Hydrological data are at the core of our understanding of physical hydrologic processes, our simulation models and forecasts of water resources and hazards, and our monitoring of water quantity and quality. However, hydrologic data are subject to multiple sources of uncertainty that can introduce bias and error into our analyses and decision-making if not properly accounted for. In this article, we summarize five categories of data uncertainty: measurement uncertainty, derived data uncertainty, interpolation uncertainty, scaling uncertainty, and data management uncertainty. Hydrologic data uncertainty magnitudes are typically in the range 10–40%. To quantify data uncertainty, hydrologists should first construct a perceptual model of uncertainty that itemizes uncertainty sources. The magnitude of each source can then be estimated using replicates (repeated, nested or subsampled measurements), or information from the literature (in-depth uncertainty results from experimental catchments, colocated gauges or method comparisons). Multiple uncertainty sources can be combined using Monte Carlo methods to determine total uncertainty. Data uncertainty analysis improves hydrologic process understanding by enabling robust hypothesis testing and identification of spatial and temporal patterns that relate to true process differences rather than data uncertainty. By quantifying uncertainty in data used for input or evaluation of hydrologic models, we can prevent parameter bias, exclude disinformative data, and enhance model performance evaluation. In water management applications, quantifying data uncertainty can lead to robust risk analysis, reduced costs, and transparent results that improve the trust of the public and water managers.

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Data, decision-making, error, hydrology, uncertainty

1 INTRODUCTION

Hydrologic data are at the core of our understanding of hydrologic processes, our simulation models and forecasts of water resources and hazards, and our monitoring of water quantity and quality. The difficulties in obtaining accurate and precise hydrologic data have long been noted (Herschy, 1970; Horton, 1923; Sevruk, 1986). In the last few decades, hydrologists have made a concerted effort to quantify and understand the implications of hydrologic data uncertainty. Their conclusions show that ignoring data uncertainty can cause error in hydrologic predictions, theory, and water resources management. Conversely, accounting for data uncertainty in water management has led to lower costs and better decisions (McMillan et al., 2017; Montgomery & Sanders, 1986).
Hydrologic data comes in many forms from the raw, such as depth to groundwater at a well, to the highly processed, such as fields of rainfall totals derived from radar. Even measurements that seem to be direct, such as the readout from a soil moisture sensor, may derive from an electric current reading translated to soil moisture content. In this article, we use the term “hydrologic data” to refer to the form in which data is commonly available to hydrologists, which may have undergone some processing from its raw form. For example, we consider rainfall data in its common forms of rain gauge totals (usually derived from tipping-bucket counts), and remotely sensed radar and satellite products (derived from multispectral radiation). Where data is derived from raw measurements, we consider this preprocessing as one of the uncertainty sources (see “derived data uncertainty” in Table 2).

The causes of hydrologic data uncertainty are numerous. Stores and fluxes of water are often difficult to access, and are highly variable in time and space. Examples include river flow through vegetation or under ice, water moving through soil macro-pores and bedrock fissures, or localized downpours from thunderclouds. Hydrologists must often combine labor-intensive measurements at the small scale (e.g., calibrated soil moisture sensors) and remotely sensed information using proxy measurements at the large scale (e.g., soil moisture data from satellites). Small scale data introduce interpolation and scaling uncertainty, while remotely sensed data introduce uncertainty due to approximation of hydrologic variables based on sensed radiation. For hydrologic measurements of contaminants dissolved or suspended in water, uncertainty is amplified as the physical processes involved are heterogeneous and field and lab measurement protocols are complicated. High processing costs further increase the tendency to rely on interpolation between few data points, and thereby increase uncertainty. A longer discussion of hydrologic data uncertainty sources is presented in Section 2.

Accounting for hydrologic data uncertainty is necessary to reach accurate conclusions. Anybody working with hydrologic data, from theory development to monitoring to model evaluation, should be aware of the need for and benefits of uncertainty information in their study (Table 1). The methods for quantifying data uncertainty that we discuss in this article do not remove the uncertainty, although they may give insight into the largest uncertainty sources, enabling future work to reduce them. Instead, the methods allow us to account for uncertainty in hydrologic analyses and therefore prevent bias and incorrect conclusions. A simple example would be a hydrologic variable such as soil moisture that has equal values for two field sites. Data uncertainty (measurement uncertainty, interpolation uncertainty; Table 2) could create differences in the measured soil moisture values between the two sites. This could lead to incorrect reasoning about the difference such as different infiltration conditions, and incorrect water management decisions such as different irrigation regimes applied to the two sites.

This overview article introduces the causes and implications of hydrologic data uncertainty. We describe the main types of data uncertainty, approaches to quantifying that uncertainty, and implications for process understanding, hydrologic modeling and water management.

### Table 1: Example uses of hydrologic data uncertainty information by different actors

| Role                  | Example needs for hydrologic data uncertainty information                                                                 |
|-----------------------|-----------------------------------------------------------------------------------------------------------------------------|
| Student               | For accurate comparison of hydrologic variables over time (trend analysis) or between field sites (spatial differences)     |
| Field researcher      | For determining the most appropriate field equipment, experimental setup and number of replicates                            |
| Data analyst          | For statistical tests such as trend analysis; and for including uncertainty bounds in graphs of hydrologic data                 |
| Modeler               | For model input specification, for data assimilation, and for fair evaluation of model output                                |
| Consultant            | To ensure that conclusions presented to decision-makers or clients are accurate                                              |
| Decision-maker        | To ensure water management decisions are not biased by uncertain data                                                       |

### Table 2: Definitions and examples of different types of data uncertainty

| Uncertainty type          | Definition                                                                                                                             | Example                                                                                                                                 |
|---------------------------|----------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| Measurement uncertainty   | Uncertainty in the measured value, compared with the true hydrologic quantity at the same scale as the measurement                   | Uncertainty in rainfall depth or soil moisture at a point.                                                                              |
| Derived data uncertainty  | Uncertainty in a hydrologic quantity that is estimated by means of a proxy measurement                                                | Uncertainty in river flow calculated using river stage as a proxy, which is related to flow using a rating curve (i.e., a model of the stage–flow relationship). |
| Interpolation uncertainty | Uncertainty when hydrologic quantities are interpolated in space or time                                                              | Uncertainty in areal average rainfall or soil moisture calculated from several gauges (space). Uncertainty in values calculated using gap filling methods during sensor failure (time). |
| Scaling uncertainty       | Uncertainty when a process measured at one scale is used to approximate the process at a different scale                               | Uncertainty where hydraulic conductivity is measured at the point scale (controlled by matrix flow) and used to approximate hydraulic conductivity at the watershed scale (controlled by preferential flow). |
| Data management uncertainty| Uncertainty in recorded values or metadata such as station coordinates due to many aspects of human error, transcription error and computing error | Rain gauge records that contain days where the gauge was not read, and accumulated rainfall was added to the subsequent day's reading (Viney & Bates, 2004, “It never rains on Sunday”). |
2 | IDENTIFYING SOURCES OF HYDROLOGIC DATA UNCERTAINTY

There are often multiple types of uncertainty affecting one data value (Table 2), each with different estimation approaches and implications. All should be accounted for to quantify the total uncertainty. The relative contribution of various sources to the total uncertainty can be unexpected: for example, in prediction of future crop yield in rain-fed agriculture, uncertainty in soils data outweighs uncertainty in weather data (Folberth et al., 2016). Through quantifying all types of uncertainty, the dominant cause(s) can be identified.

2.1 | Using a perceptual model of uncertainty

A useful approach to identifying causes of uncertainty in a particular application is to outline a “perceptual model” of uncertainty (Westerberg, Di Baldassarre, Beven, Coxon, & Krueger, 2017). The perceptual model describes the sources of uncertainty that affect each step in an analysis: here the process of measuring and processing hydrologic data. The perceptual model can be formalized and extended as a measurement model (Box 1). Thus, the perceptual model is unique to each hydrologist, and focuses on their understanding of the causes of uncertainty without concern for how to quantify or analyze that uncertainty.¹ (Quantifying and analyzing uncertainty loosely correspond to “formal” and “procedural” models following the model development terminology of Beven (2010)). Figure 1 illustrates different types of data uncertainty that we might identify as part of a perceptual model of uncertainty in watershed average soil moisture data and in aggregate pollutant loads.

An important part of the perceptual model, and which aids the process of converting the perceptual model of uncertainty into numerical estimates of that uncertainty (i.e., the formal modeling or data publication stage), is to classify uncertainty into components with different characteristics. Beven (2016; Table 1) describes a typical classification into aleatory, epistemic, semantic and ontological components. Of these, aleatory and epistemic are the most commonly discussed. Aleatory (or “random”) uncertainty components can be well approximated using statistical distributions: examples are uncertainties in a single measurement of rainfall or stream velocity due to limited precision of the sensor. These uncertainties could be represented as a normal distribution using a standard deviation estimate from the equipment manufacturer. In contrast, epistemic uncertainty components represent our lack of knowledge within the measurement process. These uncertainty components are hard to quantify, for example, unknown equipment failure such as rain gauge blockage or unknown changes in true streamflow due to changes in the cross-sectional velocity distribution of the channel. The classification of an uncertainty component into aleatory or epistemic assists with the choice of uncertainty model, for example, using a heavy-tailed distribution and thereby allowing for outliers for epistemic uncertainties.

More recently, hydrologists have questioned whether the aleatory/epistemic classification is a useful one. Beven (2013), used examples from earthquake and tsunami disasters in Italy and Japan to argue that there is no clear separation between

![Figure 1](image-url)

**Figure 1** Example perceptual models of uncertainty for (a) watershed average soil moisture data, (b) aggregate pollutant loads. Red: Measurement uncertainty, Orange: Interpolation uncertainty in time; Yellow: Interpolation uncertainty in space.
aleatory and epistemic uncertainty, as even uncertainties that appear aleatory have epistemic components that may produce dangerous “surprise” results. Nearing et al. (2016) argued that all hydrologic uncertainty is epistemic because in principle there are physical reasons behind random (aleatory) measurement error even if we never investigate those “micro” processes. Currently, the aleatory model is still widely used as a useful “macro” representation of many uncertainties.

After creating the perceptual model and identifying sources of data uncertainty, the next step is to estimate the magnitude of each uncertainty component. These methods are described in Section 3.

### 2.2 Typical magnitudes of hydrologic data uncertainty

To emphasize the importance of considering data uncertainty when working with hydrologic data, we show in Figure 2 some typical uncertainty magnitudes. These values are taken from the hydrologic literature (see Table 3 for citations), and are colored according to severity, quantified by the coefficient of variation where specified. Uncertainties are categorized by source, using the same terminology as in Table 2, and by data type; not all uncertainty sources have been recorded (or are relevant) for all data types. This figure serves to highlight the typically high magnitudes of data uncertainty, with coefficients of variation in the Medium range (10–40%) being the most common.

### 3 APPROACHES FOR QUANTIFYING DATA UNCERTAINTY

#### 3.1 Replicates

Replication of the measurement is the standard method for assessing measurement uncertainty (Table 2). Replicates (multiple measurements of the same quantity) are helpful where aleatory (approximately random) variations are expected, such as small variations in water level in a river or lake due to water movement. Once collected, a set of replicates can be used to estimate the parameters of the assumed error distribution of the variable; for example, the mean and standard deviation of a normal distribution.

**FIGURE 2** Typical magnitudes of hydrologic data uncertainty from the literature, banded values of coefficient of variation. Gray boxes indicate that no quantitative estimates were found in the literature, although these sources can still be relevant.
The concept of replication can extend to more complex situations with epistemic uncertainty and uncertainty resulting from multiple sources. For example, replicate manual measurements of streamflow at a cross-section can aggregate uncertainty due to human variations such as unintentional movement of the velocity sensor during or between replicates. Replicates are also the standard choice to quantify lab instrument precision, and can be employed to cover the whole analysis chain for water quality or water isotope samples (sampling, storage, transport, preparation, subsampling, laboratory analysis). Typically, the precision information from occasional replicate runs is interpolated over the remaining data points of a dataset. Replicates can further capture uncertainty associated with the choice of measurement technique, for example, by deploying two different types of soil moisture sensors, or by measuring river flow using both the velocity-area and dye tracer methods. Similarly, replicates can be used to estimate interpolation uncertainty by using a variety of different interpolation methods to estimate a spatial average such as areal average rainfall. However, as the case of interpolation shows best, the choice of replicates may capture only part of the total uncertainty. If, as might be the case with interpolation algorithms, the replicates are all biased in the same way, then the true uncertainty will be underestimated.

Replicates from different times and locations can be combined to increase the sample size. For example, Tomkins (2014) analyzed the set of deviations of new flow gaugings from their previous rating curve, to determine trends and controls on streamflow uncertainty. Coxon et al. (2015) similarly combined flow deviations from 26 sites with stable rating curves, enabling them to estimate flow measurement uncertainty as a function of normalized flow. This aggregated result with large sample size can then be applied to other sites not in the original sample.

### 3.2 Nested measurements

Nested measurements extend the concept of replicates to situations where the causes of spatial variation and uncertainty change with scale. For example, variations in subsurface flow may be due to macropores (small-scale) or converging/diverging topography (large-scale). Nested measurements consist of multiple clusters of measurement locations, allowing uncertainties at both within-cluster and between-cluster scales to be determined. For example, Freer, McMillan, McDonnell, and Beven (2004) used multiple clusters of tensiometers to estimate watershed-scale uncertainty in depth to water table. Expert knowledge of hydrologic processes in the watershed can be used to identify regions likely to have similar behavior (e.g., stratification by geology, hillslope position, etc.) and deploy one cluster per region. Uncertainty information from each site can then be extrapolated to the entire watershed, enabling an estimate of total uncertainty at the watershed scale.

### 3.3 Subsampling high-resolution datasets, resampling, and modeling data gaps

Interpolation and extrapolation uncertainties that occur when data are collected at low-resolution time or space scales are typically estimated by transferring uncertainty knowledge from high-resolution datasets. The high-resolution data are repeatedly subsampled to the low resolution that will be used in the remainder of the study, and the variation of the low-resolution quantity within the set of subsamples is recorded as a proxy for uncertainty. For example, information from dense rain gauge networks has been used in several studies by selecting subsets of gauges to mimic typical gauge densities, and comparing the variation of averages from these subsets against the “true” spatial average rainfall calculated from all the gauges (e.g., Horton, 1923; McMillan, Jackson, Clark, Kavetski, & Woods, 2011; Villarini & Krajewski, 2008; Villarini, Mandapaka, Krajewski, & Moore, 2008; Wood, Jones, & Moore, 2000). Other examples referring to uncertainties due to changed spatial scales include river cross-sectional scaling of contaminant concentrations (Horowitz et al., 1990; Rode & Suhr, 2007). Examples referring to uncertainties due to changed time scales include riverine aggregate concentrations of solutes and suspended solids (Krueger et al., 2012; Skeffington, Halliday, Wade, Bowes, & Loewenthal, 2015) and aggregate contaminant loads (Cassidy & Jordan,
2011; Horowitz, 2013). In all of these examples, the results provide an estimate of how much accuracy is lost when using low-resolution rather than high-resolution data.

In the absence of high-resolution benchmark data, resampling methods like bootstrapping (Hirsch, Archfield, & De Cicco, 2015) or methods that statistically model the data gaps (Krueger, 2017; McBride & Ellis, 2001) are used to approximate the scaling uncertainty. However, resampling hinges on the low-resolution sample being representative of the missing data, and modeling data gaps hinges on the accuracy of the missing data model. It should also be noted that these approaches model the missing data statistically, which means they do not identify the time or place of each infilled data point. Missing this time or place information might prevent alignment of these data with other data sources.

3.4 Using uncertainty knowledge from the literature

Often, resources within a hydrologic study are insufficient to conduct extensive experiments into data uncertainty. Using information from the literature enables us to benefit from previous in-depth uncertainty trials. However, given that uncertainty can be highly variable depending on site-specific characteristics, hydrologists should be cautious in extrapolating the results to their own catchment.

At the simplest, manufacturers for most hydrologic sensors will provide estimates of the measurement uncertainty as a standard deviation or upper and lower bounds. Uncertainty information in the scientific literature typically reports results from either a replicate or nested data uncertainty quantification (described earlier in this section). Such studies are numerous and compilations of their results are therefore helpful; prominent examples are listed in Table 3.

Literature results from in-depth uncertainty experiments provide significant advantages in several situations. Comparison studies may use more replicates, or more diverse sensors, than would be practical for most studies. These include installations of large numbers of colocated rain gauges to provide estimates of random errors (e.g., Ciach, 2003), and ADCP (Acoustic Doppler current profiler) trials for flow measurement using multiple ADCP brands (Le Coz et al., 2016). Studies can provide information on the uncertainty of typical sensors when compared against gold-standard sensors, such as standard rain gauges compared with those installed at ground level with wind baffles (Sieck, Burges, & Steiner, 2007). Similarly, comparisons of remote sensing data with networks of ground-based sensors provide excellent information on the typical uncertainties within the remote sensing products (e.g., Ciach, Krajewski, & Villarini, 2007). In-depth studies provide valuable information on uncertainties arising from equipment malfunction or data management problems. For example, Wood et al. (2000) discuss quality control of tipping bucket rain gauge data, reporting errors in summer months due to mown grass blocking the rain gauge funnels. Later, water either trickled or broke suddenly through the blockage, creating a delayed rainfall reading. By taking advantage of such previous studies, hydrologists have baseline estimates of sensor uncertainty, and advance warning of possible epistemic uncertainties due to equipment failure.

3.5 Monte Carlo methods to combine multiple uncertainty sources

Hydrologic data are often affected by multiple uncertainty sources that propagate through any subsequent analyses. For example, uncertainty in a spatial average combines uncertainty in the point measurements with uncertainty in the interpolation technique (each estimated using one of the methods above such as replication, subsampling or knowledge from the literature). Monte Carlo methods for error propagation are useful to analyze the combined effects of multiple uncertainty sources. The principle behind a Monte Carlo method is that the hydrologist draws samples of possible data values from defined uncertainty models representing each uncertainty source, and each sample is used to compute the derived value of interest. Using a large sample size, the uncertainty distribution of the derived value can thus be established (Figure 3).

As an example, given measurements of rainfall at a set of rain gauges, normal distributions or more elaborate spatial auto-correlation models could be employed to sample sets of possible true rainfall quantities at this set of gauges. Each sample set could then be used to calculate a catchment rainfall average value, selecting one method from a set of several possible interpolation methods. The resultant distribution of calculated rainfall average values would account for uncertainty in rainfall point measurement and interpolation method. Clark and Slater (2006) extend these ideas into space to create realistic gridded rainfall patterns. Overall, Monte Carlo methods are recommended because they are easy to implement and can be used with any type of uncertainty distributions.

The Monte Carlo method is a numerical extension of the classic analytical error propagation method by Taylor series expansion. While classic error propagation is limited to normally distributed errors and differentiable models (Graham, van Verseveld, Barnard, & McDonnell, 2010 show an example), Monte Carlo can accommodate any distributional form and any complex model. However, it may be limited by computational power as more complex models require more samples to be processed through longer-running model codes.
3.6 Software for estimating and managing data uncertainty

Uncertainty software can help to track and combine uncertainty information by providing a structured environment in which to manage multiple uncertain variables. This might include organizing scalar, time series, and spatial data, itemizing possible uncertainty sources with user-specified magnitudes or with default values, and generating realizations governed by uncertainty distributions for further processing in Monte Carlo studies. Some software packages are specific to particular hydrologic data types. For flow data, at least two programs are available online to estimate uncertainty stemming from the stage–flow rating curve: BaRatin from IRSTEA (https://forge.irstea.fr/projects/baratimage_v2/news) and HydraSub from the University of Oslo (https://folk.uio.no/trondr/hydrasub/ratingcurve.html). Other similar types of software (e.g., Bastin et al., 2013; Brown & Heuvelink, 2007; Harmel, Smith, King, & Slade, 2009) have previously been used to study water quality and other variables.

4 DATA UNCERTAINTY IMPLICATIONS FOR PROCESS UNDERSTANDING

Hydrologic data are essential to further our understanding of hydrologic processes. Hydrologists use experimental watersheds to collect detailed data with rich space–time coverage of many storages and fluxes within the hydrologic cycle. Such watersheds have seen the discovery of new hydrologic processes, such as the positive feedback between rising water tables and groundwater flow (Bishop, 1991). Others are used to map dominant processes in new hydro-climatic settings (e.g., cold climates; Carey et al., 2010). All depend on the accuracy and precision of the underlying data. Hypothesis testing provides an overarching framework to guide field studies, promote collaboration and clarify research aims (McKnight, 2017). However, Pfister and Kirchner (2017) show that many hypothesis-driven hydrologic field studies lack statistical rigor and consideration of uncertainties, providing potential obstacles to scientific progress.
Data uncertainties propagate into hydrologic process understanding depending on how this understanding is extracted from the data. We use as an example the method of hydrologic signatures as process indicators. Hydrologic signatures are index values derived from the data that quantify a particular aspect of a hydrologic process. Typical signatures include a fitted parameter of the shape of flow recessions that is related to the storage–discharge relationship of the watershed, or the slope of the normalized flow duration curve that is used to summarize watershed flashiness. Uncertainty in the underlying data propagates into the signature value. The resulting signature uncertainty depends on signature type, for example, long-term spatial and temporal averages have lower uncertainty because random errors average out, compared to signatures describing extreme responses. Recent work has shown that methodological choices in the signature design also have large impacts on the signature uncertainty. Short data series, typical of experimental watersheds, contribute to data uncertainty: Kennard, Mackay, Pusey, Olden, and Short (2010) found high uncertainty in 120 eco-hydrological signatures of the flow regime (covering magnitude, frequency, duration, timing, and rate of change) with at least 15 years of record needed to provide stable values. Typical uncertainty magnitudes in some signatures have potential to change our understanding of hydrologic processes (Westerberg & McMillan, 2015).

Such high uncertainty magnitudes impede our ability to determine and understand differences in processes between watersheds or between time periods. Westerberg et al. (2016) found that differences in signature values between watersheds were often due to data uncertainty rather than true process differences. As spatial patterns are so often critical to hydrology (e.g., to identify areas most sensitive to change, or to identify areas where water fluxes are highest), hydrologists must ensure that the patterns we see are real and not artifacts of data uncertainty. Uncertainty in signatures characterizing both the natural flow regime and the anthropogenically altered flow regime make it difficult to attribute hydrologic trends over time to human impacts (Vigliak et al., 2018). Accounting for uncertainty in statistical analysis of spatial and temporal patterns, as done by Lopes, Chiang, Thompson, and Dracup (2016) who linked ENSO and other atmospheric/oceanic processes to Amazonian drought, enables authors to account for missing or uncertain data, and greatly strengthens their conclusions.

Other good examples of the risks of erroneous scientific conclusions if data uncertainty is not accounted for come from the common uncertainty source of rain gauge undercatch. Rain gauges frequently record lower totals than true rain depth, especially under windy conditions (where turbulence prevents rain settling into the gauge) or snowy conditions (where snow is blown out of or sticks to the side of the gauge). A very early example is from Heberden (1769), who misinterpreted rainfall undercatch from increased wind speeds at rooftop-level compared to ground-level. This led to an incorrect theory about rainfall being created in mid-air due to an unexplained electrical phenomenon. More recently, Berghuijs, Woods, and Hrachowitz (2014) evaluated differences in runoff ratio between rain- and snow-dominated catchments. Their methods needed to account for data uncertainty because the observed differences in runoff ratio were partly due to snowfall causing greater undercatch than rainfall, and only partly related to true differences in process between rain versus snow moving through the catchment.

5 DATA UNCERTAINTY IMPLICATIONS FOR HYDROLOGIC MODELING

Hydrologic model results are affected by uncertainty in input data, model evaluation data, model parameters, and model structure. These uncertainties lead to equifinality, that is, many different model representations produce similarly good model results. Uncertainty in model parameters and model structure has been extensively studied. Uncertainty in model input and evaluation data is equally widespread, but much less discussed. In this section, we focus on data uncertainty and its impacts on models, and do not further review model parameter or model structure uncertainty, though all types of uncertainty interact and can compensate each other in the model calibration process. Interested readers are directed to Beven (2010) for a detailed treatment. In addition to input data uncertainty, hydrologists should be aware that when structuring a hydrologic model to simulate dominant processes in a watershed, the process understanding used to structure the model may be equally impacted by data uncertainty at a fundamental level (as discussed in the previous section).

Uncertainty in input data (rainfall, evapotranspiration, and other drivers) propagates through the hydrologic model to create uncertainty in predictions (Figure 4). The propagation characteristics (linear or nonlinear) are controlled by the model structure. Therefore, where data uncertainty is high, careful choice of model structure can help limit its effects. Montanari and Di Baldassarre (2013) showed that models with a structure closely matched to dominant processes in the watershed were less affected by data errors. Accounting for input rainfall uncertainty is difficult, because unlike flow uncertainty that is dominated by rating curve error and is therefore relatively stable over time, rainfall uncertainty varies from storm to storm. A popular, though computationally expensive, treatment of rainfall uncertainty is a time-dependent, multiplicative error term of various complexity (Del Giudice, Albert, Rieckermann, & Reichert, 2016; Kavetski, Kuczera, & Franks, 2006; Renard et al., 2011) that is estimated together with other model parameters in a Bayesian framework.

Uncertainty in model evaluation data (e.g., streamflow at the catchment outlet, streamflow at nested locations and other state or output variables) creates uncertainty as to which model calibration creates the most accurate predictions, because the
exact streamflow values that the model should reproduce are unknown. Therefore, accounting for evaluation data uncertainty in models reduces model parameter bias, as models are not forced to reproduce the measured rainfall–streamflow relationship that may be precise but not accurate (see Box 2 for an example). In real time, data assimilation methods use flow data to correct water storage estimates in a hydrologic model, and thus improve future forecasts. Assimilation algorithms force the user to estimate uncertainties, because they require explicit definition of evaluation data uncertainties to determine the relative trustworthiness of model predictions versus evaluation data (Liu et al., 2012).

For some periods, data errors may lead to inconsistencies where data do not satisfy the water balance. Such uncertainties are termed disinformative when calibrating a water-balance model and lead to biases and uncertainty in model parameters (Beven, Smith, & Wood, 2011; Beven & Westerberg, 2011). Disinformation can result from uncertainties in the input data, model evaluation data, catchment delineation, or unknown inter-basin flows and human influences. A common example is that discharge is greater than precipitation at the annual or event scale as a result of underestimated precipitation or neglected groundwater influxes. Lundquist et al. (2015) describe the extended effort sometimes required to track down such data errors, giving examples from California where modeled streamflow was double the observed, and from Washington where modeled snow temperatures were biased by +10 °C. Both problems were initially attributed to model failure, before eventually being traced to equipment malfunction that caused errors in the observations. Model error due to disinformative data can propagate beyond the disinformative period itself (Beven & Smith, 2015); a single disinformative event can lead to errors that last for several months (Westerberg & Birkel, 2015). Kauffeldt, Halldin, Rodhe, Xu, and Westerberg (2013) screened global hydrological datasets and found that inconsistent long-term runoff coefficients were frequent in areas where precipitation is affected by snow undercatch, demonstrating the longevity of disinformation. Disinformative periods should preferably be excluded.

**BOX 2**

**THE BENEFITS OF ACCOUNTING FOR DATA UNCERTAINTY IN MODELING APPLICATIONS: AN EXAMPLE**

Uncertainty in flow data can create parameter bias if it is not accounted for during model evaluation. McMillan, Freer, Pappenberger, Krueger, and Clark (2010) provide an example from an unstable gravel-bed river in New Zealand. River flow data is used to calibrate a hydrologic model, by tuning the model parameters to correctly predict the flow. The flow data is derived from a rating curve that converts measured river stage to flow, creating uncertainty in the derived flow data because movement of gravel often changes the stage–flow relationship. Suppose the measured flow is lower than the true flow; to mimic the lower flow, the model must somehow remove water from the catchment, with adjustments in evapotranspiration typically being the only way of achieving this. Therefore, error will be created in the model parameters, such as soil depth being very large or drainage being very slow (both would hold more water in the soil and therefore increase evapotranspiration). If instead we estimate uncertainty in the flow data, and allow the model prediction to vary around the measured flow within the uncertainty range, then the model can maintain a true water balance that does not corrupt other model parameters. McMillan et al. (2010) do not directly establish a link between flow uncertainty and incorrect process representation. However, they are able to show large changes in estimated parameters when the model is calibrated with flow data uncertainty estimation, compared to the control case without uncertainty estimation.
prior to modeling based on a model-independent data screening, for example, by analyzing runoff coefficients and actual evaporation compared to potential evaporation, to prevent data corruption and therefore increases in uncertainty.

6 | DATA UNCERTAINTY IMPLICATIONS FOR WATER MANAGEMENT

Data uncertainty propagates to uncertainties in hydrologic analyses and on to water management decisions, and may lead to increased costs and risks to society. In particular, data uncertainty can lead to wrong interpretations and attribution of hydrologic change, especially when the uncertainties are non-stationary (Wilby et al., 2017). Data uncertainty can further lead to wrong conclusions about progress towards environmental goals, such as good ecological status under the EU Water Framework Directive (Krueger, 2017; Skeffington et al., 2015).

Analyzing data uncertainty should lead to more robust analysis, better assessment of risks, and more relevant priorities for further investigation to constrain uncertainty (Juston et al., 2013). If uncertainties have been quantified, decision theory can be used to determine some optimum management strategy in the light of that uncertainty (e.g., see Davis, Kisiel, & Duckstein, 1972 for an early example in flood levee design). Decision theory considers a range of possible management strategies, and for each one quantifies the expected cost under all possible values of the uncertain variable (such as flood depth), to determine the strategy with the lowest expected cost. However, the standard risk-based approach of reducing uncertainty to probability is often an insufficient response to incomplete knowledge (Zeitoun et al., 2016). Info-Gap decision theory (Ben-Haim, 2006; Korteling, Dessai, & Kapelan, 2013) goes further in these cases by analyzing the robustness of decisions under hypothetical levels of added uncertainty. Acknowledging the reality of uncertainty and quantifying the confidence in model output will better inform policy, regulatory, and legal decisions based on models (Harmel et al., 2006).

Uncertainty analysis enables us to differentiate between situations of high or low uncertainty. For example, flow thresholds used to issue flood warnings may be relatively insensitive to the rating curve uncertainty model used (Oció, Le Vine, Westerberg, Pappenberger, & Buylaert, 2017) and therefore relatively simple models such as uncertainty estimated as a constant fraction of flow may be sufficient. Uncertainty magnitudes may also differ strongly depending on the variable to be predicted. McMillan and Brasington (2008) showed that highly uncertain flood discharge may lead to low uncertainty in inundated area due to the natural constraining functions of the floodplain, but high uncertainty in number of inundated houses due to the high concentration of housing at the floodplain margins. The uncertainty in these predicted values is relevant to end-users such as the public and decision-makers.

We argue that the robustness of water management results and their acceptance by the public and by water managers is enhanced by a transparent statement of the associated uncertainty. For example, Payment for Watershed Services schemes, where land managers are offered financial incentives in return for less intensive management practices, rely on hydrologic data. Lima, Krueger, & García-Marquez (2017) discuss the need to account for uncertainty in these data throughout the design of the scheme, the contract negotiation process and the subsequent monitoring to ensure realistic expectations and achievement of conservation goals. Similarly, McMillan et al. (2017) showed multiple examples where uncertainty analysis provided positive outcomes for water management applications, including how visual demonstration of uncertainty bounds helped to convince landowners of the need for controversial water quality management measures requiring land use restrictions. Openly discussing the limitations of our knowledge may help to engender trust where hydrologic analyses are used as a basis for risk communication with the public and decision-makers.

A counter-argument holds that communicating hydrologic uncertainty will undermine the credibility of hydrologists, but this is hard to accept due to our ethical, professional obligations as hydrologists to be transparent about what results our analyses can and cannot support. This argument is discussed by Beven (2006) and Pappenberger and Beven (2006) who refute common reasons to avoid uncertainty analysis such as the additional effort required, lack of understanding of uncertainty in hydrologic data, and fear of negative perceptions or difficulty in publishing data with high uncertainty. It is unrealistic to expect all monitoring programs to be conducted under ideal conditions with ample resources, and even data collected with concerted quality assurance effort can have appreciable uncertainty (Harmel et al., 2009). What seems equally clear, however, is that uncertainty is frequently mobilized in the political arena to serve vested interests, either to discredit knowledge claims or knowledge holders or to maintain the status quo (Milman & Ray, 2011). Transparent uncertainty management can reduce the risk of political disputes being masked as disputes over scientific analysis. Although hydrologic results have been less controversial in the past compared to more prominent fields such as climate science (Beck & Krueger, 2016), we expect hydrologists will be increasingly exposed to political dispute as water scarcity, inequitable access and pollution become ever more pressing.
FUTURE RESEARCH NEEDS

In the active area of data uncertainty research, methods to quantify uncertainty are continually being discussed, improved and updated. As methods become established, there is a need for controlled experiments using different uncertainty methods and associated assumptions to compare and contrast the resulting uncertainty estimates. This approach would be the equivalent of hydrologic model inter-comparison experiments, long used to evaluate competing models. An example from riverine sediment source apportionment is Cooper, Krueger, Hiscock, and Rawlins (2014), who test inter alia the effect of accounting for covariation in input data uncertainty estimates against the usual practice of excluding covariation, and find a bias in sediment source contribution of up to 5% in the usual practice. A first example in the case of flow data uncertainty is the meta-analysis by Kiang et al. (in press), who compare multiple software tools for estimating rating curve uncertainty and discuss differences in the estimated uncertainties, showing substantial difference in uncertainty estimates between methods. The results of Cooper et al. and Kiang et al. show that there is still “uncertainty about uncertainty”, also termed 2nd order uncertainty or uncertainty$^2$ (Juston, Jansson, & Gustafsson, 2014). Furthermore, Kiang et al. highlight the need for clarity on naming and categorizing sources of uncertainty, to aid accurate inter-comparisons. Creating clear, “recipe book” methods for hydrologists to list, quantify, and combine uncertainty sources is a need that remains largely unmet.

CONCLUSION

This article has laid out sources and implications of data uncertainty, and has summarized methods for quantifying data uncertainty (Figure 5). We have shown that the complex but essential task of estimating uncertainty in hydrologic data can be made tractable by using a structured method. First, a perceptual model enables us to identify uncertainty sources under five categories (measurement uncertainty, derived data uncertainty, interpolation uncertainty, scaling uncertainty, and data management uncertainty). Data uncertainty from each source can then be quantified using either a dedicated analysis (using replicates, nested measurements or subsampling techniques), or by transferring information from more detailed experiments reported in the hydrologic literature. Lastly, multiple uncertainty sources can be combined using the Monte Carlo method. The resulting quantified data uncertainty enables the hydrologist to improve process understanding, hydrologic model predictions and water management decisions.
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CONFLICT OF INTEREST
The authors have declared no conflicts of interest for this article.

NOTE
1 In practice our ways to measure and analyze different types of uncertainty often constrain which uncertainties we notice or overlook, and how we conceptualize these uncertainties. Also see Section 7 for a discussion of the meta-uncertainty that stems from choosing a model to estimate uncertainty.

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