Technical Memorandum

Water Temperature Modeling Platform: Estimation of Uncertainty – Sources (DRAFT)

Central Valley Project Water Temperature Modeling Platform

California-Great Basin Region



Mission Statements

The U.S. Department of the Interior protects and manages the Nation’s natural resources and cultural heritage; provides scientific and other information about those resources; and honors its trust responsibilities or special commitments to American Indians, Alaska Natives, and affiliated Island Communities.

The mission of the Bureau of Reclamation is to manage, develop, and protect water and related resources in an environmentally and economically sound manner in the interest of the American public.

Water Temperature Modeling Platform: Estimation of Uncertainty – Sources (DRAFT)

Central Valley Project Water Temperature Modeling Platform

California-Great Basin Region

prepared by

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California-Great Basin

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Cover Photo: Keswick Dam on the Sacramento River by John Hannon

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Abbreviations and Acronyms

CIMIS California Irrigation Management Information

CPP Community Participation Plan

CVP Central Valley Project

DWR California Department of Water Resources

GUI Graphical User Interface

NWS National Weather Service

PG&E Pacific Gas and Electric

QA Quality Assurance

Reclamation U.S. Department of the Interior, Bureau of Reclamation

TCD Temperature Control Device

USGS U.S. Geological Survey

WTMP Water Temperature Modeling Platform

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# Introduction

Flow and water temperature simulation models are useful and necessary tools to support resource managers in their understanding of temperature dynamics in U.S. Department of the Interior, Bureau of Reclamation (Reclamation) Central Valley Project (CVP) reservoirs and downstream river reaches. Such tools support evaluation of how operational decisions and various influencing factors can affect water temperature in reservoirs and rivers, providing needed information to evaluate potential effects on cold-water fishery species downstream of CVP reservoirs.

Flow and water temperature modeling tools to support operational decision-making provide a means to assess strategies and define objectives for water temperature management. Water temperature modeling frameworks are used to forecast and assess future conditions for real-time, seasonal operations, and biological assessments to achieve goals. Reclamation’s objective for the development and use of the Water Temperature Modeling Platform (WTMP) is to support the effective and efficient management of resources for downstream regulatory and environmental requirements within the context of an uncertain environment. Despite all their complexity, models are simplified mathematical representations of real-world processes. Developing fully deterministic field-scale models, where all processes are known and represented exactly, is beyond the current understanding of physics and other processes. Model development is inherently an ill-defined problem, which means that the available data are never sufficient to identify all the parameters and structure unequivocally, and approximation is unavoidable to preserve the integrity of parameter estimation and model calibration process and outcomes. Therefore, even with a best constructed model using all the available data and technologies, discrepancies between the model simulated results and observations are still expected and the accuracy of simulated results (or in some cases, referring to as predictions) is only a relative measure (Figure 1‑1).

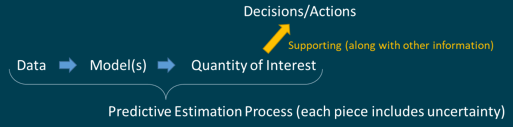


Figure 1‑1. Predictive estimation processes with uncertainty elements used in decision-making.

Models can provide insights for examining potential consequences of actions even in data-poor environments if applied appropriately. Ensuring model outputs are properly used for the intended decision-making process in terms of resolution and accuracy is important. Adequacy of calibrated model applications should be re-evaluated if there is a significant imbalance between the potential model uncertainty and the risk tolerance of decision-makers, operators, resource managers, and/or others for the simulated processes of interests (i.e., the primary model outputs).

To support the proper use of WTMP models, this TM documents the sources of model uncertainty as identified throughout the project and model development process. This TM also documents uncertainty associated with model application and use.

# Uncertainty in Model Development

This chapter introduces the concept of model uncertainty, as well as the sources of error as they relate to flow and temperature modeling in the WTMP. As previously mentioned, uncertainty is intrinsic to the modeling process, and it is important to consider the potential effects it has on modeling results when they are used for decision-making purposes. There is an extensive body of literature focused on developing uncertainty frameworks that seek to define concepts and establish a common understanding across disciplines (McIntyre et al. 2002, Walker et al. 2003, Dewulf et al. 2005, Refsgaard et al. 2007, van de Keur et al. 2008, Sigel et al. 2010, Warmink et al. 2010, Bastin et al. 2013, Refsgaard et al. 2013, Skinner et al. 2014, CWEMF 2021, Kirchner et al. 2021, Bevan 2022). Although there is no single uncertainty framework that can be applied across all disciplines and situations (Bevan 2022), understanding uncertainty is a critical part of the modeling and should be considered throughout the modeling process (Refsgaard et al. 2007, Tscheikner-Gratl et al. 2019) and communicated to decision-makers (McMillan et al. 2108).

A shared understanding of the nature, sources, and effects of model uncertainty among participants (e.g., model developers and users, stakeholders, and decision makers) is essential for a successful decision-making process using models as tools. Different participants or entities may have different levels of comfort with inherent uncertainty associated model outputs (i.e., model predictions) and therefore, being transparent about this topic could be helpful to alleviate the discomfort, or even doubt, associated with models used in this context. As a first step, it would be helpful to establish common definitions of terminologies that are essential for uncertainty discussion.

Fundamentally, uncertainty throughout the modeling process represents the outcome of multiple sources and types of errors that result in outputs that do not necessarily predict real-world conditions exactly. The degree of deviation, which can be described both quantitatively and qualitatively, depends on the specific modeling project, approach, available data, and other factors. Uncertainty is not a mask to obscure errors that always exist in data used in models and model approximations and analyses, but rather a means to accept that models are imperfect but invaluable tools in resource planning and management.

To assist in understanding the potential impacts that errors stemming from approximation and data may have on modeling results, modelers should consider the nature of uncertainty, often divided into three main categories: epistemic, aleatory, and ambiguity (Walker et al. 2003; Dewulf et al. 2005, Kirchner et al. 2021). Epistemic uncertainty arises from a lack of knowledge about a process and can be reduced with additional data collection, analysis, and research. Refsgaard et al. (2007) notes that while additional knowledge can reduce epistemic uncertainty, additional information can also identify new areas where additional understanding is needed. Aleatory (or variability or stochastic) uncertainty arises from the inherent variability and the stochastic nature of natural phenomena and cannot be notably reduced by more data collection. Additional knowledge may help to reduce or constrain aleatory uncertainty. McMillan et al. (2018) noted that processes that appear aleatory have epistemic components and that as knowledge and technology improves, processes that seemed aleatory may become epistemic, providing potential avenues to reduce uncertainty. Finally, ambiguity uncertainty arises from multiple, and sometimes conflicting, understandings of the underlying process and may or may not be reduced with additional data collection (Dewulf et al. 2005). Other categories are mentioned in the literature (see Kirchner et al. 2021), but they can be considered subsets of the three listed above. All three types of uncertainty are an outgrowth of errors and assumptions in representing a modeled system and data used for model construction. Some of these errors can be assessed through formal methods (e.g., sensitivity analysis, statistical approaches where model performance is expressed in terms of known and accepted probabilities), while other processes, and hence the possible outcomes, are poorly understood and not explicitly quantified. Most flow and water temperature modeling projects fall between the two extremes.

The final dimension of uncertainty focuses on the sources of error (Walker et al. 2003; Refsgaard et al. 2007; Warmink et al. 2010; Kirchner et al. 2021). Error refers to the (theoretically) quantifiable difference between the actual outcome and the observed or measured outcome. Sources of error herein refer to both the components of the model (e.g., approximations) and in the modeling process (e.g., data development). A more detailed discussion of the sources of error and the uncertainty they introduce into the model development process is included below.

Errors can be introduced in all phases of the modeling process, resulting in uncertainty associated with model outputs/predictions. The selection and implementation of models introduce errors through the approximation selected to represent the processes of interest. The observed data and measurements used in model development also includes errors. This review presents basic sources of error that contribute to uncertainty in the outputs of flow and water temperature models. By understanding these sources of error throughout the modeling process, modelers and practitioners can be better positioned to convey model outputs/predictions properly to decision-makers.

The modeling process can be characterized into five broad stages: 1) model conceptualization, 2) model development, 3) data development, 4) parameter estimation (calibration), and 5) model applications (Refsgaard et al. 2007, Kirchner et al. 2021) or variations thereof (Mahadevan and Sarkar 2009). Model conceptualization focuses on identifying the goals and objectives and key processes and features to be included in the model, along with developing a common terminology among involved parties and other potential users of information. Model development focuses on the selection and implementation of mathematical representations of the processes with selected parameters and other specifications. Data development refers to the collection, management and processing of data used by the model. Parameter estimation (calibration) is the process of determining values of selected parameters used in the model. Model use focuses on model applications to simulate specific conditions (e.g., scenarios) and how results may be used.

Errors and thus, resulting model uncertainty, introduced in these five stages can mutually influence each other and associated error propagation can be complicated. Quantification of uncertainty of a specific step in the process and error propagation can be a research-based exercise and many are in progress and published in literature (Wang et al. 2022, Kirchner et al. 2021, Yen et al. 2014). While the following TM provides separate discussions of uncertainty broken into distinct stages, for the purposes of the WTMP model, uncertainty is approached through a global sense for practical purposes. In other words, errors associated with facility and infrastructure representation, measurement errors associated with available data, and errors associated with commonly accepted mathematical equation for the processes of interest (e.g., heat budget calculation) are not reviewed and evaluated individually but combined in the uncertainty characterization and estimates reflected in model calibration. This treatment was discussed with the Model Technical Committee (MTC) established for the WTMP development.

## Uncertainty Associated with Model Conceptualization

Model conceptualization is the first step in the modeling process. Conceptualization necessarily starts with identifying modeling objectives and goals. Conceptualization also includes identifying the key processes and features that need to be incorporated into the model to meet the identified objectives and goals, including the determination of system boundaries (i.e., spatial and temporal extents), modeling approach(es) (e.g., physically based, statistical, etc.) to be used, and spatial and temporal resolution/representation (e.g., 1-D or 2-D, hourly, daily, monthly, seasonal, or annual time step). Including or omitting certain processes and features should be a deliberate determination based on the objectives and goals, and practical considerations of data availability and other considerations unless their relative importance of a process is not understood or not known (i.e., the unknown unknown) (Walker et al. 2003). Also, as part of this step, participants should identify how potential inadequacies in conceptualization may impact the modeling results (Refsgaard et al. 2007). Technically, the conceptualization process provides the basis for development of certain model specifications, dictates the associated mathematical representation for the primary physical process(es) or system representation, and identifies other features that are required for model selection and subsequent development. The necessary system approximations based on reconciliation of a desired level of model accuracy and precision, and the extent and quality of available data and information results in a certain system representation in the model development process. The degree of uncertainty introduced by conceptualization may vary significantly – ranging from potentially limited for well-established and understood process to potentially unknown levels for a heuristic approach to certain process that is not well understood. Any decisions made based on the model outputs should take into consideration the uncertainty associated with the selected representations of the processes of interest.

For the WTMP, model conceptualization was based on Reclamation’s objective for the development and use of the WTMP: to manage water temperature in river reaches downstream of storage reservoirs to meet regulatory and environmental requirements. To this end, model conceptualization identified the available model representations of flow and temperature, spatial representations for each of the river systems (extent and within domain resolution), period of record and available data, geometric representation (one- and two-dimensional model considerations), flow and temperature conditions in the identified project area, facility representations and available information, incorporation of unique facility, and other factors (Reclamation 2023c, 2020). Thus, the specifications of system representation and associated modeled processes necessary to represent the major reservoirs, tunnels, and river reaches for each basin were identified early in the project based on above-mentioned needs. For most of the processes considered in WTMP models, the conceptualization is relatively straightforward; however, treatments of certain unique features and localized conditions could introduce uncertainty that is not easily quantified and thus, require careful evaluation of the approach to model these features and localized conditions in model development process. When necessary, revising the conceptualized modeling approach may be required.

## Uncertainty Associated with Model Development

Based on the specifications and requirements from model conceptualization, model development involves implementation of the assumed system representation and, if necessary, specific process representations as part of the model structure in the computational environment. Model structure refers to the mathematical relationships used to represent the processes of interest (Chapra 1997, Martin and McCutcheon 1999, Roache 1998, Walker et al. 2003, Warmink et al. 2010) (e.g., mathematical representations of outlet works, temperature control curtains). Areas where error can be introduced include a lack knowledge or understanding about the processes being modelled, unknown or unaccounted for inter-dependencies with other processes in the model or that have been excluded, incorrect or incomplete mathematical representations, oversimplification and overparameterization (Guzman *et al.* 2015). Additionally, there can be multiple acceptable formulations to represent processes of interest, each with their own assumptions and simplifications (Walker *et al.* 2003). Individually, embedded within each representation are assumptions about what drives the processes of interest and how it relates to the key outputs.

The WTMP modeling effort leverages existing mathematical representations (i.e., literature) and accepted modeling packages for efficiency and effectiveness. This practice is common when popular models that have been widely applied and consistently supported are used for applications, such as CE-QUAL-W2 and ResSim. The general mathematical representation of the system and processes, as well as the implemented computational method(s) embedded in a software package, are accepted as is without separate assessments on associated errors and resulting uncertainty. Uncertainty investigation of specific customized modules or processes added to the standard software package by modelers to meet the unique conditions of the modeled system may be of interest.

Model technical uncertainty arises from software and hardware (Warmink et al. 2010). Model software relates to programming language (i.e., model coding) and compiling topics, and hardware relates to RAM, computer processor stability, and similar aspects. With the current technology advancements and significant improved computational capacity, this area of uncertainty still exists; however, this uncertainty is not typically an area of concern unless the model used is significantly impacted by dated software and hardware technologies.

Based on the above discussion, selected elements of uncertainty associated with model development aspects of model structure were not investigated as part of the WTMP process. Specifically, areas not investigated include:

* Both CE-QUAL-W2 and ResSim are physically based, sub-daily, dynamic models and the mathematical relationships used to represent flow and water temperature the processes of interest were assumed appropriate.
* The reservoirs representations (one- and two-dimensional) and rivers representation (one-dimensional) were consistent with the project objective and design (i.e., one dimensional reservoir for “screening level" analysis and two-dimensional reservoir representation for detailed analysis).
* Detailed geometric representations (i.e., bathymetry and cross-sections) and installed infrastructure (e.g., dams, tunnels, etc.) were assumed fixed in time and space.

These and other aspects are addressed in Reclamation (2023e) to ensure the selected models include key model features and capabilities to meet the objectives and goals for developing the WTMP. For the WTMP, these include selective withdrawal representations, temperature control curtains, and submerged weirs/dams.

* **Selective withdrawal capabilities:** representations of the physical structure and associated operation of the Shasta Dam Temperature Control Device (TCD) and the Folsom Dam Temperature Control Shutters were developed for CE-QUAL-W2 in previous projects and have undergone extensive testing (Deas et al. 2020, PCWA 2015). These representations effectively parameterize the selective withdrawal systems using available features within the model and logic to represent the structure, flow distribution, and progression of gate use (e.g., blending). The logic for these two selective withdrawal systems were implemented accordingly in ResSim. Certain settings and overall representation were modified in the ResSim to develop the one-dimensional representation that are functionally equivalent to that of two-dimensional representations in CE-QUAL-W2 at the dam.

As detailed in the Model Development Technical Memorandum (Reclamation 2023d), the final representations of Shasta Dam TCD and Folsom Dam Temperature Control Shutters are the result of significant efforts in exploring more advantageous representations of these structures to improve representativeness and results of model calibration. Although these infrastructure elements are integrated into model calibration (and potentially multiple representations and logic exists for the same outcomes of downstream water temperature), the uncertainty introduced from these representations was not evaluated independently. Rather, errors associated with model representations of temperature control infrastructure at Shasta and Folsom dams are included in the overall calibrated model uncertainty (see parameterization uncertainty described below).

Significant effort beyond the current project scope is required to investigate uncertainty associated with the current representations of temperature control infrastructure. Further, this effort would benefit from the ongoing field work (Berry et al. 2021, Friedrichs et al. 2023) because, as noted in Reclamation (2023d), currently field studies are in progress and information to develop an improved representation are unavailable at this time.

* **Temperature control curtains:** representation of temperature control curtains in Lewiston Lake and Whiskeytown Lake (Oak Bottom, Spring Creek) are included explicitly in CE-QUAL-W2 as a curtain weir (Wells 2021a, 2021b). Temperature control curtains in Lewiston Lake and Spring Creek (Whiskeytown Lake) are full depth. The Oak Bottom curtain in Whiskeytown Lake was set at half of the curtain depth after extensive testing (see discussion in Reclamation 2023d). While an explicit representation is included in the CE-QUAL-W2, the complex flow conditions in the vicinity of the curtain with a simple curtain representation can introduce error into simulation results, as exemplified by the parameterization of the Oak Bottom curtain depth in CE-QUAL-W2.

The temperature control curtain in Lewiston Lake is not included in ResSim model representation due to the one-dimensional representation of the reservoir and the location of the curtain approximately 3,500 ft (1,066 m) upstream of the dam. Simulations by Jayasundara and Deas (2012) and design observations (Vermeyen 1997) suggest modest impact of the curtain on reservoir outflow temperatures.

Temperature control curtains at Whiskeytown Lake are not explicitly represented in ResSim but are considered on the inflow and outflow points implicitly (the extent of the model starts at Oak Bottom Curtain and the Spring Curtain assumes a withdrawal point located approximately 1 mile (1.6 km) upstream of the dam) . The inflow at the upstream (Oak Bottom) curtain is the upstream extent of the reservoir, and no specific representation of inflow elevation is specified. In this case the model simply assigns a depth of inflows based on density. At Spring Creek Tunnel outflow, the outflow is assigned a depth that is at the bottom of the curtain to represent this passive temperature control feature.

Consistent with the approach for uncertainty investigation for the Shasta and Folsom temperature control infrastructure representations, errors and resulting uncertainty associated with curtain representations in Lewiston and Whiskeytown lakes in CE-QUAL-W2 and ResSim. These curtain representations, though explored in model development and calibration (Reclamation 2023d), were not individually investigated and are included in the overall calibrated model uncertainty.

* **Submerged weirs/dams:** The submerged dam in New Melones Lake was represented as a submerged weir in CE-QUAL-W2 and ResSim; however, with different approaches. CE-QUAL-W2 represents a submerged weir through specific logic that is similar to the weir curtain (Wells 2121a, 2021b). ResSim represents flow that passes over the submerged dam by constraining the extent of the withdrawal envelope of the upper outlet to the elevation of the top of the dam. This is similar the CE-QUAL-W2, with the exception that the one-dimensional representative of New Melones Lake requires locating the submerged dam at the existing dam (the distance between the submerged dam and the existing dam is approximately 2,500 ft (762 m)). Consistent with the above discussion, the impact of errors on model uncertainty associated with the representations of submerged dam in New Melones Lake in CE-QUAL-W2 and ResSim, though explored in model development and calibration (Reclamation 2023d), were not individually investigated, and are included in the overall calibrated model uncertainty.

## Uncertainty Associated with Data Development

Uncertainty associated with data development encompasses a wide range of sources, but the primary sources are due to measurement error or filling data gaps where field observations are absent (Bastin et al. 2013, McMillan et al. 2018). Measurement error is associated with the collection of field data used to prepare the model (Warmink et al. 2010) and includes both direct measurements (e.g., stages) and calculated values (e.g., streamflow rates from a stage-rating curve). All measurements have errors even when using the most accurate and advanced devices. Major sources of measurement errors arise from the instrumentation (e.g., device accuracy, calibration approach, sensor degradation), collection method (e.g., methodology, location) or analysis method (e.g., laboratory analysis), extent of spatial representation (e.g., the number of devices deployed in a given reach), and period of record (e.g., timing, frequency, and duration of measurements).

Measured data is typically used as model boundary conditions for applications (e.g., calibration, analyses). Flow, temperature, and meteorological observations are typically collected for a range of purposes (Kirchner 2006) and prior to use in models measured data must often be processed. Typically, this involves either spatially or temporally interpolating and/or scaling the measured data (McMillan et al. 2018), disaggregating monthly data to daily data, or filling data gaps prior to use. Each approach introduces error into the final model data set.

Data management can also be a source of errors. For WTMP, the embedded Data Management System (DMS) was designed to reduce data management errors[[1]](#footnote-2) (such as transcription errors and data handling error; see Reclamation 2023b). Data management is related to, but independent, of the model development process and therefore data management error is not investigated herein.

The WTMP relies on data from multiple sources to calibrate and apply the reservoir and river models. Reclamation (2023a) identifies data sets, sources, data quality issues, gap filling, and other facets of this information as they relate to the use of models in the WTMP. Basic elements of data development uncertainty that are quantifiable include measurement or instrumentation error and errors stemming from missing data.

Data used for model development originates from many sources. Typically, methods of data collection and assessment for data quality are provided by corresponding managing entities. Specific methods have been developed and documented and instrumentation requirements specified to manage error within an acceptable range, or at minimum, quantify the quality of measurement. Consider the data used to develop model boundary conditions for Shasta Lake, which includes information from Reclamation, U.S. Geological Survey (USGS), California Department of Water Resources (DWR), Pacific Gas and Electric (PG&E), National Weather Service (NWS), and California Irrigation Management Information System (CIMIS). The collection methods, instrumentation, and overall data quality assurance (QA) procedures and available metadata for various groups vary widely and are not available from all reporting agencies. Additionally, in many cases the methods, instrumentation, monitoring locations, and QA and metadata change over the historic period.

Data gaps that need to be filled to provide appropriate boundary conditions for models range from missing a few data points (i.e., hours to days) to appreciable amounts (i.e., from weeks to years). For WTMP, major data gaps exist in multiple cases for some systems, including Sacramento River tributary temperatures, Trinity Lake and Trinity River inflows and temperatures, New Melones Lake inflow temperatures, and others. These conditions, coupled with the limited available information on instrumentation, collection methodology, and lack of metadata, precluded explicitly characterizing error associated with data inputs to the models in these and other cases. The accuracy of measurements can vary significantly between locations due to different age and make of instruments used for measurement and the physical conditions where measurements are taken. While it is important to understand that such errors exist, the uncertainty resulting from errors in data development was considered as part of the overall model uncertainty considered during the model calibration process.

## Uncertainty Associated with Model Parameter Estimation (Calibration)

Separate from the uncertainty associated with error in the collection and processing of field data, is the uncertainty that arises from how values of model parameters are used for calibration (Warmink et al. 2010, McMillan et al. 2018). Mechanistic models that are designed to be applied to a wide range of systems (e.g., CE-QUAL-W2 and ResSim) typically include parameters that can be adjusted to accommodate specific reservoir or river system attributes. The calibration process typically aims to adjust or “fit” these model parameters to minimize differences in model results and observed/measured data (Chin 2013). Examples include Manning roughness coefficient in flow models and empirical coefficients representing evaporative heat loss in temperature models. A model may have multiple parameters that are subject to calibration, ideally with additional reference information to support their use and selected values (e.g., default values and/or known ranges) (Walker et al. 2003, Tscheikner-Gratl et al. 2019).

Model parameter estimation or calibration uncertainty reflects several factors, including the modeling objective, performance metrics selected for calibration process and assumptions regarding the parameters included and excluded in calibration (Deletic et al. 2012, Ji 2017, CWEMF 2021). The objectives define how the differences between simulated results and observed/measured data are quantified and assessed in the context of model performance (e.g., accuracy), regulatory considerations, data availability/quality considerations, selected models, or other factors as they contribute to the objectives. Performance metrics may be displayed in graphical format and statistical measures.

The inclusion or exclusion of certain parameters for calibration is typically related to the availability of relevant data to support parameter estimates and the sensitivity of the model to the parameters. Parameters that are typically used or well-understood are often explored during calibration within an accepted range of values (e.g., literature values), while parameters that are poorly characterized or understood for certain processes may be excluded from consideration. Decisions on inclusion or exclusion of parameters for calibration may occur throughout the process. The model can be tested for a range of realistic possible parameter values (Guzman et al. 2015) and results are then assessed in terms of the calibration objectives and metrics, potentially resulting in changes in which parameters are included or excluded for calibration. When multiple model parameters are available for calibration, modelers should consider the possibility that different sets of parameter values may yield similar model result (i.e., the modeled outcome is not unique to a single set of parameter values) (Kelleher et al. 2017, Khatami et al. 2019). Simply focusing on minimizing differences between model results and field observations may mask errors in the processes being modeled (Kirchner 2006, Harmel et al. 2006). Additionally, modelers should be cautious when adjusting or adding parameter values to address model performance issues, particularly for unique processes/events, that could lead to model over-parameterization or parameters selected outside of typical ranges.

Sensitivity analyses are used to assist the calibration process to determine if the calibrated model is stable for intended applications, but it does not alleviate the need to review uncertainty associated with estimated parameters. Sensitivity analysis identifies the relative effect of changes in model parameter values on model results. In its most basic form, sensitivity analysis is performed by selecting a single parameter of interest and changing the value (within a range of values that are close to the estimated value and within a reasonable range) and observing the change in model results. This process can be repeated for all model parameters of interest but is usually performed for those with more significant effects based on experience, known system characteristics or the particular interests of the investigation.

The systematic process of calibration and validation defined for the WTMP provided an approach to accommodate not only parameter uncertainty, but also the other forms of uncertainty discussed herein and as outlined in Reclamation (2023d). The process included the following steps:

* Identify potential model parameter values based on reasonable value or range determined from a literature review or known theory, and documenting conditions where the selected value deviated from a typical value or range in literature.
* Assess model performance through graphical and statistical means with preliminary considerations of defined performance metrices. Graphing provides a qualitative evaluation to effectively assess short- and long-term temperature variability, magnitude, diurnal phase, rate of change, and other information that is often not apparent in statistical analysis. Statistical assessments provide quantitative comparison of simulated and observed values with respect to model performance metrics.
* Develop model performance metrics (e.g., measures of bias, mean absolute error, root mean squared error, and goodness of fit) that considered regulatory requirements, geometric representations, model spatial and temporal resolutions, overall model (CE-QUAL-W2 and ResSim) structure and process representations (e.g., governing mathematic equations, numerical solution techniques, selective withdrawal logic representations, wind forcing approximations, etc.), typical instrument measurement and reporting resolution, and past experience in applying models (see Table 2‑1).
* Calibrate model parameters to specific temperature signatures for reservoir (large, medium, small) and river temperatures to effectively represent key attributes of the cold-water pool and release temperature (for large and medium-sized reservoirs) and longitudinal heating and diurnal range in temperature in small reservoirs and rivers.
* Perform sensitivity analysis on key parameters. While qualitative, definitions of high, medium, low, and insensitive can be used to relate parameters to meaningful (or not) model responses as a guide for further adjustment.

Table 2‑1. Model performance metrics for hourly water temperature, flow, and reservoir stage in WTMP models. MAE is mean absolute error. RMSE is root mean squared error. NSE is Nash Sutcliffe efficiency.

| Parameter | Mean Bias | MAE | RMSE | NSE |
| --- | --- | --- | --- | --- |
| Stage | ±0.5 ft (0.15 m) | ≤1.0 ft (0.3 m) | ≤1.5 ft (0.45 m) | ≥0.65 |
| Flow | ±150 cfs (4.2 cms) | ≤300 cfs (8.4 cms) | ≤500 cfs (14.2 cms) | ≥0.65 |
| Water Temperature | ±1.3oF (0.75oC) | ≤1.8oF (1.0oC) | ≤2.7oF (1.5oC) | ≥0.65 |

Extensive calibration and validation results are presented in Reclamation (2023d) and the outcome is a set of parameters that result in models that perform consistent with performance metrics. Matching of model results and observed/measured data exactly during the calibration process is a warning of potential over-parameterization. Therefore, the review of calibration results for the identified performance metrics can identify systematic trends of bias (or other errors) that may exist and/or outliers caused by unique processes/events that are not captured in a model. The review informs modelers and practitioners if additional refinements of model parameter estimation or adjustments of system representation and specifications are required. This process was described in the Model Development TM (Reclamation 2023d).

The WTMP development and its uncertainty investigation are approached from a global perspective. In other words, errors incurred through the individual steps described above are evaluated in aggregate during the model parameter estimation and calibration process. Through ongoing applications of the WTMP and associated models, additional insights associated with the effects of uncertainty stemming from model calibration may be examined for potential refinements, improved process representation, and additional data acquisition. Uncertainty analysis can also be used to prioritize additional data acquisition (e.g., data type and location) and experimental design for field studies.

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# Uncertainty Associated with Model Application

Model applications involve the use of a calibrated model to predict outcomes, including flows and water temperature in reservoirs or rivers. The model inputs and boundary conditions (e.g., projected meteorological conditions, inflow conditions, and project operations) vary according to the objective of the model application and are subject to their own uncertainty depending on how they were measured or developed. The uncertainty associated with model application is closely related to approaches and processes used in assessing and quantifying system responses in model outputs (Guzman et al. 2015). For assessing WTMP model uncertainty, human errors such as data entry error, model misapplication, and other similar conditions are not considered.

Considering WTMP model applications, uncertainty arises from three major areas: (1) the input and boundary conditions, (2) the processes and procedures in the modeling workflow that produce model outputs , and (3) overall error in the calibrated model. Chapter 2 provides detailed discussions on the last item. The first item is an important consideration in model application; however, assessing input uncertainty external to the model for every potential application not within the scope of the WTMP models. Such an investigation requires a different assessment based on the methodology, processes, and implementation of the data collection methods for each input and boundary condition. Therefore, the discussion herein focuses on the second item: the additional and necessary processes and procedures that may introduce errors and resulting uncertainty when using the model (model application).

Two types of model use uncertainty that are of interest as they relate to the WMTP are (1) model linkage and (2) forecasting. Models can be applied alone or as part of a suite of models. In the latter case, the results from one model as inputs to a subsequent model (i.e., model linkage). Common sources of uncertainty due to model linkage arise when the models have different spatial and temporal scales and/or resolution (e.g., results from an hourly model used by a daily model, a local system model used as part of a regional model) or different objectives or key processes of interest. Uncertainty associated with a model is inherited by the next model, along with any new uncertainties that are introduced by linking the models. However, uncertainty impacts are not necessarily cumulative. Tscheikner-Gratl et al. (2019) illustrated that while uncertainty can accumulate, it can also be decreased depending on the specific processes and spatial/temporal scales of the linked models. The models can be used to determine if uncertainty is accumulated or decreased (“compensation effect”) during the model linking process, but without extensive, detailed research, the relationship is unknown; in some cases, isolation of individual effects is not always possible either.

Flow and temperature models are often used in conjunction with forecast data to estimate future conditions. Under this condition, when a model is used as a forecasting tool, uncertainty is introduced into the analysis by the forecast data (especially if forecast conditions are outside of the range of data used to calibrate the model) and through the forecasting processes and assumptions (Refsgaard et al. 2006, Deletic et al. 2012). Forecast data is developed external to the WTMP and thus the uncertainties associated with estimated forecast flow, meteorology, inflow temperatures, and operations are not investigated herein. Forecast processes and assumptions are presented below.

The WTMP can be used for a wide range of applications that include short-term and long-term planning and forecasting simulations. The extensive historic record in the DMS can be used to assess different operational strategies, assess the imposition of new infrastructure, and similar analyses. Forecasting simulations for annual temperature management plans make use of seasonal (multiple months) forecast runoff, operations, inflow water temperature, and meteorology conditions. The WTMP can also be used for long-term planning analyses accepting hydrology and operations from models such as CalSim3[[2]](#footnote-3) that simulate decades long periods. Using the historic period and long-term simulations based on external water resources planning models, the calibrated WTMP models can be used in a comparative manner (Refsgaard *et al*. 2007). The model can be run for multiple scenarios and the results may be compared with each other or a baseline simulation. This assumes that the uncertainty associated with the model (e.g., due to conceptualization, structure and technical, and parameter estimation) remains similar in magnitude so that the comparison yields useful information regarding the differences between the scenarios and/or the baseline simulation.

## Linkage

The WTMP is designed to use CE-QUAL-W2 and ResSim, where different models can be used for reservoir reaches and river reaches. An example schematic of this configuration is shown in Figure 3‑1. When applying calibrated models in this fashion the information from an upstream model (outflow from the reservoir or river reach) is passed to a downstream model as an upstream boundary condition, and model error in the upstream reach is passed to the downstream model.

For the CE-QUAL-W2 models, reservoir models were calibrated individually. After calibration, and as part of the WTMP, the models were linked. Consider Shasta Lake and Keswick Reservoir where linkage uncertainty was assessed explicitly with the model performance metrics identified for the WTMP (Deas et al. 2020). Findings indicated that model error for simulated temperature at Keswick Dam was at times higher than the individual calibrated models and lower (bias, MAE, RMSE) and NSE was similar, indicating that model error at times canceled out and at times was larger than the sum of the individual model error. While these results illustrate the complex nature of error propagating through the linked models, the results also indicate that for the Shasta-Keswick linked models, the error did not increase substantially compared to the error associated with the individual reservoir models.

For the ResSim system, the reservoirs and river are linked within a single model, and calibration explicitly accounted for model uncertainty in one reach being passed to a subsequent reach (see Reclamation (2023d)). Thus, the ResSim model results (herein and Reclamation (2023f)) are based on the calibrated linked models, and linkage uncertainty is included in the results.

There are numerous potential WTMP applications that include many different potential model combinations. Assessing error propagation for all possible model combinations is impractical. The results suggest that there is not a consistent bias, and errors do not accumulate disproportionately. Modelers should consider potential error propagation through the WTMP as they develop their model applications and perform assessments as necessary.

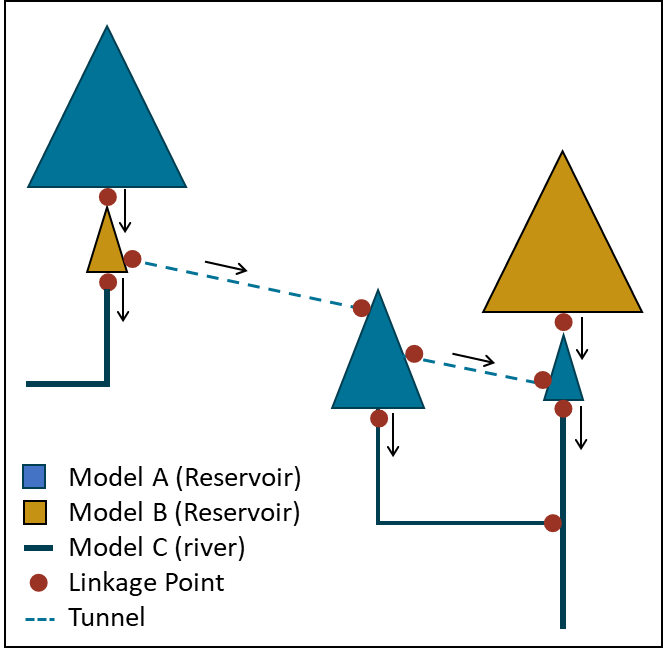


Figure 3‑1. Schematic of reservoir and river models in the WTMP with linkage points.

## Forecast: Processes and Assumptions

Seasonal forecasting to support annual temperature planning is a principal application of the WTMP. The process includes using the computationally efficient one-dimensional ResSim models to assess a wide range of options as a screening tool, to identify a subset of potential operational plans for assessment using the more detailed two-dimensional CE-QUAL-W2 models. Forecast processes and assumptions include using monthly forecast information and disaggregating this to daily or sub-daily information. The example presented herein evaluates model uncertainty associated with each step in the preparation of forecast boundary conditions to support seasonal temperature management plans.

Central Valley Project (CVP) operations forecasts are provided for a range of future hydrology (varying from wet to dry) and future meteorologic conditions (with varying periods of warm and cool weather). The combination of a specific operations forecast and a specific meteorological forecast is used to create a full set of boundary conditions needed to run the models. The process of preparing boundary conditions from operational forecasts and estimated future meteorologic conditions may introduce additional uncertainty in the numerical model results beyond the baseline uncertainty quantified through the calibration process discussed previously and in Reclamation (2023d).

Key characteristics of boundary conditions for temperature forecast simulations that are different from calibration simulations include:

* Dam release temperature targets are defined as weekly or monthly values (approximately) to achieve a desired downstream temperature,
* Selective withdrawal strategy (e.g., TCD operation) are determined by model logic,
* Reservoir inflow and release operational forecasts are provided as monthly average flow values,
* Meteorologic data estimated from historic data or forecasts, and
* Inflow temperatures are estimated based on historic data or using flow rates and meteorologic forecasts.

Outlined herein is an approach for quantifying uncertainty in the temperature model results stemming from approximations in the process of translating flow, operational, and meteorological forecasts into a set of boundary conditions needed to run the models in forecasting mode. Note that this approach is focused on bounding the error associated with the result of a temperature simulation for one set of flow, operations, and meteorology forecasts. The approach does not address the accuracy of flow, operations, or meteorology forecast data, which is developed by the CVP operations team and others. Quantifying uncertainty in a temperature forecast simulation for a range of flow, operations, and meteorologic forecasts is a topic for future study.

### Objective

The overall objective of this section is to quantify uncertainty associated with running the models given boundary conditions developed from flow, operational, and meteorology forecasts. The expected outcomes of this analysis include:

* An estimate of error bounds about predicted water temperature at key locations based on a forecast simulation with start times varying from March through July,
* Identified primary contributors to the forecasting process (e.g., approximations and assumptions) uncertainty, and
* Examples presentation/reporting of uncertainty in forecast results.

### Approach

A series of “retrospective forecast” simulations is performed to determine how processes and assumptions (and approximations) introduced by forecast boundary condition processing and automatic TCD gate selection affect the accuracy of model predictions. A set of forecast simulations is performed starting on the first of each month from March through July of each year in the historical data period used for calibration (2000 to 2019). Theoretically, forecasts starting earlier in the year would have more uncertainty than those later in the season. By running the simulations with different starting months, this uncertainty effect can be assessed. The set of simulations performed for each start time progressively moves from direct use of the historical boundary conditions to approximations of the historical boundary conditions representing a “best estimate” forecast. All simulations use the initial reservoir temperature profiles that most closely match the start of the simulation (March 1, April 1, May 1, etc.). Each set of simulations includes four uncertainty types (A-D below; also see Table 3‑1):

1. Calibrated Model Uncertainty – historical boundary conditions that defined the system (initial temperature, volume, and flow conditions, TCD gate settings, etc.), and the model uncertainty is defined by the difference between calibration and data model output.
2. Selective Withdrawal Logic Uncertainty – uncertainty associated with the model selecting the gate settings in the TCD (Shasta Dam) and shutter system (Folsom Dam) versus historical gate settings.
   1. Upper Sacramento System – A weekly average temperature target time series is developed based in the observed Shasta Dam outflow temperature, the Shasta TCD shutter operation will be controlled by the selective withdrawal (blending) model logic.
   2. American River – A monthly average temperature target time series is developed from the observed Folsom Dam outflow temperature, the Folsom TCD shutter operation will be controlled by the selective withdrawal (blending) model logic.
3. Flow Disaggregation Uncertainty – uncertainty associated with disaggregating monthly average flows to daily average flows, distributing total inflows among tributary streams, and estimating inflow temperature. This includes changes from step B, plus processing of reservoir inflows and releases in a manner similar to the process used in the operations forecast monthly data. The observed reservoir inflows and releases from the historic period are used to calculate a monthly average value. This is disaggregated to daily inflows using the standard forecasting process and approach, resulting in a daily time series that is equivalent to the monthly average. Reservoir inflow temperatures are then estimated based on the daily inflow time series and the historical meteorologic record.
4. Meteorology Forecast Uncertainty – uncertainty associated with meteorology forecast . This includes all changes from step Cand an estimated meteorology forecast. As a proxy for hourly meteorology, the monthly average air temperature is computed from the historical met data for each month in the forecast simulation. This average monthly air temperature is used to select a representative monthly meteorology (hourly) from historical years in the period of record. For example, if the March 2000 average monthly air temperature was 63oF, the March average monthly air temperature from the remaining 19 years (exclusive of 2000) that was closest to the March 2000 value would be selected as the estimated meteorology forecast, i.e., the hourly data from the selected March would be used in March 2000. This process was repeated for all months in all years. In this manner an alternate meteorology data series was created that was similar (based on average monthly air temperature) but did not directly match the historical simulation year.

Table 3‑1. Summary of simulation set boundary conditions for cumulative forecast uncertainty analysis.

| Boundary Condition | Base Model Uncertainty  (Type A) | Uncertainty Associated TCD Operation  (Type B) | Uncertainty Associated with Monthly Average Flows  (Type C) | Uncertainty Associated with Estimated Meteorology  (Type D) |
| --- | --- | --- | --- | --- |
| Temperature Target | Historical | Weekly or monthly average of historical | Weekly or monthly average of historical | Weekly or monthly average of historical |
| TCD Shutter Operation | Historical | Model determined | Model determined | Model determined |
| Inflow | Historical | Historical | Downscaled daily from monthly average of historical | Downscaled daily from monthly average of historical |
| Reservoir Releases | Historical | Historical | Monthly average of historical | Monthly average of historical |
| Meteorologic Data | Historical | Historical | Historical | Each month selected from historical record based on monthly average air temperature |
| Inflow Temperature | Historical | Historical | Derived from downscaled monthly inflow and historical meteorology | Derived from downscaled monthly inflow and estimated meteorology |

The uncertainty analysis was performed with HEC-ResSim for 20 years using python scripts to automate the process and facilitate data management, computation of error metrics, and reporting. The identical process was also completed for CE-QUAL-W2 at Shasta Lake and Keswick Reservoir for a single year (due to computational times) to illustrate similar application of the models.

### Error Statistics

The difference between observed temperature time series data and simulated results was computed for the daily mean temperature and daily maximum temperature from each simulation and grouped according to forecast start date and uncertainty type. For example, to compute error statistics for April-start forecasts, biases from the available April-start simulations (up to 20 years, across the available data years of 2000-2019) was computed for the above metrics. The 95 percent confidence interval (twice the standard deviation of the error, assuming a normal distribution of the biases) of the metrics was computed across weekly and monthly periods. A graphical representation of the uncertainty types, bias generation and processing is shown in Figure 3‑2. The 95 percent confidence intervals were calculated for key locations (e.g., below dam, selected downstream river temperature compliance locations) to capture the linked model performance.

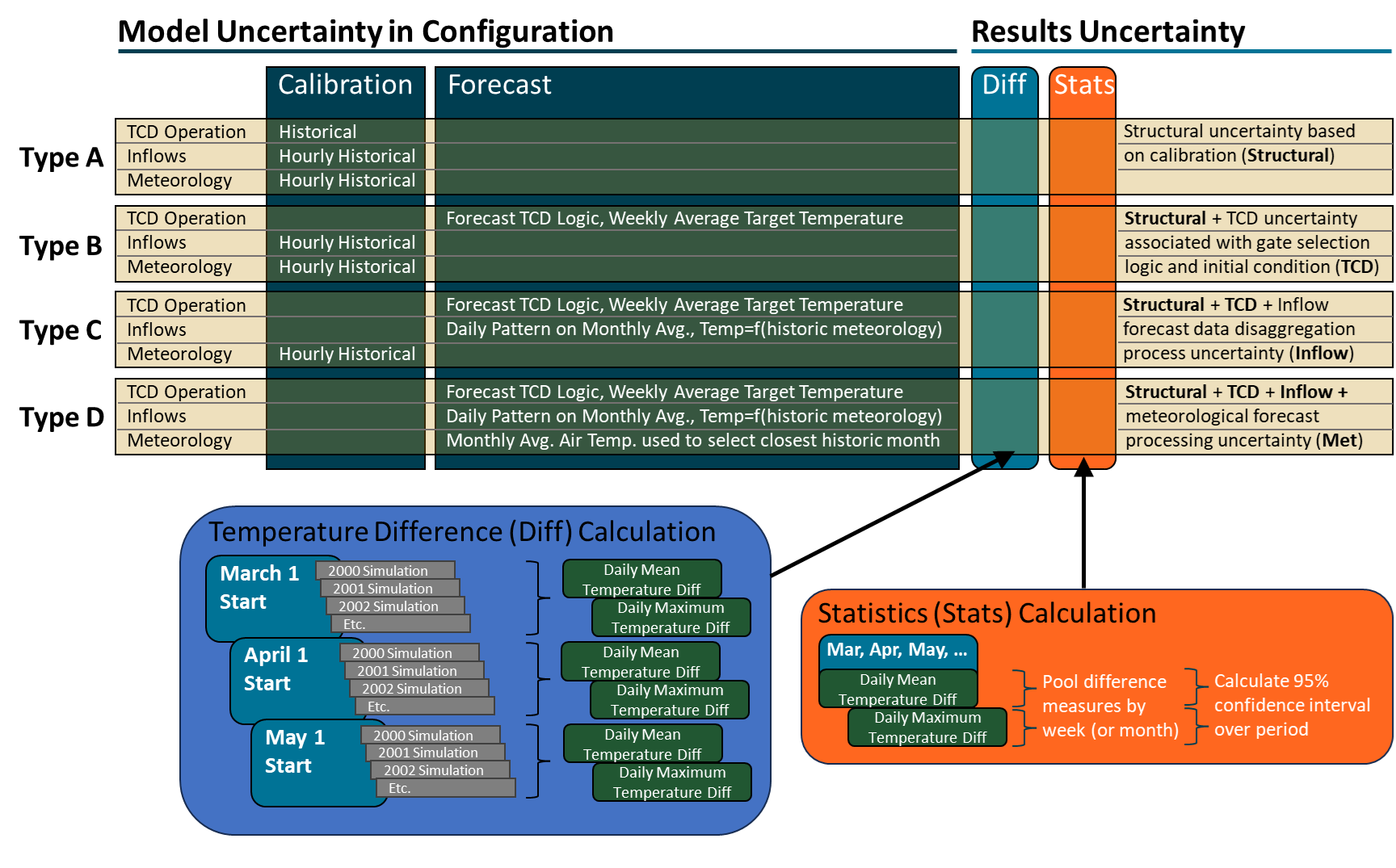


Figure 3‑2. Schematic of cumulative forecast uncertainty analysis processes showing the progression of assumed boundary conditions from Type A (all calibration assumptions) to Type D (all forecast assumptions) and associated statistical calculations to assess performance.

### Future Investigation

Additional analyses could be applied to explore sensitivity to sources of uncertainty individually, rather than as the cumulative uncertainty described above. Further, the models could be used to explore the impact of actual operations forecasts for a specific year and forecast start date (initial condition). For example, the forecast boundary conditions could be developed and applied from the CVP operations forecasts for 10, 25, 50, 75, 90, and 99 percent runoff exceedance forecasts. Potential methods to address uncertainty in propagation of error through models, model parameter estimation (calibration), and model applications include Monte Carlo analysis, additional sensitivity analysis, first order analysis, probabilistic approaches, surrogate modeling, and other methods (Albert 2020, Mahadevan and Sarkar 2009, Wang et al. 2022, Yen et al. 2014, others). While such tools and approaches are widespread in research and literature, these approaches are not addressed herein because the majority of these require a considerable undertaking in terms of expertise, time, and resources for the extensive spatial and temporal domain represented in the WTMP (Faes and Moens 2020, Kirchner at al. 2021). Such studies can be considered in the future depending on needs specific to application of the WTMP.

# Summary and Conclusions

For all their complexity, models are still simplified mathematical representations of real-world processes that cannot exactly represent natural systems. Uncertainty is an intrinsic part of any modeling process and thus, mechanisms to address error in the modeling are important for defining accuracy so the results can be responsibly used in making informed decisions.

Uncertainty exists in all phases of the modeling process: model conceptualization, model development, data development, parameter estimation (calibration), and model applications. Several areas of model uncertainty were investigated within these phases, including system representation of unique features (model development), data error and data gaps (data development), and calibration parameters (parameter estimation). All assumptions, estimations, and errors in the model development phases were characterized during parameter estimation (calibration). Subsequently, the calibrated models were used to define uncertainty in forecast processes and assumptions.

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# References

Ajami, N. K., Q. Duan, and S. Sorooshian. 2007. An Integrated Hydrologic Bayesian Multimodel Combination Framework: Confronting Input, Parameter, and Model Structural Uncertainty in Hydrologic Prediction. *Water Resour. Res*., 43.

Albert, D.R. 2020. Monte Carlo Uncertainty Propagation with the NIST Uncertainty Machine. Journal of Chemical Education 2020 97 (5), 1491-1494

Baecher, G. and J. Christian. 2023. Natural Variation, Limited Knowledge, and the Nature of Uncertainty in Risk Analysis. *Risk-Based Decisionmaking in Water Resources* *IX*.

Bastin, L., D. Cornford., R. Jones, G.B. Heuvelink, E. Pebesma. C. Stasch, S. Nativi., P. Mazzetti, and M. Williams. 2013. Managing Uncertainty in Integrated Environmental Modelling: The UncertWeb Framework. *Environmental Modelling & Software*, 39, pp.116-134.

Benke, K.K., K.E. Lowell, and A.J. Hamilton. 2008. Parameter Uncertainty, Sensitivity Analysis and Prediction Error in a Water-Balance Hydrological Model. *Mathematical and Computer Modelling*, 47(11-12), pp.1134-1149.

Bevan, L.D. 2022. The Ambiguities of Uncertainty: A Review of Uncertainty Frameworks Relevant to the Assessment of Environmental Change. *Futures*, 137.

Beven, K. and A. Binley. 1992. The Future of Distributed Models: Model Calibration and Uncertainty Prediction. *Hydrological processes*, 6(3), pp.279-298.

Beven, K. 2007. Towards Integrated Environmental Models of Everywhere: Uncertainty, Data and Modelling as a Learning Process. *Hydrology and Earth System Sciences*, 11(1), pp.460-467.

California Water and Environmental Modeling Forum (CWEMF). 2021. Protocols for Water and Environmental Modeling. November 19.

Chapra, S.C. 1997. Surface water quality modeling. McGraw-Hill, New York, NY.

Chin, D.A. 2013. Water-Quality Engineering in Natural Systems, 2nd Ed. John Wiley and Sons. New Jersey. 454 pp.

Deas, M.L., I.E. Sogutlugil, A.E. Bale, and S.K. Tanaka. 2020. Shasta Lake and Keswick Reservoir Flow and Temperature Modeling – Development Report. Prepared for the Sacramento River Settlement Contractors. December.

Deletic, A., C.B.S. Dotto, D.T. McCarthy. M. Kleidorfer, G. Freni. G. Mannina, M. Uhl, M. Henrichs, T.D. Fletcher, W. Rauch, and J.L Bertrand-Krajewski. 2012. Assessing Uncertainties in Urban Drainage Models. *Physics and Chemistry of the Earth*, Parts A/B/C, 42, pp.3-10.

Dewulf, A., M. Craps, R. Bouwen, T. Taillieu, and C. Pahl-Wostl. 2005. Integrated Management of Natural Resources: Dealing with Ambiguous Issues, Multiple Actors and Diverging Frames. *Water Science and Technology*, 52(6), pp.115-124.

Faes, M. and D. Moens. 2020. Recent Trends in the Modeling and Quantification of Non-probabilistic Uncertainty. Archives of Computational Methods in Engineering. 27, 633-671.

Friedrichs, D., A. Forrest, and M.L. Deas. 2023. Acoustic Velocity Measurements of Flow Into the Shasta Dam Temperature Control Device Under Low Reservoir Conditions. 47 pp. Draft manuscript.

Guzman, J.A., A. Shirmohammadi, A.M. Sadeghi, X. Wang, M.L. Chu, M.K. Jha, P.B. Parajuli, R.D. Harmel, Y.P. Khare, and J.E. Hernandez. 2015. Uncertainty Considerations in Calibration and Validation of Hydrologic and Water Quality Models. *Transactions of the ASABE*, 58(6), pp.1745-1762.

Harmel, R.D., R.J. Cooper, R.M. Slade, R.L. Haney, and J.G. Arnold. 2006. Cumulative Uncertainty in Measured Streamflow and Water Quality Data for Small Watersheds. *Transactions of the ASABE*, 49(3), pp.689-701.

Jayasundara, N.C. and M.L. Deas. 2012. Lewiston Reservoir Water Temperature Modeling. Prepared for the U.S. Bureau of Reclamation, Trinity River Restoration Program., January.

Ji, Z. 2017. Hydrodynamics and Water Quality – Modeling Rivers, Lakes, Estuaries, 2nd Ed. John Wiley and Sons. New Jersey. 581 pp.

Kelleher, C., B. McGlynn, and T. Wagener. 2017. Characterizing and Reducing Equifinality by Constraining a Distributed Catchment Model with Regional Signatures, Local Observations, and Process Understanding. *Hydrology and Earth System Sciences*, 21(7), 3325–3352.

Khatami, S., M.C. Peel, T.J. Peterson, and A.W. Western. 2019. Equifinality and Flux Mapping: A New Approach to Model Evaluation and Process Representation Under Uncertainty. *Water Resources Research*, 55(11), pp.8922-8941.

Kirchner, J. W. 2006. Getting the Right Answers for the Right Reasons: Linking Measurements, Analyses, and Models to Advance the Science of Hydrology. *Water Resources Res*., 42(3).

Kirchner, M., H. Mitter, U.A. Schneider, M. Sommer, K. Falkner, and E. Schmid. 2021. Uncertainty Concepts for Integrated Modeling – Review and Application for Identifying Uncertainties and Uncertainty Propagation Pathways. *Environmental Modelling & Software*, 135, p.104905.

Khu, S.T. and M.G. Werner. 2003. Reduction of Monte-Carlo Simulation Runs for Uncertainty Estimation in Hydrological Modelling. *Hydrology and Earth System Sciences*, 7(5), pp.680-692.

Martin, J.L. and S.C. McCutcheon. 1999. Hydrodynamics and Transport for Water Quality Modeling. Lewis Publishers. New York. 794 pp.

McIntyre, N., H. Wheater, and M. Lees. 2002. Estimation and Propagation of Parametric Uncertainty in Environmental Models. *Journal of Hydroinformatics*, 4(3), pp.177-198.

McMillan, H.K., I.K. Westerberg, and T. Krueger. 2018. Hydrological Data Uncertainty and its Implications. *Wiley Interdisciplinary Reviews: Water*, 5(6), p.e1319.

Moges, E., Y. Demissie, L. Larsen, and R. Yassin. 2020. Review: Sources of Hydrological Model Uncertainties and Advances in Their Analysis. *Water 13*, (1), 28.

Moreno-Rodenas, A.M., F. Tscheikner-Gratl, J.G. Langeveld, and F.H. Clemens. 2019. Uncertainty Analysis in a Large-Scale Water Quality Integrated Catchment Modelling Study. *Water Research*, 158, pp.46-60.

Nearing, G.S., Y. Tian, H.V. Gupta, M.P. Clark, K.W. Harrison, and S.V. Weijs. 2016. A Philosophical Basis for Hydrological Uncertainty. *Hydrological Sciences Journal*, 61(9), pp.1666-1678.

Oreskes, N., K. Shrader-Frechette, and K. Belitz. 1994. Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences. *Science*, 263(5147), pp.641-646.

Placer County Water Agency (PCWA). 2015. Folsom Reservoir CE-QUAL-W2 Temperature Model Report

Refsgaard, J.C., J.P. Van der Sluijs, J. Brown, and P. Van der Keur. 2006. A Framework for Dealing with Uncertainty Due to Model Structure Error. *Advances in Water Resources*, 29(11), pp.1586-1597.

Refsgaard, J.C., J.P. van der Sluijs, A.L. Højberg, and P.A. Vanrolleghem. 2007. Uncertainty in the Environmental Modelling Process – A Framework and Guidance. *Environmental Modelling & Software*, 22(11), pp.1543-1556.

Refsgaard, J.C., K. Arnbjerg-Nielsen, M. Drews, K. Halsnæs, E. Jeppesen, H. Madsen, A. Markandya, J.E. Olesen, J.R. Porter, and J.H. Christensen. 2013. The Role of Uncertainty in Climate Change Adaptation Strategies - A Danish Water Management Example. *Mitigation and Adaptation Strategies for Global Change*, 18, pp.337-359.

Roache, P.J. 1998. Verification and Validation in Computational Science and Engineering. Hermosa Publishers, Albuquerque, New Mexico. 446 pp.

Rougier, J. and K.J. Beven. 2013. Model and Data Limitations: the Sources and Implications of Epistemic Uncertainty. *Risk and Uncertainty Assessment for Natural Hazards*, 40.

Sargent, R.G. and O. Balci. 2017, December. History of Verification and Validation of Simulation Models. In 2017 Winter Simulation Conference (WSC) (pp. 292-307). IEEE.

Mahadevan, S. and S. Sarkar. 2009. “Uncertainty Analysis Methods,” in CBP-TR-2009-002, Review of Mechanistic Understanding and Modeling and Uncertainty Analysis Methods for Predicting Cementitious Barrier Performance (Editors: C. Langton, D. Kosson), U.S. Department of Energy, Washington DC.

Shirmohammadi, A., I. Chaubey, R.D. Harmel, D.D. Bosch, R. Muñoz-Carpena, C. Dharmasri, A. Sexton, M. Arabi, M.L. Wolfe, J. Frankenberger, and C. Graff. 2006. Uncertainty in TMDL Models. *Transactions of the ASABE*, 49(4), pp.1033-1049.

Sigel, K., B. Klauer, and C. Pahl-Wostl. 2010. Conceptualising Uncertainty in Environmental Decision-Making: the Example of the EU Water Framework Directive. *Ecological Economics*, 69(3), pp.502-510.

Skinner, D.J., S.A. Rocks, S.J. Pollard, and G.H. Drew. 2014. Identifying Uncertainty in Environmental Risk Assessments: The Development of a Novel Typology and its Implications for Risk Characterization. *Human and Ecological Risk Assessment: An International Journal*, 20(3), pp.607-640.

Stow, C.A., K.H. Reckhow, S.S. Qian, E.C. Lamon III, G.B. Arhonditsis, M.E. Borsuk, and D. Seo. 2007. Approaches to Evaluate Water Quality Model Parameter Uncertainty for Adaptive TMDL Implementation. *JAWRA*, 43(6), pp.1499-1507.

Tscheikner-Gratl, F., V. Bellos, A. Schellart, A. Moreno-Rodenas, M. Muthusamy, J. Langeveld, F. Clemens, L. Benedetti, M.A. Rico-Ramirez, R.F. de Carvalho, and L. Breuer. 2019. Recent Insights on Uncertainties Present in Integrated Catchment Water Quality Modelling. *Water Research*, 150, pp.368-379.

Turnipseed, D.P., and V.B. Sauer. 2010. Discharge Measurements at Gaging Stations: U.S. Geological Survey Techniques and Methods Book 3, chap. A8, 87 p. (Also available at http://pubs.usgs.gov/tm/tm3-a8/.)

U.S. Bureau of Reclamation (Reclamation). 2023a. Water Temperature Modeling Platform: Data Development. June.

U.S. Bureau of Reclamation (Reclamation). 2023b. Water Temperature Modeling Platform: Data Management Plan. May.

U.S. Bureau of Reclamation (Reclamation). 2023c. Water Temperature Modeling Platform: Framework Selection. May.

U.S. Bureau of Reclamation (Reclamation). 2023d. Water Temperature Modeling Platform: Model Development, Calibration, Validation, and Sensitivity Analysis. July.

U.S. Bureau of Reclamation (Reclamation). 2023e. Water Temperature Modeling Platform: Model Selection and Design. May.

U.S. Bureau of Reclamation (Reclamation). 2023f. Water Temperature Modeling Platform: Model Implementation. July.

U.S. Bureau of Reclamation (Reclamation). 2020. Temperature Model Development, Solicitation 140R2020Q0064. Central Valley Operations Office, 3310 El Camino Avenue, Suite 300, Sacramento, CA 95821-6377. July 2.

U.S. Bureau of Reclamation (Reclamation). 2017. Water Temperature Management in Reservoir-River Systems through Selective Withdrawal. Reference Technical Memorandum for Central Valley Project Operation, California. September.

U.S. Geological Survey (USGS). 2018. “How Streamflow is Measured.” Water Science School. June 13. https://www.usgs.gov/special-topic/water-science-school/science/how-streamflow-measured (Accessed: June 1, 2023).

Van der Keur, P., H.J. Henriksen, J.C. Refsgaard, M. Brugnach, C. Pahl-Wostl, A.R.P.J. Dewulf, and H. Buiteveld. 2008. Identification of Major Sources of Uncertainty in Current IWRM Practice. Illustrated for the Rhine Basin. *Water Resources Management*, 22, pp.1677-1708.

Walker, W.E., P. Harremoës, J. Rotmans, J.P. van der Sluijs, M.B. Van Asselt, P. Janssen, and M.P. Krayer von Krauss. 2003. Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. *Integrated Assessment*, 4(1), pp.5-17.

Wang C, X. Qiang, M. Xu, and T. Wu. 2022. Recent Advances in Surrogate Modeling Methods for Uncertainty Quantification and Propagation. *Symmetry*. 14(6):1219. https://doi.org/10.3390/sym14061219

Warmink, J.J., J.A.E.B. Janssen, M.J. Booij, and M.S. Krol. 2010. Identification and Classification of Uncertainties in the Application of Environmental Models. *Environmental Modelling & Software*, 25(12), pp.1518-1527.

Wells, S. A., editor. 2021a. CE-QUAL-W2: A two-dimensional, laterally averaged, hydrodynamic and water quality model, version 4.5, user manual part 2, theoretical basis for CE-QUAL-W2: hydrodynamics and water quality, particle transport and numerical scheme. Department of Civil and Environmental Engineering, Portland State University, Portland, OR.

Wells, S. A., editor. 2021b. CE-QUAL-W2: A two-dimensional, laterally averaged, hydrodynamic and water quality model, version 4.5, user manual part 3, model input and output file descriptions and input/output file examples. Department of Civil and Environmental Engineering, Portland State University, Portland, OR.

Yen, H., X. Wang, D.G. Fontane, R.D. Harmel, and M. Arabi. 2014. A framework for propagation of uncertainty contributed by parameterization, input data, model structure, and calibration/validation data in watershed modeling. Environmental Modelling & Software. 54. 2011-2021.

1. The DMS is a relational database for data collection and management, creating a system for data storage with consistent metadata definitions and formats; and other related tasks (Reclamation 2023b). This approach establishes procedures for data acquisition, identifying necessary data and data sources, and an inventory system for adding new data as it becomes available. These features reduce the time and labor required to assemble the high-quality datasets that are used for model input. Further, the DMS facilitates consistent application of data management rules, establishes hierarchical relationships that make the inventory and reporting process more efficient, minimizes transcription error, and institutes measures for data quality analysis and data quality control. Importantly, data can be queried and graphed within the DMS and exported for additional assessment prior to modeling. Ultimately, the system exports model-ready data to improve the efficiency of the modeling process, reduce the potential for data handling error, and track the data/metadata sources to inform model simulations. [↑](#footnote-ref-2)
2. <https://water.ca.gov/Library/Modeling-and-Analysis/Central-Valley-models-and-tools/CalSim-3> [↑](#footnote-ref-3)