Predictive modeling of Lake Tahoe's clarity: Next steps

John Melack, Geoff Schladow, and Steve Sadro

Executive Summary

Lake Tahoe's clarity is a defining feature of the lake's renown, and the lake's clarity has declined over recent decades due to factors including watershed inputs and ecological processes. Predictive models are tools for anticipating future conditions and guiding management actions. The Tahoe Science Advisory Council convened in May 2015 a two-day workshop of scientists and managers to evaluate the status of Lake Tahoe clarity science and predictive tools. The goal was to strengthen the links between monitoring, modeling, and management decisions. Key points from workshop and actionable next steps are summarized here.

Why models matter
Predictive models allow managers to explore how clarity will change under different scenarios—such as land use change, restoration efforts, or warming climate—and to plan accordingly.

Current status

1. The original clarity model (LCM) developed in the early 2000s lacks key physical and ecological processes.
2. Recent improvements in the LCM added more physical and ecological realism, but is not yet an operational tool for clarity prediction.
3. Statistical and machine learning models can help understand clarity trends.

Primary challenges

1. Current models do not include ecological aspects important for clarity prediction, such as abundance and growth of zooplankton and very small phytoplankton.
2. Models of particle supply and loss are incomplete.
3. Some factors needed to inform a clarity model are not currently being monitored.

Recommendations
Lake Tahoe needs both near-term, multi-year forecasts and an improved clarity model to ensure management actions are guided by the best available science. Near-term tools help respond to immediate challenges; long-term models prepare for climate change and future land use pressures.

1. Develop near-term, multi-year analysis and forecasting tools to support adaptive management
2. Support development of an improved clarity model that represents relevant ecological, physical and optical dynamics and augmented monitoring of essential inputs.
3. Develop Requests for Proposals for predictive clarity models with clear evaluation criteria tied to management needs.

Background

In May 2025 the Tahoe Science Advisory Council (Council) hosted a two-day workshop focused on current understanding and modeling of Lake Tahoe's mid-lake clarity. Models allow scientists to understand how lake clarity changes in response to environmental factors, and managers to test or predict how land use, restoration, and climate change could affect Lake Tahoe's clarity. These tools provide a science-based way to understand and forecast clarity, evaluate management actions, and identify uncertainty. The workshop provided a venue for managers and scientists to improve mutual understanding of recent scientific reports and management issues. As an outcome of the workshop, this memorandum outlines steps to better understand in-lake processes and develop tools to predict clarity in Lake Tahoe.

We start with a brief introduction to the purpose of modeling, summarize the status of current models, and then present options for improved predictive modeling of Lake Tahoe's clarity in light of scientific advances in the understanding and modeling, and management priorities.

Introduction to modeling

Models are formulations of scientific understanding that can be applied to quantify deterministic relationships, to yield forecasts or predictions, to simulate various management scenarios, and to identify gaps in understanding and in data. Models require data for their development, calibration, validation, and uncertainty analyses.

Models come in many forms that can be grouped into three categories: (1) mechanistic (process-based) models that simulate how the system works and allow scenario testing; (2) empirical, data-driven models (machine learning, empirical dynamic modeling, state-space models) that can forecast based on observed data; and (3) hybrid approaches that combine strengths of both. Arhonditsis et al. (2008) note that 'all models are simplistic representations of aquatic systems and even the most well studied ecological processes can be mathematically described by a variety of relationships that entail different assumptions and complexity levels.' Hence, when evaluating model performance, it is important to recognize that different model structures and parameter sets can appear to be equally valid simulators of the natural system, so-called, model equifinality. This is important because a model that fits prior conditions is not necessarily the one that will predict the future reliably. Managers should compare different modeling approaches such that decisions are based on a range of credible outcomes.

Status of current models of the clarity of Lake Tahoe

The Lake Clarity Model (LCM), used in the Lake Tahoe Total Maximum Daily Load Final Report (2010), is described in Sahoo et al. (2010) and Swift et al. (2006). The LCM was a state-of-the-art, one-dimensional (1-D), process-based model designed to account for the processes that impact clarity in the pelagic zone of Lake Tahoe, and to evaluate potential management scenarios to address and reverse long-term clarity decline. The model was based on an existing 1-D hydrodynamic and ecological framework (Hamilton and Schladow 1997; Schladow and Hamilton 1997). The LCM comprises a nested set of sub-models, including a hydrodynamic model, an ecology model, an inorganic particle model and an optical model. LCM is driven by a set of external inputs including meteorology, loading of particles and nutrients from streams, an atmospheric model, a groundwater model and a hydrology model. An operational version of the source code and user manual for LCM and other relevant models are no longer available.

The Council (2019; 2020) recommended advances to the LCM by using a three-dimensional (3-D) hydrodynamic model in place of the 1-D hydrodynamic model and improvements to the ecological components, including discrete algal functional groups, carbon-based plankton components, and explicit modeling of zooplankton grazing and mysis predation and grazing. These updates to the Lake Clarity Model were implemented and tested on data from two multi-week periods in contrasting years and results compared to available data (Cortes et al. 2022). An updated optical model and inorganic particle model have not been developed.

A machine learning modeling approach (Melack and Deyle 2022) was also undertaken to evaluate whether insights could be gained and forecasting done with an equation-free analysis based on a theoretical structure. The study demonstrated that a data-driven, nonlinear forecasting approach could achieve some forecast skill for key water quality indicators such as Secchi depth. Likewise, various statistical and time-series approaches have been done to evaluate historic trends and quantify variances associated with changing environmental conditions (Naranjo 2024; Smits 2024).

These reports offered further recommendations for additional data collection and modeling efforts. In addition, the Council's review of Lake Tahoe monitoring (2024) provides 1) an evaluation of the existing monitoring activities related to off-shore clarity and factors influencing clarity (e.g., zooplankton and picoplankton abundances, suspended particle inputs and losses) and 2) suggestions for program improvements. Evaluation of the watershed model (LSPC; Tetra Tech 2007) and urban runoff model (PLRM; Northwest Hydraulic Consultants and others 2009) are also required.

Options for improved predictive modeling of Lake Tahoe's clarity

Lakes are three-dimensional systems with vertical and horizontal variations in physical, chemical and biological processes and conditions occurring across a broad range of temporal and spatial scales. Hence, water clarity and related conditions in Lake Tahoe result from complex interactions among the physics, chemistry and ecology of the lake and its surroundings. These factors fluctuate at short time scales (minutes to hours), vary by season, and have changed over years due to management actions and natural variability. The interconnections and interdependencies among these factors make accurate predictions or forecasts of future conditions challenging.

Two fundamentally different and complementary approaches to predictive modeling are available, and both were recommended for consideration during the May 2025 clarity workshop.

One approach is further development of a 3-D version of the LCM or similar model. To do so would entail utilization of existing and new measurements at Lake Tahoe. Measurements are complementary to modeling and are needed to parameterize algorithms for specific process, as well as to calibrate and validate a model. For example, a clarity model will need to account for optically important particle dynamics, including biological processes (e.g., algal growth, zooplankton grazing, aggregation of organic material) and fine suspended particle transformations. Deterministic models are widely used in lake restoration studies as they can be used to evaluate the importance of individual model components, both physical and ecological (e.g., Lehman and Hamilton 2018; Dresti et al. 2021; Zamani et al. 2021). The relative importance of variables, within the structure of the model, can be determined through a sensitivity analysis. Thus, while the potential number variables may appear large, they may be reduced to a tractable subset (Schladow and Hamilton 1997). This information can guide and streamline new and ongoing data collection efforts.

Alternative approaches, referred to machine learning (ML) or state-space estimation, derive predictions from empirical data rather than algorithms that parameterize the underlying processes. ML approaches excel at pattern recognition but often lack interpretability. Examples of recent applications include weather prediction (Allen et al. 2025). State-space models excel at capturing temporal dynamics and filtering noise in time series data but often rely on assumptions about system structure and may be sensitive to how hidden states are specified. A state-space model tries to estimate statistically the underlying condition of the system from noisy observations, such as inferring the clarity of the lake from scattered and imperfect measurements. State-space models have been successfully applied to lakes and freshwater tidal systems to decompose true clarity dynamics from observational noise and attribute shifts to ecological drivers (Walsh et al. 2016; Smits et al. 2025).

Another approach derives from theoretical work on the dynamical behavior of non-linear, coupled systems (empirical dynamic modeling (EDM); Sugihara et al. 2012; Munch et al. 2020). EDM has been applied successfully to financial markets, fisheries and ecological systems. Nonlinearity means that the system must be studied synergistically, and the factors and their interactions that determine clarity in Lake Tahoe represent a non-linear, dynamic system. The EDM approach involves the use of time series data to represent the dynamics of the system, and is a conceptual departure from parameterized, numerical models and statistical methods. The multi-year time-series data for Lake Tahoe are amenable for application of EDM, as demonstrated by Melack and Deyle (2022). An integrated approach combining empirical and parameterized elements has been applied to forecast changes in eutrophication in Lake Geneva, a large, deep lake (Deyle et al. 2022). Further applications of EDM or other machine learning approaches could include other types of data and analytical techniques. However, data-driven approaches are inherently limited by the data available, whether those data allow reliable predictions and for how far into the future.

Thus, managers can choose between or combine modeling approaches: mechanistic 3-D clarity models that simulate processes, and data-driven statistical or machine learning approaches. Both reveal causal relationships and allow testing of management scenarios. Each has strengths and weaknesses. A hybrid approach could address multiple management needs across a spectrum of time scales and effort. While EDM and other empirical methods are powerful tools for uncovering causal structure and short-term forecasting, mechanistic models are essential for simulating future conditions, such as land use changes, management practices or climate scenarios. Hybrid approaches, which use empirical models to inform or constrain mechanistic models (or vice versa), may offer a path forward by combining explanatory power with flexibility and computational efficiency.

Recommended next steps

The workshop concluded that Tahoe needs both near-term, multi-year forecasting tools and longer-term scenario models. By investing in both, managers will gain the ability to plan for near-term challenges while also anticipating the long-term effects of climate change and management interventions.

Two key aspects of Lake Tahoe's clarity of particular importance are optical changes associated with different types of suspended particles and the related issues of changes in the number and distribution of these particles, i.e., factors that lead to the growth of optically-relevant plankton, and the loss by grazing, aggregation and sinking of suspended particles, both biogenic and inorganic. Such efforts will require additional measurements combined with mechanistic modeling. Given the recent advances in machine-learning approaches and evidence for its application to ecological forecasting, further use of such techniques are complementary to mechanistic modeling and may be used in a hybrid manner.

To implement these activities, we recommend:

1. Align and revise monitoring programs with modeling needs.
2. Invest in near-term forecasting capacity, such as multi-year clarity predictions.
3. Support development of 3-D, process-based models, to simulate climate and land-use change scenarios beyond the range of existing data.
4. Develop Requests for Proposals (RFPs) for predictive clarity models. Proposals should be evaluated based on management relevance, time periods to be modeled, data needs, costs, and time necessary for model development. A workshop focused on these issues will be necessary as part of the RFP development process.

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