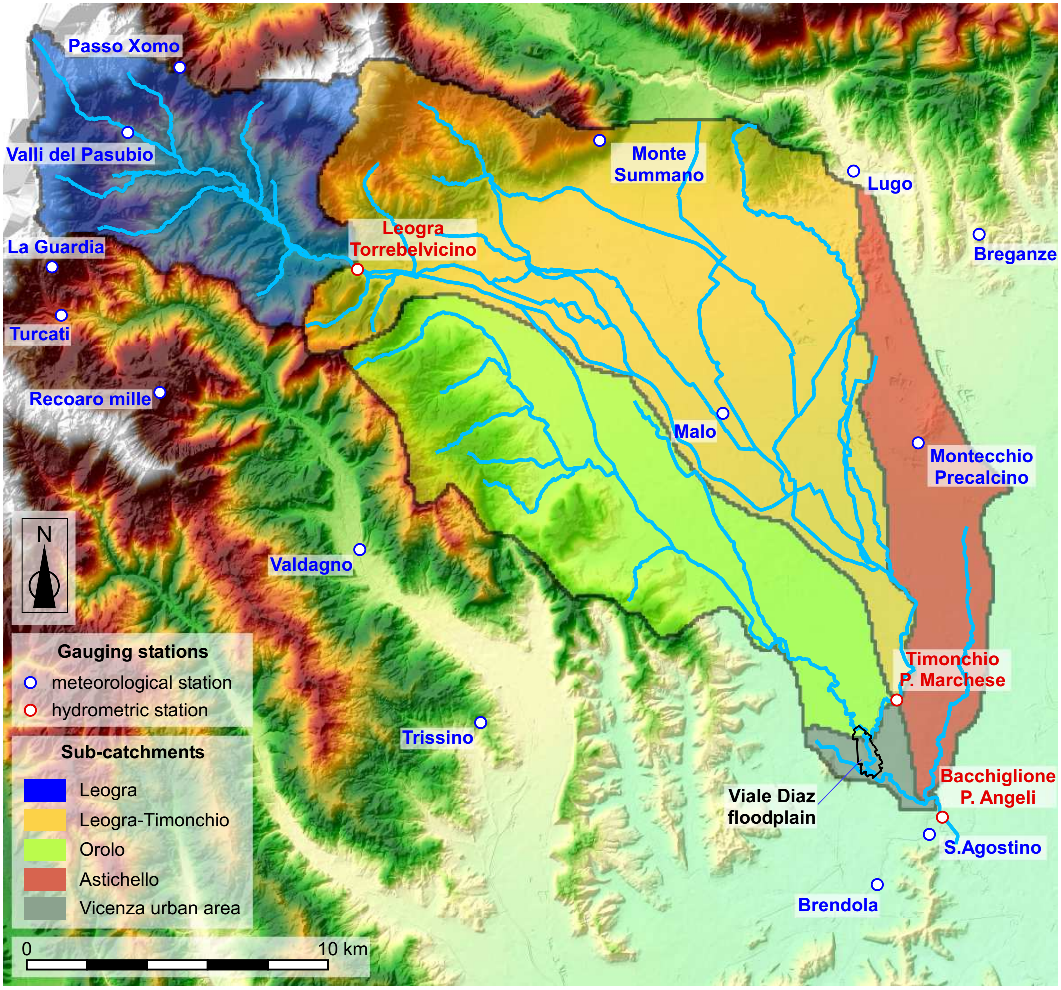

Figure 1. The catchment of the Bacchiglione River closed at Ponte degli Angeli, Vicenza (Italy).

quantitative precipitation estimates (QPE) for the upper Bacchiglione catchment. ~~, due to both insufficient spatial and temporal resolution, and to the actual complexity of this environment.~~ An example of this inadequacy is given, for instance, by Fig. 13 in Mazzoleni et al. (2017). The discharge simulated using forecasted input is very different from that obtained using recorded rainfall, ~~showing~~ with a significant time shift and errors in predicted discharge ranging between 25 and 50% at the flood peak (and up to 90% if considering synchronous data).

~~From an hydraulic point of view,~~ The upper Veneto plain is a highly populated and urbanized area, with extremely complex drainage and irrigation networks that significantly affect both runoff production and propagation (Viero and Valipour, 2017). Within this plain, the Bacchiglione River and ~~all~~ its tributaries are provided with relatively high levees (Viero et al., 2013), which prevent the exchange of water from inside to outside the riverbed (and vice-versa) when the inner water levels are relatively high. As a consequence, the minor channel networks are not always allowed to deliver their drainage water towards the nearest tributary, i.e., the inflow points along the main river reaches change during a flood event depending on the instantaneous water level within the river. This occurrence ~~change~~ modifies the network connectedness which, in turn, leads to different mechanisms of hydrologic response in the overall catchment.

Just upstream of the City of Vicenza, ~~a~~ an area of up to 1 km^2 of the “Viale Diaz” floodplain (Fig. 1) ~~of about 1 km^2~~ is flooded when the Bacchiglione flow rate ~~in the Bacchiglione~~ exceeds ~ 160 m^3/s. Since about $2 \cdot 10^6$ m^3 of water can be temporarily stored in this area, a significant flood attenuation can be produced, particularly in case of floods with a steep rising limb (which is often the case due to the climatic regime and the catchment characteristics).

Moreover, the lower part of the Bacchiglione basin, North of Vicenza, includes a vast groundwater resurgence zone, in which it’s difficult to assess both the actual contribution of resurgence to the Bacchiglione streamflow (up to ~ 30 m^3/s) and the time-variable behaviour of soil moisture.

Clearly, such a system is highly non-linear. Nonetheless, significant parts of the Bacchiglione catchments are poorly monitored, and the remaining parts are completely unmonitored. The Leogra subcatchment (blue shaded area in Fig. 1) is provided with a pressure-transducer for the measure of water level at Torrebelvicino (Fig. 1). A rating curve derived from theoretical considerations is available for this cross-section. However, the absence of ~~Its reliability is clearly low, since no~~ instrumental measures of flow discharge ~~are available for this site~~ limits its reliability. The Leogra-Timonchio subcatchment (orange shaded area in Fig. 1) is monitored by an ultrasonic stage sensor located at Ponte Marchese, just upstream of the confluence with the Orolo River. ~~operated by ARPAV~~ ~~; Located in Ponte Marchese, just upstream of the confluence with the Orolo River, it is not provided with any rating curve. Available~~ Flow rate measurements at Ponte Marchese refers only to low hydraulic regimes, and show great variability due to the operations of a hydroelectric power plant located just downstream of Ponte Marchese. The Orolo River (green shaded area in Fig. 1), with a discharge capacity of more than one third of the Bacchiglione at Ponte degli Angeli, is one of its major tributaries. ~~The catchment of the the Orolo River leans against a ridge, which increases the spatial variability of precipitation fields.~~ Unfortunately, not only ~~this area~~ the Orolo subcatchment is completely uncovered by meteorological gauging stations, but also no hydrometric gauging stations are present along ~~the reach of the Orolo River~~ its reach. Similarly to the Orolo, the Astichello catchment (red shaded area in Fig. 1) is unmonitored and, due to backwater effects, significant areas adjacent to the Astichello are flooded when water levels in the Bacchiglione are relatively high. Hence, the discharge that effectively flows from the Astichello into the Bacchiglione River may significantly reduce~~d~~ depending on the water stage within the main course of the Bacchiglione River.

Attention must be paid to the fact that the three major tributaries (Orolo, Timonchio, and Astichello) meet just upstream of the closing section of Ponte degli Angeli (Fig. 1), making it difficult to correctly estimate the actual contribution of each single tributary to the total streamflow ~~correctly.~~ By looking at the tree-like structure of the drainage network in an electrical analogy (Rodríguez-Iturbe and Rinaldo, 2001), the major tributaries of the Bacchiglione are in fact “conductors in parallel”.

~~Moreover, the lower part of the Bacchiglione basin, North of Vicenza, includes a vast groundwater resurgence zone, in which it’s difficult to assess both the actual contribution of resurgence to the Bacchiglione streamflow (up to ~ 30 m^3/s) and the time-variable behaviour of soil moisture.~~

Certainly, given the irregular topography of the catchments, the heterogeneity of the landscape, and the complexity of the hydraulic network, it can be stated that the Bacchiglione catchment ~~of Bacchiglione~~ is poorly monitored.

2.2 The semi-distributed model of the Bacchiglione catchment

In catchments like that of the Bacchiglione River, for all the reasons reported in the previous section, the accurate prediction of flood hydrographs by performing continuous time simulations is unquestionably a hard task (Anquetin et al., 2010).

Mazzoleni et al. (2017) used an available semi-distributed hydrological model coupled with a Muskingum–Cunge scheme for flood propagation within the main river network, which was originally set up to forecast flood hydrographs at the closing section of Ponte degli Angeli (Vicenza). Sensibly, the model was calibrated by minimizing the root mean square error between observed and simulated values of water discharge only at Ponte degli Angeli, which is the only hydrometric station provided with a reliable rating curve. The semi-distributed model, although explicitly representing the hydrological processes within the main subcatchments, has to be intended as a lumped model from a practical standpoint, since the discharge in Ponte degli Angeli is its only control point.

Therefore, no matter the accuracy of the ~~model in forecasting flood hydrographs~~ streamflow predictions in Ponte degli Angeli, little can be said about the accuracy of the ~~same~~ model in describing the internal states of the system, such as the streamflow along the upstream tributaries. This limitation has to be ascribed to uncertainty in precipitation fields, to the paucity of (reliable) flow rate data upstream of Vicenza, and to inherent limitations of the model itself.

Indeed, it has to be remarked that the Muskingum–Cunge model for flood propagation used in Mazzoleni et al. (2017) considers rectangular river cross-sections for the estimation of hydraulic radius, wave celerities, and other hydraulic variables (Todini, 2007). Accordingly, the effects exerted by the "Viale Diaz" floodplain, which acts as a sort of in-line natural flood control reservoir on flood propagation, can not be properly accounted for. This means that, if the flood hydrograph is correctly modelled at Ponte degli Angeli, it ~~is not~~ can not be correctly modelled upstream of the Viale Diaz floodplain (and vice-versa).

2.3 The use of synthetic CSD in the Bacchiglione case study

In ~~the work by~~ Mazzoleni et al. (2017), ~~the~~ synthetic ~~hourly crowdsourced data (~~CSD~~)~~ of streamflow are ~~the~~ results of the model itself. ~~Indeed,~~ Similarly to the "observing system simulation experiment" (OSSE) approach, synthetic CSD were calculated by forcing the hydrological model ~~of the Bacchiglione catchment~~ with measured precipitation recorded during the considered flood events (post-event simulation). ~~As a matter of fact, these data are representative of the actual model internal states of the best-fit scenario.~~

~~Importantly, the synthetic CSD used by Mazzoleni et al. (2017) in the Bacchiglione case study do not refer to calibration points of the model. This aspect can be seen as typical of crowdsourced data, whose natural purpose is to enhance (rather than replace) data from traditional sensors. Indeed, historical data recorded by traditional sensors are first used to calibrate a model; then, in real-time mode, the same sensors provide data both to force the model and to update the model states (e.g. Ercolani and Castelli, 2017); moreover, the reliability of data from traditional sensors outperform that of CSD.~~

~~The Author claimed that the synthetic CSD they used are realistic. For the Bacchiglione case study, recalling the global picture given in Sections 2.1 and 2.2, and that the semi-distributed model was calibrated only at closing section of Ponte degli Angeli, this statement is at least questionable. Indeed, for synthetic streamflow CSD to be realistic, two specific requirements have to be met: *i)* a reliable rating curve must be available for the cross sections where hydrometric CSD are recorded, and *ii)* the model has to be calibrated at these locations. Unfortunately, none of these requirements are met for the Bacchiglione River. The first issue (i.e., lack of rating curves) was assessed inasmuch the Authors considered different degree of uncertainty in streamflow CSD. In this way, they accounted for, e.g., measuring errors and inaccuracy in rating curves. However, nothing was said (nor can be said) about the model performance at locations where CSD are collected, since these locations do not corresponds to calibration points. Here, the model predictions are likely biased but, contrarily to Mazzoleni et al. (2016), this aspect was not accounted for in Mazzoleni et al. (2017).~~

~~What can occur if, due to over-parametrization, the model badly reproduces the actual states at the CSD locations? In this case, the true crowdsourced data don't match the internal model states needed to produce an accurate prediction of the flood hydrograph at the downstream section. Their assimilation into the model can even lead to worse results than no assimilation at all or, at least, to fewer benefits than expected.~~

~~As warned by Dee (2005) and by Liu et al. (2012), great care should be taken in assimilating data if systematic biases or phase errors in the data or model exist, since the optimality of the data assimilation techniques is realized only if the observations and the models are not biased in the mean sense.~~

~~This observation is particularly important given that the results of the study by Mazzoleni et al. (2017) pointed out that the model performance is more sensitive to the accuracies of CSD than to the moments in time at which the streamflow CSD become available. Be careful that here, given the characteristics of CSD used by the Authors, "accuracy of CSD" implies a close similarity between the true crowdsourced data and the internal states of the model.~~

~~This problem is of general interest, and not limited to the study by Mazzoleni et al. (2017). Actually, the complexity of catchments, the relatively paucity of data, and the over-parametrization of semi-distributed rainfall-runoff models are likely the rule rather than the exception.~~

~~Therefore, the main aim of this comment is to warn about the subtle drawback hidden behind the (bad) practice of using traditional and crowdsourced data, recorded at different locations, disjointly; the former to calibrate (semi-)distributed models and to force them in real-time, the latter only to update the model states in operational forecasting. But the same problem, due to equifinality of (semi-)distributed models, could emerge due to a similar, incorrect use of only traditional data.~~

The Authors claimed that these synthetic CSD are realistic; however, for this condition to be met, the model must represent well the physics of the real system (i.e., it must be calibrated or, at least, verified) at locations where CSD are first generated and then assimilated, which is a fundamental hypothesis behind the OSSE approach. As a matter of fact, the synthetic CSD used in Mazzoleni et al. (2017) for the Bacchiglione case study are representative of the model internal states of the best-fit scenario. But, recalling that such CSD do not refer to model control points, nothing can actually be said about the model performance at locations where CSD are generated and, as a consequence, about their accuracy.

From one point of view, such an inconsistency could have led to overrate the importance of CSD in Mazzoleni et al. (2017), who considered issues related to CSD precision, but not accuracy. In other words, real CSD are likely biased with respect to the synthetic CSD they used but, contrarily to Mazzoleni et al. (2016), this aspect was not accounted for in Mazzoleni et al. (2017). From a more general point of view, additional care must be taken in operational flood forecasting when assimilating CSD into (semi-)distributed hydrological models at locations other than model control points. This last point is further discussed in the next section.

3 The use of CSD in operational flood forecasting

As remarked by Mazzoleni et al. (2017), the success of assimilating SCD in hydrological modelling strictly depends on their accuracy, quantity, and spatial-temporal distribution. However, attention must be paid not only to CSD, but also to the model.

First, it must be observed that CSD typically do not refer to model calibration points, since their natural purpose is to enhance (rather than replace) data from traditional sensors. In general, historical data recorded by traditional sensors are first used to calibrate a model; then, in real-time mode, the same sensors provide data both to force the model and to update the model states (e.g. Ercolani and Castelli, 2017); moreover, the reliability of data from traditional sensors outperforms that of CSD. Hence, CSD have limited usefulness at locations already equipped with traditional sensors.

Accordingly, particular care has to be taken when dealing with physically-based, (semi-)distributed models, which are known to suffer from equifinality and identifiability of model parameters (Beven, 2006). After the critical work by Beven (1989), detailed investigations were carried out about the model complexity needed to simulate rainfall-runoff process. Several studies indicated that the information content in a rainfall-runoff record is sufficient to support models of only very limited complexity (Jakeman and Hornberger, 1993; Refsgaard, 1997). This implies that distributed, or semi-distributed, hydrological models are seldom calibrated; rather, they are commonly over-parametrized, since calibration rarely involves their internal states (Sebben et al., 2012; Viero et al., 2014).

In addition, flood routing processes are typically oversimplified in operational models meant to real-time flood forecasting (Mejia and Reed, 2011). For instance, significant effects related to either compound sections, large floodplains connected to the main channel, or confluences causing backwater effects, are seldom accounted for.

As a consequence, semi-distributed rainfall-runoff models may provide accurate predictions of outflow discharge at the closing section and, at the same time, poor predictions of internal states of the system (e.g., the soil moisture content, or the relative contribution of upstream tributaries); in other words, one can likely get the correct answer for the wrong reason (Loague et al., 2010). Therefore, (semi-)distributed models can be said calibrated only at calibration (or control) points, and verified only at locations in which model results are shown to compare favourably with enough (and accurate enough) measured data.

This caveat particularly applies to assimilation of CSD in hydrological modelling for operational, real-time flood forecasting. Indeed, while CSD typically refer to model internal states, they are assimilated in order to improve the accuracy of the main outputs of the model, such as streamflow hydrographs at closing sections (model internal states are relatively less important in this context).

Recalling that model input, states, parameters, and outputs (or a subset of them) can be updated using different data assimilation techniques (Refsgaard, 1997), assimilation of CSD in operational flood forecasting can be helpful provided that the model is able to well represent the physics of the system at locations where CSD are collected. When only internal states are updated (as in Mazzoleni et al., 2017), this condition is met if (and only if) the model is properly calibrated and verified at locations where CSD refer to. Otherwise, correcting internal states of a poorly calibrated model can even lead, in principle, to worse predictions at the outlet than performing no corrections at all (Crow and Van Loon, 2006). It is undoubtedly difficult to assess this issue when only synthetic CSD, generated by the same model, are available for testing the overall method.

As a valid alternative for operational forecasting, ensemble based data assimilation methods (e.g., the Ensemble Kalman Filter or the Particle Filter) can be used to update jointly model states and parameters and to provide a direct measure of uncertainty. In this way, models cope directly with equifinality and problems of over-parametrization, since parameter posterior distributions are represented by ensembles. Note that typical data assimilation algorithms are in principle able to screen out noisy data automatically, but need to be modified to tackle possible data bias, which otherwise leads to poorly calibrated models. Thus, it is important, regardless of the nature of the data, to verify if such bias exists before any data assimilation is applied.

Nonetheless, also such sophisticated tools may fail if the model has structural deficiencies that make it unable to represent true system states at given locations. As a representative example, consider the Bacchiglione River (Fig. 1) and, specifically, the "Viale Diaz" floodplain described in Sec. 2. The role played by such an in-line flood control reservoir on flood routing can not be accounted for using a basic Muskingum–Cunge model that considers rectangular cross-sections. It follows that the assimilation of accurate streamflow data referring to a section located just upstream of the Viale Diaz floodplain (e.g., Ponte Marchese, see Fig. 1) can likely deteriorate the model predictions in Ponte degli Angeli, downstream of the floodplain.

Shortcomings similar to the one described above, which can be found in many different case studies, can be a-priori conjectured through a close inspection of both the physical system and the model characteristic. Their quantitative assessment needs an extensive comparison with measured data; of course, a "blind" use of CSD (i.e., their assimilation at locations where the model is neither calibrated nor verified) is at least questionable.

4 Summary

The approach proposed and investigated by Mazzoleni et al. (2017), based on the ~~use~~ assimilation of crowdsourced data (CSD), can be generally valuable to improve real-time flood forecasts ~~, is in general valuable, and shows a promising way to improve the accuracy of hydrological predictions~~ using non-traditional information ~~, which now active citizens and new technologies make now available to hydrologists~~ now available thanks to active citizens and new technologies.

However, it has to be remarked that ~~the correct description of the physical~~ physically based modelling of rainfall-runoff and flow routing processes ~~processes~~ has to face actual limitations ascribed to the paucity of ~~forcing~~ measured data, to the complexity of real ~~physical~~ environments, and to ~~the~~ lacks in model structure and parametrization. As a consequence, (semi-)distributed rainfall-runoff models used for operational flood forecasting ~~such as that used in Mazzoleni et al. (2017)~~ can provide ~~quite~~ reliable predictions at locations where calibration is performed (i.e., control points) and, at the same time, ~~still provide unacceptably wrong predictions~~ incorrectly represent system states elsewhere ~~of internal system states at the same time~~ (e.g., discharges in upstream, ungauged tributaries).

In a context of equifinality ~~Beven (2006)~~and simplified representation of real physical processes, the accurate prediction of outflow hydrographs can be achieved even though model internal states don’t match the true system states. ~~measured data that do not refer to calibration points of (semi-)distributed models are likely biased for data assimilation purpose (actually, at these locations, it is the model states that are biased rather than the measured data!).~~ In such cases, ~~the performance~~ the assimilation of real CSD ~~of model updating can be~~ can lead to a substantially lower performance than ~~expected when~~ the use of synthetic CSD would suggest, as it corresponds, in fact, to ~~assimilating~~ update a model using biased data (e.g., Dee, 2005; Liu et al., 2012). ~~In other words,~~ When only internal states (and not model parameters) are updated, or when the model suffers structural deficiencies, the assimilation of real (i.e., not synthetic) streamflow data ~~referring to a poorly parametrized subcatchments or tributary~~ at internal points can lead, in principle, to even worse model prediction at the outlet than no assimilation at all (Crow and Van Loon, 2006). The problem can arise due to the disjoint use of traditional and crowdsourced data ~~that refer to different locations~~, with the former used to calibrate (semi-)distributed models at control points, and the latter used only in real-time to update model ~~updating~~ states at different locations.

A possible solution is the use of ensemble based data assimilation methods to update jointly model states and parameters. An additional, pragmatic~~, operative~~ recommendation is the collection of ~~crowdsourced~~ accurate measured data for a suitable ~~test~~ period, for at least two reasons: i) to develop reliable rating curves at locations where water level CSD are planned to be collected, and ii) to calibrate and verify the model ability in describing the system states correctly at the locations in which CSD are collected~~, and possibly to update the model calibration using all the available data~~.

It must be observed that, while scarce control on the collection of CSD can be exerted during significant flood events, the locations at which citizens can collect CSD is always determined a-priori, since the availability of rating curves is a necessary condition in order to convert water levels into discharges. The amount of measured data needed to develop reliable rating curves can also be profitably used to calibrate the model at those sections as well.

As a final remark, ~~in order to take the maximum advantage in term of accurate and reliable real-time flood forecasts,~~ both modellers and environmental agencies should comprehensively account ~~in a comprehensively manner~~ for the characteristics of the physical system, for ~~the~~ model structure and parametrization, for the design of the sensors network, and for data to be used both in calibration and in operational mode.

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