Predictive modeling of Lake Tahoe's clarity: Next steps

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In May 2025 the Tahoe Science Advisory Council hosted a two-day workshop focused on the current understanding and modeling of Lake Tahoe's mid-lake clarity. The workshop provided a venue for managers and scientists to improve mutual understanding of recent scientific reports and management issues. One product expected from the workshop is this memorandum outlining steps to develop tools to predict clarity in Lake Tahoe.

We start with a brief introduction to the purpose and limitations of models, followed by a summary of 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 purposes, advances, challenges and limitations of models

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

Aquatic ecosystem models vary from steady state and regression models to complex dynamic models, trait-based models and neural networks. 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.' Different model structures and parameter sets can appear equally valid simulators of the natural system, so-called, model equifinality. Thus, equifinality means that models may produce similar outputs under different assumptions about the underlying processes, reducing confidence in management decisions based on those outputs. An inherent modeling challenge is matching the time and space scales of the relevant physical, chemical and biological processes.

Status of current models of the clarity of Lake Tahoe

The Lake Clarity Model (LCM) is described in Losada (2001), Sahoo et al. (2010), Swift et al. (2006) and the Lake Tahoe Total Maximum Daily Load Final Report (2010). At that time, the LCM was a state-of-the-art, one-dimensional (1-D), process-based model designed to account for the processes that impacted 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). The LCM comprises a nested set of sub-models – a hydrodynamic model, an ecology model, an inorganic particle model and an optical model and 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 are not now available.

TSAC (2019; 2020) suggested modifications to the LCM by using a three-dimensional (3-D) hydrodynamic model and improvements to the ecological components, including introduction of discrete algal functional groups, changing to a carbon-based model instead of a chlorophyll-based model, and explicit modeling of zooplankton grazing and mysis predator and grazing . Based on these recommendations, updates of the Lake Clarity Model and an alternative approach were done (Cortes and others 2022; Melack and Deyle 2022). These reports offer further recommends for additional data and modeling efforts. The Tahoe Science Advisory Council review of Lake Tahoe monitoring (2024) provides 1) an evaluation of the existing monitoring activities related to off-shore clarity and factors influencing clarity; and 2) suggestions for program improvements and prioritizing potential modifications of monitoring activities. Several aspects of these results require evaluation of the watershed model (LSPC; Tetra Tech 2007) and urban runoff model (PLRM; Northwest Hydraulic Consultants and others 2009).

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 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, vary by season, and have changed over years due to management actions and natural variability. The interconnections and interdependencies among these factors makes predictions or forecasts of future conditions quite 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 the model. For example, clarity models should also explicitly account for optically important particle dynamics, including biological processing (e.g., zooplankton grazing, microbial aggregation) and fine suspended particle transformations. These may be among the most important (and least well-represented) components requiring additional measurements. Prioritizing updates and improvements to the LCM should consider the state of algorithms and the availability of data, the time, and hence the cost, to do so, and the urgency of the related management questions.

The available hydrodynamic and optical models are mature and verified as functional for Lake Tahoe when driven by extant and on-going data collection. In contrast, ecological algorithms and available data suffer from considerable weaknesses. For example, calibration is required and depends on data that is not available for key organisms; therefore, validation is often difficult. Hence, uncertainties are quite large. Given the large number of weakly constrained parameterizations, equifinality is a serious problem.

Alternative approaches, referred to machine learning (ML), state-space estimation or artificial intelligence (AI), derive predictions from empirical data rather than numerical algorithms that parameterize the underlying processes. ML approaches (e.g., random forests, neural networks) excel at pattern recognition but often lack interpretability. 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 the hidden states are specified. Recent applications include weather prediction (Allen et al. 2025) and estimation of chlorophyll in lakes using remotely sensed data (Cao et al. 2020). Efficient algorithms for models and state-estimation forecasts are being available (Bentéjac et al. 2021; Course and Nair 2023). State-space models such as MARSS have been successfully applied to lake and freshwater tidal systems to decompose true clarity dynamics from observational noise and attribute shifts to ecological drivers. For example, in Lake Mendota, invasion by the spiny water flea caused a 1 m decline in Secchi depth via trophic cascade (Walsh et al. 2016) and in the Sacramento-San Joaquin Delta, changes in water clarity were linked to drought and the increase in submerged aquatic vegetation within terminal sloughs (Smits et al. 2025).

Another approach derives from recent 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 cannot be decomposed one factor at a time. Indeed, the factors and their interactions that determine clarity in Lake Tahoe represent a non-linear, dynamic system. The approach involves the use of time series data to represent the dynamics of the system, and is a conceptual departure from traditional 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 combines empirical and parameterized elements has been applied to forecast changes in eutrophication in Lake Geneva, an iconic, large, deep lake (Deyle et al. 2022).

Further applications of EDM or other machine learning approaches could include other types of data, e.g., thermocline depths, fine suspended particles, etc., plus other analytical techniques. However, data-driven approaches are inherently limited by the data available and whether those data allow reliable predictions and for how far into the future. While EDM and other empirical methods are powerful tools for uncovering causal structure and short-term forecasting, mechanistic models are essential for simulating novel future conditions, such as land use changes or climate scenarios, where empirical analogs may not exist. 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.

Evaluation of possible implementation

We recommend development of requests for proposals for predictive models of Lake Tahoe's clarity based our examination of existing models and possible options for further work. Key issues to consider in development the RFP and evaluation of the proposals include:

1) Management goals, time periods to be modeled and urgency
2) Existing data and additional data needed
3) Time and costs required
4) Alignment with specific management questions and clarity timeframes (e.g., near-term forecasts vs. long-term TMDL goals)

Each approach or specific model will have advantages and disadvantages. We suggest that the RFPs request that these strengths and weaknesses be stated clearly.

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