# Impacts of observational uncertainty on analysis and modelling of hydrological processes: Preface

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## 1 Introduction

Observational data is the foundation for most of hydrological science. However, observational data uncertainty can often have high magnitudes (e.g. ±50–100% typical low flow uncertainty, McMillan et al., 2012) and be of complex character (e.g. Viney and Bates, 2004), which means that in some cases our data may be of limited use or even misleading in our quest to understand hydrological processes (e.g. Kauffeldt et al. 2013). Discussion of the impacts of data uncertainty on process understanding reaches from very early hydrological observations (Heberden, 1769), through early uncertainty estimation techniques (Horton, 1923) and continuing to the plea from Sevruk (1987) that data errors must not be ignored. The impacts of intrinsic data limitations and uncertainties on modelling of hydrological processes has also been long discussed by for example Klemes (1986), Beven (2002), Sivapalan et al. (2003), and Kirchner (2006). Understanding, quantifying and documenting observational uncertainty and their impacts on hydrological analysis and modelling in any study is therefore essential to draw robust conclusions about hydrological processes.

Hydrologists have documented the high value of observational data for predicting flood events, protecting ecosystems and water resources, for example from experimental watersheds (Tetzlaff et al., 2017), and for soil moisture measurements (Vereecken et al., 2008). Recently, increased attention has been given to providing well-documented datasets for monitored watersheds, e.g. (McDonnell et al., 2021; Zhang et al., 2020), and an appreciation of how that information helps us to understand hydrological processes (Aulenbach et al., 2021). However, observational uncertainties are rarely documented and published together with datasets. Understanding and quantifying uncertainties in these data will enable more robust inference of hydrological processes, evaluation of hydrological models, and water management decisions such as cost-benefit analyses (McMillan et al., 2017, 2018).

Hydrological modeling techniques often require specific information on data uncertainty. For example, model calibration requires information on uncertainty in the data used for model input and evaluation, to ensure that calibrated parameters are not biased through forcing a model to exactly reproduce uncertain or disinformative data (Beven et al. 2011). Data assimilation techniques such as Kalman or Particle filtering require data uncertainty information to enable them to correctly balance the information content of model predictions and new data observations (Smith et al., 2008; Ocio et al., 2017). Even when uncertainty analysis is not explicitly required for a model analysis, it brings a deeper appreciation of the strengths and limitations of our data, and of subsequent inference based on that data (Juston et al., 2013; Hughes et al., this issue).

Working with observational uncertainty in any study means that the potentially multiple sources of uncertainty that contribute to the total data uncertainty need to be understood, documented and quantified. McMillan et al. (2018) provide an overview of the whole process of working with observational uncertainty from identifying and documenting individual sources of uncertainty in a perceptual model, to methods such as replicates and sub-sampling to estimate individual sources, and Monte Carlo methods to quantify combined data uncertainty from multiple uncertainty sources (e.g. Reitan & Petersen-Øverleir, 2009; Le Coz et al. 2014).

This special issue is focused on observational uncertainty, its sources and impacts on analysis and modelling of hydrological processes. The special issue encompasses a broad spectrum of papers (see Figure 1, and Table 1) focusing on different facets of observational uncertainty from uncertainty in measurement techniques to the impacts of observational uncertainty on process representation in hydrological models. They also focus on different components of the hydrosphere including precipitation, soil moisture, river flow and water quality. In this preface, we give an overview of each contribution and discuss their key results. We emphasise the importance of these studies and how they can be used by the community. We discuss the challenges associated with incorporating the results of detailed uncertainty investigations into everyday hydrological studies, and suggest potential routes to progress this topic.

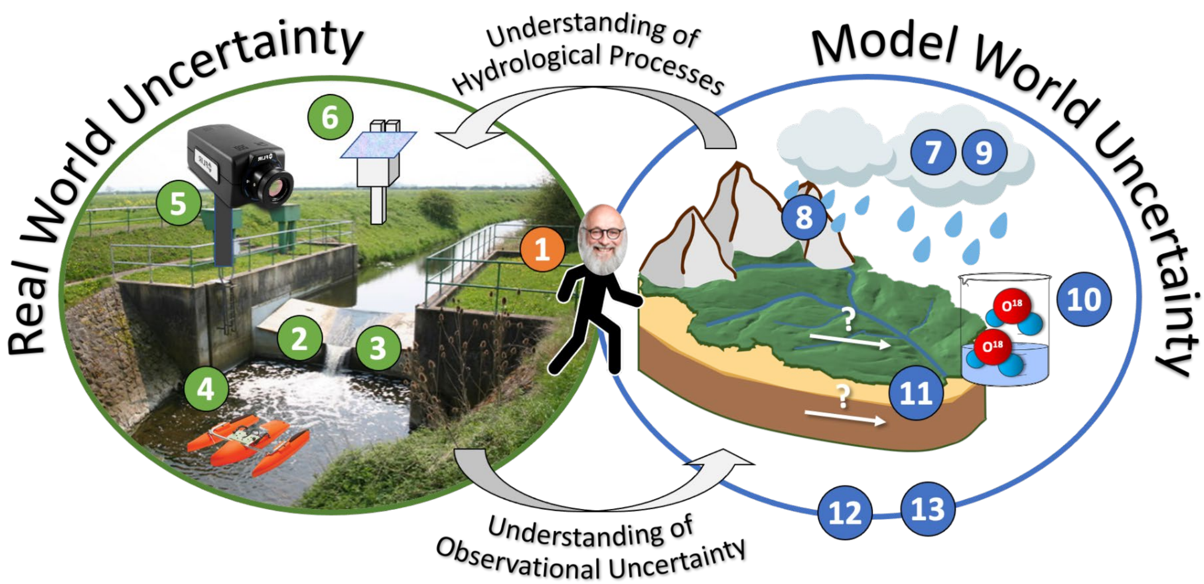


**Figure 1.** Contributions to this special issue and their key focus. The paper ID's referenced in each circle can be found in Table 1. Image shown on the left is of Brant Broughton gauging station taken from geograph.org.uk and is reproduced under a CC BY-SA license.

**Table 1.** Lead author, paper title and type of contribution to this special issue

| ID | Lead Author | Paper Title | Type |
|---|---|---|---|
| 1 | Beven | An epistemically uncertain walk through the rather fuzzy subject of data and model uncertainties | Invited Commentary |
| 2 | Horner | Streamflow uncertainty due to the limited sensitivity of controls at hydrometric stations | Observational Uncertainties |
| 3 | Regina | Automated Correction of Systematic Errors in High Frequency Stage Data from V-Notch Weirs using Time Series Decomposition | Observational Uncertainties |
| 4 | Muste | Impact of the sampling duration on the uncertainty of averaged velocity measurements with acoustic instruments | Observational Uncertainties |
| 5 | Le Coz | Estimating the uncertainty of video-based flow velocity and discharge measurements due to the conversion of field to image coordinates | Observational Uncertainties |
| 6 | Iwema | Accuracy and precision of cosmic-ray neutron measurements and their impact on estimated soil moisture at humid environments | Observational Uncertainties |
| 7 | Liu | Leveraging ensemble meteorological forcing data to improve parameter estimation of hydrologic models | Model Input Uncertainty |
| 8 | Culler | A Multi-sensor Evaluation of Precipitation Uncertainty for Landslide-triggering Storm Events | Model Input Uncertainty |
| 9 | Beven | Issues in Generating Stochastic Observables for Hydrological Models | Model Input |

| | | | |
|---|---|---|---|
| | | | Uncertainty |
| 10 | Stevenson | Effects of streamflow isotope sampling strategies on the calibration of a tracer-aided rainfall-runoff model | Model Evaluation Uncertainty |
| 11 | Wu | Incorporating multiple observational uncertainties in water quality model calibration | Model Evaluation Uncertainty |
| 12 | Hughes | Unpacking some of the linkages between uncertainties in observational data and the simulation of different hydrological processes using the Pitman model in the data scarce Zambezi River basin | Whole System Uncertainty |
| 13 | Hankin | Reducing macro-scale uncertainty using micro-catchment experiments for multi-local scale modelling of nature-based solutions | Whole System Uncertainty |

# 2 Observational uncertainty in old and new measurement techniques

The hydrological community is continually working to improve measurement techniques for hydrological variables, and to develop new measurement methods. Beven (2019a) identified better data collection techniques, and better estimates of data uncertainty, as a key requirement for advances in hydrological modeling. One of the 23 unsolved problems in hydrology identified by Blöschl et al. (2019) is “How can we use innovative technologies to measure surface and subsurface properties, states and fluxes at a range of spatial and temporal scales?”. One aspect of developing both old and new observational techniques is a better characterisation of the associated uncertainties. In this section, we present five papers that provide expert information on observational uncertainty in new and old measurement techniques, including stream gauging via weirs, acoustic dopplers and videography; and soil moisture sensing using cosmic ray neutron probes. Authors using any of these data types may need to estimate data uncertainty magnitudes for use in subsequent analyses. The papers described below provide uncertainty estimates from expert teams, which may reduce the need for study-specific uncertainty analysis. These papers provide valuable guidance on improving hydrometric procedures to reduce uncertainty, from field equipment design, to data collection, to data post-processing.

During experimental design, Horner et al (2021) show how the shape of a weir impacts the sensitivity of streamflow measurements to errors in measured stage. They show that weir design is particularly important for low flow measurement accuracy. Using synthetic examples derived from the Yzeron River at Craponne, France, the authors showed that adding a triangular notch to a flat weir could reduce maximum uncertainty in daily (low) flows from +/- 300% to +/- 25%. The reduction in uncertainty carried over into metrics such as the annual minimum of 30-day discharges, used to characterize annual low flow behaviour. The benefits are demonstrated in a real-life situation where a weir with a rectangular notch was added to a previous flat concrete step at a gauging station in the Yzeron catchment. Because uncertainties derived from stage measurements are large at low flows, these recommendations on weir design will be of particular value for rivers that commonly experience extreme low flows, such as intermittent rivers. Le Coz et al (this issue) analyze a different flow gauging technique: image processing procedures used to estimate water surface velocity from video footage. In particular, they show how two previous methods to orthorectify images (transform from oblique camera angle to a plan view) can be combined to reduce uncertainty in the derived velocity. The first method uses ground reference points which are located in the image and whose locations are precisely measured; the second method uses prior knowledge of the camera position and angles. By combining these two methods, limits on the flow uncertainty of +/- 15% can be achieved using only three reference points. Using six reference points reduces the uncertainty to +/- 12% while the influence of errors associated with the orthorectification parameters reduces to less than 14% of the total uncertainty budget, showing that little further advantage is gained by adding more than six reference points.

During data collection, two papers show how sampling duration impacts on data uncertainty. When using acoustic instruments to measure water velocity, Muste et al (this issue) show how channel environment and position within the channel cross-section impact the sampling duration needed to reach a specified level of uncertainty. As well as providing guidelines on sample duration (90 s and 150 s for ADV and ADCP instruments, respectively), they demonstrate how to determine suitable sample durations tailored to individual locations by comparing velocities from shorter samples to those from samples collected over an excessive long-duration measurement. When using cosmic-ray neutron probes to measure soil moisture, Iwema et al (this issue) show that the wetness state of the catchment is the most important control on the sampling duration needed to match the precision levels of competing sensing techniques. To match the precision (in $cm^3cm^{-3}$) of time domain transmissometry (TDT) sensing, 2 hours is needed during dry conditions, but 40 hours is needed for wet conditions. The latter may prevent precise measurements of short-term effects of storm rainfall or irrigation. These guidelines can assist hydrologists in attaining required measurement precision in the most efficient way.

During post-processing, knowledge of the causes and properties of hydrological data uncertainty enables automatic correction or accounting of uncertainties. For example, Iwema et al (this issue) investigated environmental factors such as biomass, leaf litter, and surface and atmospheric water that can absorb or slow cosmic-ray neutrons and therefore cause errors in soil moisture estimates. They show that accounting for these factors in a site with shrub land cover could change soil moisture estimates by 10%. These factors were most important during dry conditions when the environmental factors account for a greater proportion of total hydrogen in the environment. Regina et al (this issue) show how uncertainty knowledge that was previously implicitly incorporated into manual post processing of river stage data can be made explicit. They used their previous experience in causes of systematic stage errors to create an automatic method to correct stage data based on time series decomposition. Both papers make expert knowledge and detailed investigations of data uncertainties accessible to hydrologists using these data sources.

# 3 Impact of observational uncertainty on process representation in hydrological models

The impact of observational uncertainty on parameter calibration and process representation in hydrological models is a key problem for the hydrological community, yet is commonly overlooked. Observational uncertainties are often difficult to quantify because the necessary information is not available at all or not published together with standard datasets, even if there are positive developments in this area, e.g. demands on streamflow monitoring agencies from their funders to publish uncertainty magnitudes. To avoid drawing the wrong conclusions, it is essential to include observational data uncertainty when testing models as hypotheses about how catchments function (Beven, 2019a, Beven this issue, a), and to consider how the available data uncertainty information may limit the inference about process hypotheses (Westerberg and Birkel, 2015). This special issue contains eight papers focused on the impact of observational uncertainties in hydrological modelling that we split into three sub-groups focused on (1) model input uncertainty, (2) model evaluation uncertainty and (3) whole system uncertainty.

### 3.1 Model input uncertainty

Model input uncertainty, beside parameter uncertainty, is the uncertainty source that is most often investigated in hydrological modelling. Input data uncertainty propagates through hydrological models and thus may affect process understanding and decisions made on model results. Observed forcing variables used for hydrological models are generally uncertain due to several reasons such as measurement, interpolation or scaling errors (McMillan et al. 2018). These errors contribute further to uncertainty related to the representativeness of the estimated model input values for the actual catchment (Beven 2019b, Beven this issue, a, b), particularly for input variables that demonstrate high temporal and spatial variability such as precipitation in mountainous terrain (Berghuijs et al. 2014, Sikorska and Seibert 2018, Grundmann et al. 2019), whereas it is less pronounced for input variables that are assumed to change smoothly in space and time such as temperature in flat terrain.

Among the input data usually required for a hydrological model, uncertainty in precipitation data has received the most attention in the hydrological community (e.g., Kavetski et al. 2006, McMillan et al. 2010, Renard et al. 2011, Sikorska et al. 2012, Del Giudice et al. 2016). Works on observational uncertainty connected to other model inputs such as temperature or evaporation are less frequent. One reason for that is that precipitation is often the strongest predictor of river streamflow in humid or temperate catchments (Müftüoğlu 1991), and also has the strongest impact on model output errors (Sikorska-Senoner & Quilty 2021). Precipitation data products have also been demonstrated to have a higher impact on the hydrological model than temperature data (Tarek et al. 2020) or evaporation data (Shoaib et al. 2018). However, in (semi-)arid catchments or in wet environments, uncertainty in input evaporation data may also be of high importance (Dembélé et al. 2020, Page et al. 2020).

In our special issue, all three papers dealing with input uncertainty similarly focus largely on precipitation uncertainty. The papers investigate input (precipitation) uncertainty and its impact on parameter identification in hydrological models (Liu et al. this issue), input uncertainty in observed and generated variables for hydrological models and process representation (Beven this issue, b), and precipitation uncertainty impact on the rainfall-triggered landslide events (Culler et al. this issue). Beven (this issue, b) also discusses uncertainties in other input variables, i.e. temperature and evapotranspiration.

In detail, Liu et al. (this issue) investigate the effect of using a forcing ensemble of precipitation time series, represented as an ensemble meteorological dataset or a collection of multiple deterministic meteorological datasets, on the ability to determine robust parameters of a hydrological model. Based on 30 synthetic datasets and 20 real case studies, they find that using an ensemble of forcing inputs is beneficial over a single deterministic input because it improves the overall simulation skills of ensemble-based flow simulations and reduces the potential effect a poor-quality input data can have on model calibration. They recommend using ensemble forcing-based modelling to account for input uncertainty and to better constrain model parametric uncertainties.

Culler et al. (this issue) investigate the effect that different precipitation products can have on the accuracy in rainfall-triggered landslide event prediction. They compare different precipitation products such as satellite, radar and rain-gauge data, to assess the effect of the uncertainty in precipitation data on predicted landslide magnitudes in the continental US and Canada. Generally, they find that the value of different precipitation products for landslide predictions varies widely across the different precipitation products tested. For example, peak intensities of precipitation events triggering the landslides varied in the range of 7.8 mm/h to 57 mm/h depending on the precipitation product used. This scale demonstrates that the choice of the precipitation data used for prediction of landslides can have a large effect on the predictability skills one can achieve. The authors thus recommended using more than one precipitation product for predicting landslides triggered by intense precipitation events.

Finally, Beven (this issue, b) provides a comprehensive overview of the development of stochastic generators for simulating observed time series inputs to hydrological models such as precipitation and evaporation, and on streamflow time series outputs. The author discusses critical uncertainty issues that arise for any observables and in particular those originating from stochastic generators, emphasizing uncertainty arising from the temporal and spatial representativeness of the input observables for the catchment and uncertainty linked to non-stationary and persistent stochastic behaviour in assessing future variability. This paper raises awareness of different uncertainty types, such as hydrological model uncertainty for extreme events, unverified extreme tail behaviour in underlying distributions, and issues of extreme values being generated by chance, that are connected with the use of stochastic generators for the purpose of providing time series of input (or output) variables. It serves as a valuable guidance on uncertainties in modelling studies that rely on stochastically generated variables.

### 3.2 Model evaluation uncertainty

Many different types of data can be used to evaluate hydrological models including streamflow, groundwater levels, soil moisture, stable water isotopes and water quality data. These observational datasets all have associated uncertainties which need to be quantified (e.g. Blazkova et al., 2002; Freer et al., 2004; McMillan et al, 2012) and accounted for through the modelling chain to ensure robust conclusions about model results and hydrological process representations. Commonly, hydrological models are calibrated and evaluated against streamflow data. However, the contributions in this special issue focus on using water quality and stable water isotope data to calibrate hydrological models and develop our understanding of hydrological processes. These papers provide guidance on the quantity of data and sampling strategy required to provide a robust characterisation of catchment functioning (Stevenson et al, this issue), and on effective strategies of incorporating observational uncertainties in water quality data for model calibration (Wu et al, this issue). They quantify data uncertainty in each case and provide valuable guidance on incorporating observational uncertainties in model evaluation.

Stevenson et al, (this issue) gives guidance on the opportunities for using stable water isotope data to better constrain model parameters. Analysing a seven year time series of daily stable water isotope data from precipitation and rainfall, Stevenson et al, (this issue) find that appropriate sampling strategies of water isotope data are critical to robust model calibration and reducing model uncertainty. In particular, they found that while weekly sampling yielded almost identical model performance and calibrations compared to daily, monthly sampling led to greater uncertainty in the derived parameter sets. They also found that the model was sensitive to the conditions when the samples were taken, with increased model sensitivity during dry conditions due to non-linear interactions between input fluxes and storage dynamics such as the expansion/contraction of saturation areas. This type of guidance is essential for designing robust data sampling strategies to minimise uncertainty in subsequent hydrological modelling.

In principle, the use of tracer and other complementary data in model calibration should help move us towards more reliable model calibration. In practice it is not so simple, since the use of such data might require the incorporation of additional parameters or consideration of commensurability uncertainties where observed variables are different in scale or meaning from simulated variables. This then introduces a greater potential for parameter interactions in fitting the uncertain observations. Tracer data provide an example. The effective storages required to predict hydrographs might be different from those to predict tracer mixing because of the way in which the hydrograph is controlled by the celebrities of pressure waves in the system, and the tracer mixing by water velocities (e.g. Beven, 1989, 2020; McDonnell and Beven, 2014). Another example is the use of distributed observations to estimate effective parameter values at the catchment scale, as in the use of water tables in Lamb et al. (1998). In that case, adding local parameters helped in reproducing water tables, but did not have a great effect on uncertainty in the discharge predictions.

Our final contribution in this sub-group develops a Bayesian error analysis method to accommodate multiple sources of observational errors (Wu et al, this issue). When tested with total suspended solid data in a conceptual water quality model, they demonstrated that the new algorithm successfully quantifies sources of observational error. They also illustrate the significance of incorporating observational errors in input and output data to constrain model uncertainty.

### 3.3 Whole System Uncertainty

Typically, hydrologists use a wide range of data when analysing and modelling hydrological processes. Every dataset will be subject to its multiple sources of uncertainty (McMillan et al, 2018), which will likely be non-stationary in time and space. Hence, a specific challenge for hydrology is accounting for multiple sources of observational uncertainty that can arise from many different sources, and their impacts on the analysis and modelling of hydrological processes. While the previous papers in this special issue have typically focused on a single source of uncertainty, three of the contributions have taken a broader outlook focusing on multiple sources of observational uncertainty. These papers provide valuable guidance on evaluating observational uncertainties in both data rich (Hankin et al, this issue) and data poor (Hughes et al, this issue) regions, alongside an outlook and future directions for assessing observational data and model uncertainties (Beven, this issue, a).

Modelling the impact of Nature Based Solutions on flows requires accurate data at high spatial and temporal resolutions. Hankin et al (this issue) evaluate how to reduce macro-scale uncertainty in these analyses using data from 18 well-monitored micro-scale catchments. They demonstrate that even with highly accurate data at small scales there are issues with equifinality: they find that detected shifts in model parameters are place and storm-specific, and that additional data (satellite event footprints of flood inundation) are needed to further constrain results. They conclude that a greater focus on observations at local scales in multiple locations is needed to better constrain uncertainties, particularly when assessing change.

In contrast to the focus on well-monitored local-scale catchments in Hankin et al (this issue), Hughes et al (this issue) consider observational uncertainties and their impacts on hydrological modelling and process understanding in a data scarce region. They focus on observational uncertainties from multiple data sources (evaporation, soil moisture, water use, rainfall, streamflow and groundwater recharge) and assess their role in identifying the relevant contribution of different hydrological processes. While quantitative estimates of observational uncertainties are rarely available in data-scarce regions, Hughes et al (this issue) demonstrate other techniques to assess observational uncertainties such as comparing multiple datasets of the same observation or assessing the consistency and completeness of the dataset. They conclude that while model equifinalities still dominate in terms of identifying the relative occurrence of different runoff-generating processes, observational uncertainties are still a key issue and that there is not enough data to resolve equifinalities in their model. They identify that improved independent estimates of groundwater recharge could help in constraining the model parameter space.

Finally, in the invited commentary of this special issue, Beven (this issue, a) takes the reader on a tour of the fuzzy subject of observation and model uncertainties, providing a brief summary on how uncertainty awareness arose in the hydrological community and summarizing current and future direction of uncertainty research. He discusses the challenges of epistemic observational uncertainties, equifinality and likelihood measures, and their implications for process understanding (i.e. how can we ensure we get the right results for the right reasons?). Looking to the future, Beven (this issue, a) advocates that there should be more interaction between observational and computational hydrologists to better define critical observations that could help us to distinguish between model formulations and/or parameterisations. He also discusses the need for the *starting point* of hydrological analyses to be focused on quantifying and evaluating observational uncertainties, as is showcased in the papers within this special issue.

# 4 Discussion

This special issue provides a collection of 13 papers on different aspects of observational uncertainty and its impact on hydrological modelling and process representation. These papers focus on observational uncertainty, input uncertainty, model evaluation uncertainty, and whole system uncertainty (Table 1). Hence, the contributing papers provide a broad spectrum of different commonly applied methods for uncertainty quantification from sensitivity analysis, to Monte Carlo techniques, to Bayesian methods, from a single case study to a study with several catchments. Therewith, reported uncertainty magnitudes are linked to the method selected for uncertainty quantification and the data used, and this should be kept in mind when transferring uncertainty values to other studies.

The papers of this special issue suggest five overarching themes. First of all, while most papers use standard methods to quantify uncertainty, some papers provide **novel methods** to observe, quantify or deal with specific uncertainty components. For instance, Iwema et al. (this issue) address the issue of applying new hydrological techniques to non-ideal locations, by applying cosmic-ray soil moisture sensing to sites in a humid environment and with high above-ground biomass. The authors address unexpected uncertainty sources such as sheep gathering near the sensor and introducing a time-variable source of biomass. Testing new (hydrological) techniques at non-optimal locations enables us to test the limits of such techniques and apply them in a broader range of locations, while accounting for uncertainty. Another example is given by Liu et al. (this issue) who propose using an ensemble of input forcings, instead of only a single input product, to address input uncertainty in model simulations and to better constrain model parameters.

Second, the reader should be more **aware of the way the hydrologic measurements are derived** and the methods standing behind the measured values. Unfortunately, it is still a common practise to assume values calculated from a 'measurement model' as direct hydrologic measurements, i.e., where there is a transform function required to calculate the desired quantities (e.g., streamflow). When this transform is highly non-linear, such as a stage to discharge, or neutron count to soil moisture, even small fluctuations in the measured quantity have the potential to create large uncertainties in the hydrologic quantity of interest (e.g. streamflow). Papers focusing on observational uncertainty (Horner et al. this issue, Iwema et al. this issue, Muste et al. this issue, Le Coz et al. this issue, Regina et al. this issue) raise awareness of this issue to the hydrological community. A detailed overview on different methods for quantifying uncertainties in streamflow data derived with the commonly used rating curve model is provided in detail by Kiang et al. (2018). Finally, Beven (this issue, b) raises awareness of uncertainties linked to the use of stochastically generated time series of model input and output variables in hydrology. We call for a better dialogue between experimentalists and modellers in hydrology that encompasses not only soft data on process understanding (Seibert and McDonnell, 2002), but also soft data on observational uncertainties and their possible impacts on our process understanding and models.

Third, several papers have also highlighted the **value of thoughtful study design in experimental and modelling studies** to reduce the impact of observational uncertainties on study results and conclusions. Based on papers from this special issue, it is recommended to use long-duration or intensive sampling campaigns to investigate and reduce observational uncertainty and for development of efficient observational methods (Muste et al. this issue). Another possibility is using subsampling pre-campaigns to define the correct sampling interval for the study of interest that optimizes the uncertainty and sampling efforts (Stevenson et al. this issue). A correct design of the modelling study should consider a proper selection of the input (precipitation) products for hydrological models because the model parameters and modelling uncertainty will largely depend on this forcing product. Based on papers from this issue, it could be recommended to either test different products to choose the most appropriate one for the purpose of the study (Culler et al. this issue), or to use an ensemble of input forcings instead of using only a single product (Liu et al. this issue).

Next, some papers focus on **providing approaches for better constraining model parameters, reducing modelling uncertainty and improving process understanding**. In this respect, a multi-data approach can be recommended that conditions model parameters either on multiple input or output datasets. In this way, the impact of observational uncertainty on model simulations can be reduced. A great milestone has here been achieved with more frequently available remote sensing data (Silvestro et al. 2015), opening new possibilities for gathering information on soil moisture, snow depth, evapotranspiration, etc., particularly for remote or ungauged locations. Among papers of this special issue, four papers used multiple datasets for model calibration to more robustly constrain model parameters and in this way reduce modelling uncertainty. Three of these papers focused on multiple output datasets, i.e. using more than one output variable, with total suspended solid data in addition to streamflow (Wu et al. this issue) or stable isotopes together with streamflow data (Stevenson et al. this issue). One paper recommends using multiple input precipitation products to account for input uncertainty and to better constrain parameter uncertainty of hydrological models (Liu et al. this issue). Nevertheless, assessing the effect of using multiple datasets on model identification and process understanding remains an ongoing research avenue, specifically as new datasets, new techniques for data collection, or new methods for data uncertainty assessment become more available.

Finally, an important issue raised by some papers is linked with **developing or supporting open-access softwares** through integrating the authors' advances in quantifying and reducing observational uncertainty into commonly-used software packages. Le Coz et al (this issue) integrate camera calibration uncertainty and other uncertainty sources into the openly available fudaa-LSPIV software to estimate discharge uncertainty. Iwema et al (this issue) include neutron mitigating factors such as biomass, leaf litter, and surface and atmospheric water that influence soil moisture estimates into the Cosmic-ray Soil Moisture Interaction Code (COSMIC). Use of commonly available or open-access softwares and models fosters reproducible research and enables generalising uncertainty estimates from case studies and to transfer them to other locations or studies. This is an important step towards improved uncertainty treatment in hydrology.

# 5 Contribution, Challenges and Outlook

Taken all together, the contributions of this special issue demonstrate that understanding and quantifying the different components of observational uncertainty are of great importance for robust model calibration, model predictions and process understanding. The papers of this issue can serve as a guidance for a reader in designing their own uncertainty study and selecting proper materials, data and tools for model calibration and uncertainty quantification. They also give an overview of state-of-the-art methods and novel approaches applied to uncertainty quantification in hydrological modelling and how they may impact on process understanding. Finally, they can awaken awareness of the uncertainty problem in hydrological data and models.

Despite the broad uncertainty spectrum covered by this special issue, several points were not raised by any of the contributing papers. Among others, the issue of uncertainty in large scale and large-sample hydrology was not covered, whereas the impact of uncertainty on process understanding was only touched upon. In addition, some recent measurement developments, such as the use of mobile phone networks to measure precipitation rates and data crowdsourcing, were not tackled by any of the papers.

Accounting for observational uncertainty in large scale and large-sample hydrology is challenging for several reasons. First, detailed spatial and temporal data, together with knowledge and metadata about site-specific measurement methods and conditions that are needed for in-depth analyses of observational uncertainties is typically not available at the large scale. Second, methods for assessing observational uncertainties developed for individual catchments may be prohibitively time-consuming at the large scale. Third, there are currently still computational limitations for comprehensive assessment of data observational uncertainty or modelling uncertainty at a large sample of catchments (Arheimer et al. 2020).

Large scale studies have therefore typically used multidata approaches to assess uncertainty for input variables such as precipitation, temperature and potential evaporation for which many large-scale remote-sensing and rain gauge products are available (e.g. Alvarez-Garreton et al. 2018). Another readily available approach that has been applied at the large scale is to assess dataset consistency in terms of water-balance closure prior to modelling to better understand observational data limitations and their impacts on modelling results (Kauffeldt et al. 2013). For discharge uncertainty, studies for large samples of catchments are still rare (see Petersen-Øverleir et al. 2009 and Coxon et al. 2015), and generalised uncertainty estimates have been used where site-specific data are not available (Westerberg et al. 2014). While progress is being made for the inclusion of observational uncertainty estimates in large-sample studies (e.g. Alvarez-Garreton et al, 2018; Coxon et al, 2020; Klinger et al, 2021), these datasets still generally lack consistent uncertainty estimates (Addor et al. 2020). More research is needed in this direction, especially because studies of observational uncertainties at the large scale can provide important information on estimates of observational uncertainty that could be generalized or transferred to other regions (McMillan et al. 2018).

Several novel measurement techniques are of interest to hydrologists, such as use of eddy covariance or microwave links from mobile phone networks and drone camera techniques for water surface. The eddy covariance technique is a micrometeorological method for direct observation of the exchange between ecosystem and atmosphere in terms of gas, energy, and momentum (Grelle and Keck 2021). It can be applied to measure $H_2O$ fluxes. Microwave links from mobile phone networks have been adapted to estimate precipitation rates and are particularly suitable for areas with a low density of traditional rainfall measurement devices such as mountainous, urban areas and the developing world (Uijlenhoet et al. 2018). Another steadily growing measuring technique is the use of image-based data gathered either with unmanned aerial systems, drones (Tokarczyk et al. 2015) or from surveillance cameras to identify water levels during urban flooding (Leitão et al. 2018). However, these novel measuring techniques are currently still missing uncertainty considerations.

Another rapidly growing branch of hydrological measurement is crowdsourcing that involves active contribution of citizens via citizen science (Nardi et al. 2021). As a low-cost method that relies on already available sensors (e.g., private mobile phones), it has a great potential for supporting professional measurement campaigns at a large spatial scale, despite the quality of crowdsourced data being lower (Zheng et al. 2018). To provide good quality crowdsourced data, training or instruction is essential, particularly for non-intuitive variables or more complex tasks. The uncertainty of such crowdsourced data remains unexplored for hydrological modelling.

These novel measurement techniques generate new observational uncertainty challenges in providing high quality data for hydrological modelling and process understanding. We encourage future research studies to understand, quantify and document these observational uncertainties related to new and old measurement techniques. At the same time, an improved dialogue on observational uncertainties between field hydrologists, modellers and analysts will help to reduce their impact on the conclusions of our hydrological studies.

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