Central Valley Lakes and Reservoirs Eutrophication Assessment

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Executive Summary

California's Central Valley is an agriculturally dominated region, with a broad valley floor that is bounded by mountain ranges. Concern is increasing about the effects associated with nutrient point and non-point source pollution and eutrophication, particularly in the region's lakes and reservoirs. Eutrophication in lakes can result in the increased volume of hypoxia water, loss of biodiversity, decreased water clarity, as well as increases in both pH and harmful algal blooms. Harmful algal blooms, especially those caused by cyanobacteria (cyanoHABs), cause health and safety concerns for humans, domestic animals, and wildlife. To date, no widespread assessment of eutrophication has been conducted in the lakes and reservoirs of the region. Reports of cyanoHABs in the region are among the most frequent in the state, underscoring the importance of understanding the extent and magnitude of eutrophication in the region's lakes and reservoirs.

A challenge with conducting region wide assessment of eutrophication is the lack of routine water quality monitoring in many of the lakes and reservoirs of the Central Valley and the absence of a framework for routine interpretation of water quality data (e.g., report card). We addressed these data gaps by conducting the region's first lakes and reservoirs eutrophication assessment. This consisted of 1) development of a multi-indicator eutrophication assessment framework; 2) compilation of a dataset of eutrophication relevant indicators from publicly available datasets that conform to this assessment approach; 3) application of the framework to quantify the extent and magnitude of eutrophication regionally and 4) assessment of the representativeness of assessed lakes and reservoirs and identification of priority data gaps.

Key Product: Eutrophication Assessment Framework

The eutrophication assessment framework consisted of three categories: 1) risk of eutrophication (as indicated by total nitrogen (TN) and total phosphorus concentrations (TP)), 2) evidence of eutrophication (as indicated by *in situ* chlorophyll-a or satellite remotely sensed cyanobacterial biomass) and 3) eutrophication impact (as indicated by cyanobacterial toxin concentrations). Thresholds that were used to assign lakes into categories were derived from various sources. Evidence and risk of eutrophication were classified by trophic state (level of biological productivity at a specific point in time), an approach adapted from several existing frameworks, in categories ranging from oligotrophic, mesotrophic, eutrophic, and hypereutrophic (Table 1). Currently, no existing thresholds link cyanotoxin concentrations to trophic state. We evaluated our dataset to determine if we could identify suitable cyanotoxin thresholds for this purpose but were unable to do so due to a paucity cyanotoxin data from a gradient of trophic conditions. Additionally, we note that the assessment covered a mix of cold water (salmonid) and warm water lakes, and that the assessment framework categorization marks the degradation of cold-water fisheries support at mesotrophy, while for warm-water fisheries that occurs at categories of eutrophic 1 and beyond. Our assessment did not attempt to benchmark each lake in their reference state (e.g., cold versus warm water), as that was beyond the scope of this study.

Table 1. Trophic state definitions, modified from Carlson et al. (1977), convey a narrative description of how the gradient of trophic state translates to use support.

Trophic State	Description/definition
Oligotrophic	Clear water, low algae and nutrient concentrations, usually blue in color. Oxygen is typically present throughout the year in the hypolimnion. Salmonid fisheries dominate, particularly in deep colder water lakes.
Mesotrophic	Moderate algae and nutrients and moderate water clarity. Increasing probability of hypolimnetic anoxia during summer. Iron, manganese, taste, and odor problems worsen. Raw water turbidity requires filtration. Hypolimnetic anoxia results in partial loss of salmonids in cold water lakes. Warm water fisheries are preserved.
Eutrophic 1	High algae and nutrients, low water clarity, usually green in color. Anoxic hypolimnion, macrophyte problems possible. Salmonid fisheries lost in cold water; loss of some warm water fisheries.
Eutrophic 2	Similar to Eutrophic 1, slightly higher of algae and nutrients, similar green color Blue-green algae dominate, algal scums and macrophyte problems. Episodes of severe taste and odor possible. Nuisance macrophytes, algal scums, and low transparency may discourage swimming and boating.
Hypereutrophic	High algae and nutrients, low to no water clarity, water color green. Higher severity of dense algae and macrophytes. Warm water pollution tolerant fish only.

Assessment Findings

Data were compiled from a publicly available database then employed in the assessment framework to assess eutrophication. A total of 86 lakes and reservoirs out of a regional target population of 4499 had appropriate data. 47 lakes had enough data to assess eutrophication risk and 71 lakes had sufficient data to assess eutrophication evidence; 35 waterbodies had data on cyanotoxins though roughly 2/3rds of the observations came from a single lake (Clear Lake). Our findings are substantially constrained by applying this assessment framework to existing data which were not specifically collected to support this study. There were substantial data gaps, both in terms of the number of lakes that could be assessed as well as coverage across indicators in any lakes that were included. Data gaps were particularly apparent for eutrophication impact, as indicated by cyanotoxin concentrations, which were largely absent across the dataset, with a substantial proportion of the data coming from just a handful of lakes.

Of assessable lakes, our findings indicate a roughly equal split of lakes and reservoirs at risk of being in a eutrophic state (44.7%) and those below the eutrophication risk threshold (55.3%) based on observed nutrient concentrations. Biomass indicators suggested 38% of assessed lakes had biomass levels indicating evidence of eutrophication, while 62% of lakes had biomass levels at the oligotrophic or mesotrophic level. The satellite remote sensing observations provided insights on the temporal variations in biomass and how that might influence the assessment. Our results indicated that most lakes and reservoirs in the Central Valley region experienced seasonal and interannual variations and trends in biomass that could impact the results of the assessment depending on the timing and frequency of when *in situ* observations were collected.

The ecoregional distribution and land use characteristics of the assessed waterbodies were generally representative of the larger lake and reservoir population. However, the waterbodies identified as identified as either "at risk" or experiences eutrophication were disproportionately found in disadvantaged communities.

Caveats and Recommendations

Caveats in the scientific findings and research recommendations to address these uncertainties include:

1. Our assessment was spatially limited, and insufficient data existed to investigate the statistical significance between eutrophication and variables such as land use and disadvantaged communities. Strategic collection of data is needed to support strategic monitoring and risk management in the future.

2. Trophic status classification is not static. Seasonal and interannual variations in biomass accumulation underscore the importance of the timing and frequency of observations. Special studies should also be considered to untangle the effects of large-scale drivers such as precipitation and climate on the eutrophication status of the region's lakes and reservoirs.

3. Few lakes were able to be assessed using all the indicators we selected in our framework. Future work should assess the comparability of these indicators and the relationship between waterbodies ranked with eutrophication risk and eutrophication evidence.

4. Standardized operating procedures for combined harmful algal bloom and eutrophication assessments are needed for lakes and reservoirs to generate the dataset that can provide for more robust assessment in the future. This includes a more detailed classification of lakes by depth and the management goal (e.g., warm and/or cold-water fisheries). We note that waterbodies have both warm and cold beneficial use designations, however many waterbodies have been assigned both uses in the CV region and deeper investigation to assign classifications based on these uses will likely be needed. It is also notable that cold water lakes that are characterized by mesotrophy may have lost some fisheries support function, but this cannot be fully resolved at this time.
5. Integration of satellite remote sensing technologies into the eutrophication assessment provided more insights and a broader, more comprehensive assessment than using only *in situ* datasets (as has traditionally been done). Future eutrophication assessments should prioritize using the combination of remotely sensed and *in situ* eutrophication information, including the integration of higher spatial resolution remote sensing platforms that are becoming more readily available that would increase the number of waterbodies with resolvable data.

TABLE OF CONTENTS

Acknowledgements ... i
Executive Summary ... ii
Key Product: Eutrophication Assessment Framework ... ii
Assessment Findings ... iii
Caveats and Recommendations ... iv
Table of Contents ... vi
Table of Figures ... viii
Table of Tables ... x
Introduction ... 1
Materials and Methods ... 2
Approach to the Eutrophication Assessment ... 2
Description of Study Region and Target Population of Lakes and Reservoirs ... 4
Study Region ... 4
Inventory of CV Lakes and Reservoirs ... 5
Compilation of Existing Data ... 6
In situ field data ... 6
Remotely sensed satellite imagery data ... 7
Landscape context: land use and disadvantaged communities ... 8
Eutrophication Assessment Framework ... 9
Terminology ... 9
Selection of priority indicators and categorical thresholds ... 10
Data inclusion criteria and data calculations ... 14
Statistical Analyses ... 15
Land Use ... 15
Remotely sensed satellite imagery data time series analysis ... 15
Results ... 16
Lake and Reservoir data availability and distributions in the Central Valley region 16
Application of eutrophication assessment framework in the Central Valley region . 19
Eutrophication Risk ... 19
Eutrophication Evidence ... 21
Seasonal and Interannual Trends in the Central Valley Region ... 22

Spatial Characteristics and Representativeness of Assessment 24
Land Use 24
Distribution of Assessed Lake Across Disadvantaged Communities................... 26
Discussion.. 29
Forty Percent of Central Valley Lakes and Reservoirs Show Evidence or Risk of Eutrophication 29
Eutrophication Assessment as a Decision Support Tool for Prioritizing Monitoring 31
Scientific Data Gaps and Management Recommendations................................... 31
References.. 34
Appendix A. Supplementary Materials 39

TABLE OF FIGURES

Figure 1. Top panel of blue boxes shows an overview of conceptual approach to Central Valley lakes and reservoirs eutrophication assessment with white arrows indicating the flow of the steps. The assessment indicators considered are shown below the black box and include the key eutrophication impact and evidence indicators (green boxes), risk factors (blue boxes) and landscape context (grey boxes). 3

Figure 2. Maps of the Central Valley region of California showing the geographic distributions of waterbodies with assessment data. Points indicate locations with framework indicator data, both *in situ* and remotely sensed. Data type is indicated by the colors of the points. Locations with more than one type of indicator present are indicated with wedges that are colored by the types of indicators present. This data is available in tabular format in Supplemental Table 2.. 18

Figure 3. Percentage of lakes with each trophic risk state observed based on total phosphorus (A) and total nitrogen (B) thresholds and measurements. Panel C shows the breakdown of overall risk scores for all lakes with nutrient measurements meeting the assessment inclusion criteria of at least 3 or more observations. 20

Figure 4. Map of lakes and their overall eutrophication risk levels. 20

Figure 5. Percentage of lakes with eutrophication evidence indicators. Panel A shows the chlorophyll-a based metric, panel B shows the percentage of lakes in each trophic category derived from remotely sensed imagery data (note that the oligotrophic and mesotrophic categories are combined due to the decreased sensitivity at lower cyanobacterial biomass levels making it difficult to differentiate these categories) and panel C shows the integrated evidence of eutrophication. 21

Figure 6. (A) Summary of total annual weekly cyano-bloom occurrence counts at the 7 µg/L cyanobacterial chl-a intensity between 2017-2023 from remote sensing imagery observations, colored by season. The season during which blooms were detected throughout the year are indicated in the legend. (B) Annual total count of cyano-blooms per year for each lake plotted by year between 2017-2023, which each point colored by year. The black dashed line (n=3) indicates the number of weeks used within the assessment framework to identify a given lake as eutrophic. Lakes with a minimum of 3 years with 3 blooms were identified as eutrophic 1 or greater...................................... 22

Figure 7. Annual time series of weekly cyano-bloom occurrences at the 7 µg/L cyanobacterial chl-a intensity detected via satellite remote sensing across the Central Valley. The colored line in each panel shows the count of blooms in all resolvable lakes each week for that specific year. The black solid line is the average number of blooms per week across all seven years, providing a ‘typical’ bloom climatology for the resolvable lakes in the region. The grey intervals show the maximum and minimum weekly count of cyano-blooms observed between 2017 and 2023. 23

Figure 8. Box plot of average weekly cyano-bloom occurrence counts at the 7 µg/L cyanobacterial chl-a intensity by year for each lake assessed by satellite imagery. Boxes are colored based on the Water Year Hydrologic Classification Indices for the Sacramento and San Joaquin Valley conducted by the California Department of Water Resources to indicate if the year was designated as a wet water year (wet, indicated in purple), below normal water year (below normal, indicated with red), dry water year (dry, indicated with aqua) or critically dry water year (critically dry, indicated with green) based on the historical climate of the region. 24

Figure 9. Map of disadvantaged communities and the 86 assessed lakes and reservoirs within the Central Valley region. Panel A shows a synoptic view of the entire region outlined in with a dark black line, Panel B shows a zoomed view of the Sacramento River Basin subregion, Panel C shows a zoomed view of the Tulare Lake Basin subregion, and Panel D shows a zoomed in view of the San Joaquin River Basin and the Sacramento-San Joaquin Delta. Shaded areas with grey outlines are individual census tract areas and are colored based on light pink if the track is identified as a disadvantaged community, light grey if not identified as a disadvantaged community and dark grey if data is not available for that tract. Points indicate locations of the assessed lakes and the point colors are based on the data sources available to conduct the assessment. 28

TABLE OF TABLES

Table 1. Trophic state definitions, modified from Carlson (1977), convey a narrative description of how the gradient of trophic state translates to use support. 11

Table 2. Total phosphorus and total nitrogen concentrations associated with each of the five trophic states that comprise the eutrophication risk categories. 13

Table 3. Summary counts of lakes and reservoirs in the Central Valley region with data relevant to the eutrophication assessment framework. 17

Table 4. Data distributions and summary statistics from the assembled dataset. Standard deviation was calculated including non-detect values which were set to zero. 19

Table 5. Data count and mean watershed land use percentages from the total inventory of Central Valley lakes and reservoirs and of assessed lakes and reservoirs separated by ecoregion groups. 25

Table 6. Wilcoxon test results comparing eutrophication risk with no eutrophication risk and evidence of a eutrophic/hypereutrophic state with evidence of an oligotrophic/mesotrophic state for the different land use categories and ecoregions. ... 26

Table 7. Count of lakes in disadvantaged communities based on the trophic risk and eutrophication evidence. The presence of an assessed waterbody in a DAC was determined based on if the lake or reservoir was located directly within the geographic area designated as a DAC. Note that lakes and reservoirs assessed for eutrophication risk do not fully overlap with those assessed for eutrophication evidence..................... 27

Table 8. Sensitivity comparison of trophic state assignments based on eutrophication risk nutrient indicators and eutrophication evidence biomass indicators for the 32 lakes and reservoirs where data were available for each type of assessment. 32

INTRODUCTION

Freshwater lakes and reservoirs are being increasingly stressed by the influence of global change ranging from increasing temperatures, drought and hydromodification to anthropogenic nutrients (Wurtsbaugh et al. 2019; Paerl and Huisman 2009). These causal factors increase the risk of eutrophication, defined as the accelerated delivery, *in situ* production, and/or accumulation of organic matter (Nixon 1995), one of the most common causes of water quality impairments in inland waters (Brooks et al. 2017; Le Moal et al. 2019). Eutrophication results in multiple pathways of impacts to humans and aquatic life in lakes and reservoirs, including hypoxia, taste and odor problems, impacts to biodiversity, fisheries yield, and water clarity, as well as toxic harmful algal blooms (Azevedo et al. 2013; Smith et al. 1999; O'Neil et al. 2012). The proliferations of toxic cyanobacteria (cyanoHABs) are of particular concern when it comes to the health and safety of lakes and reservoirs for humans, domestic animals, and wildlife (Paerl and Otten 2013; Brooks et al. 2017). Cyanotoxins pose serious threats to the health of humans, domestic pets, wildlife, and livestock (Li et al. 2011; Mehinto et al. 2021; Stewart et al. 2008; Trevino-Garrison et al. 2015). While nutrients are critical for the proper functioning of the aquatic food webs, excessive levels of nutrients, primarily nitrogen (N) and phosphorus (P), are one of the primary causes of eutrophic conditions in lakes and reservoirs (Wurtsbaugh et al. 2019). Eutrophication is particularly common in highly populated areas due to a combination of treated municipal or industrial wastewater point source or agricultural and urban non-point discharges (Hobaek et al. 2012; Withers et al. 2014).

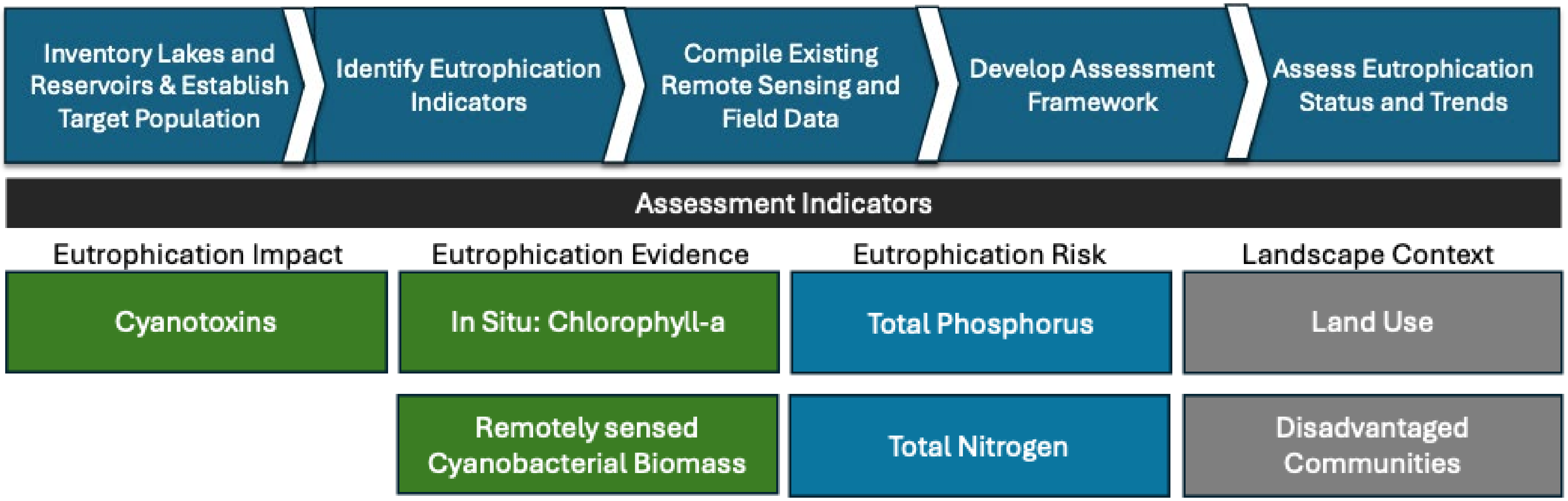
Reports of harmful algal blooms in the lakes and reservoirs of the Central Valley (CV) Region of California, U.S.A., particularly those caused by cyanoHABs, are among the most frequent in the state since tracking began in 2016 (Jang and Otim 2023). This region, which comprises nearly 40 percent of the state, contains some of the most valuable and diverse habitats in the world, but also hosts 80 percent of California's irrigated agricultural lands and the major population centers of Bakersfield, Fresno, Sacramento and Redding. Several large lakes and reservoirs in the region, including Clear Lake, Lake Hensley, and H.V. Eastman Lake (Smith et al. 2023a; Huie et al. *in prep*) have regular reports of cyanotoxins levels that are an order of magnitude or more above California's human recreational guidelines (CCHABs 2016) as well as levels that are harmful to aquatic life (Mehinto et al. 2021). Eutrophic conditions have been implicated as one of the drivers of cyanoHABs in these waterbodies.

Despite the growing concern with eutrophication and cyanoHABs in the region, no widespread assessment of eutrophication has been conducted to date in CV lakes and reservoirs. The goal of this study was to utilize a combination of existing *in situ* and satellite remote sensing imagery data to quantify the status and trends of eutrophication of the lakes and reservoirs in the CV Regional Water Quality Control Board geographic jurisdiction and identify key data gaps. To conduct a regional assessment of eutrophication, we confronted multiple challenges. First, no centralized and publicly accessible database of water quality data exists for CV lakes and reservoirs in the Region. Second, no State-funded ambient monitoring programs exists for lakes or reservoirs and little public funding has been dedicated to routine monitoring, outside of monitoring mandated by site-specific actions such as total maximum daily loads and specific permitting actions. Most of the relevant data are held by privately managed water resource agencies who are not currently required to make these data public. Third, while California Water Boards have a narrative biostimulatory objective to protect beneficial uses from eutrophication, the State lacks numeric guidance to translate that narrative objective to goals that protect lakes and reservoirs from impairment from eutrophication. Therefore, our approach required: 1) development of a comprehensive inventory of lakes and reservoirs, from which we developed the target population for the assessment, 2) compilation of existing field and remote sensing data and 3) development of a numeric framework to assess eutrophication, prior to conducting an assessment, the details of which are described Materials and Methods below. We expected substantial data gaps and thus assessment of key gaps and future recommendations was a key step in the assessment.

Materials and Methods

Approach to the Eutrophication Assessment

To conduct the study, multiple steps were required (Figure 1.1). We first assembled an inventory of CV lakes and reservoirs and used that initial inventory to identify the targeted waterbodies. From a comprehensive review of eutrophication indicators and causal factors featured in the California FHAB monitoring strategy (from Table 2.3 and Table 2.4, respectively, found in Smith et al. 2021), we identified three categories of indicators: 1) risk of eutrophication, 2) evidence of eutrophication and 3) eutrophication impact (Figure 1.1). We also added to two landscape indicators (developed/undeveloped/agricultural land uses and disadvantaged community status) to provide context for interpretation of the findings. Cyanotoxins (with a focus on total microcystins due to extremely limited data availability for the other cyanotoxin classes) as an indicator was considered, then was ultimately not included in the assessment due to observations only being available from a limited number of waterbodies. Field (*in situ*) data and remote sensing data were compiled from public databases and quality assurance conducted. We then developed a multi-metric eutrophication assessment framework to score the status and trends in CV lakes and reservoirs, in multiple categories representing the disturbance gradient. We then applied this assessment framework to the compiled data and assessed both status and trends. Finally, we assessed the representativeness of the waterbodies included in the study and identified priority data gaps for the region.



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Description of Study Region and Target Population of Lakes and Reservoirs

Study Region

The California's CV Region contains the basins of the Sacramento River, San Joaquin River and the Tulare Lake. This region encompasses a range of elevations and ecosystems with broad valley floor areas bounded by mountain ranges. The CV Region includes 36% of the State's total acreage and spans approximately 50 miles in width and 400 miles in length. The valley floor region is marked by shallow gradients at elevations below 800 feet and is bounded by the foothills and mountains of the Sierra Nevada to the east, Cascade Range to the north, Coast Ranges to the west and Tehachapi Mountains to the south. The CV region is characterized by a Mediterranean climate and precipitation primarily occurs during the winter and spring, followed by a hot and dry summer and fall.

The dominant land use in the valley floor is agriculture (71%), while developed urban and residential (10%) and open lands and natural habitats comprise the remainder (19%; Soulard and Wilson 2013). The valley floor supplies 8% of U.S. agricultural output (by value) and produces a quarter the U.S.'s food, including 40% of the fruits, nuts, and other table foods (Pathak et al. 2018). Up to 90% of the crops grown in agriculturally-dominated areas of California, including the valley floor, are irrigated (Pathak et al. 2018), particularly during hot dry summer months.

Nonpoint pollution originating from agriculture can be a major contributor to eutrophication, making the lakes and reservoirs of the CV at particular risk for eutrophication. Previous studies in agricultural areas have suggested that a major proportion of N and P fertilizers can be lost from the fields where they were applied and enter the environment including local waterways (Sutton et al. 2013). Confined animal feedlots are an additional source, as excretion from manure is the second largest source of nitrogen in California and thus represents another pathway of enrichment (Tomich et al. 2016). Beyond agriculture, the CV is also home to several large population centers including Bakersfield, Sacramento and Redding. These developed land uses can contribute other sources of nutrient pollution occur, including municipal wastewater and septic systems, lawn fertilizer and pet wastes from residential areas. Finally, atmospheric wet and dry deposition of nutrients is an additional pathway, estimated to be among the highest rates in the U.S. (Tomich et al. 2016). Collectively, these sources of nutrient pollution have the potential to accelerate the eutrophication of lakes and reservoirs in the CV Region.

Inventory of CV Lakes and Reservoirs

We created a lake and reservoir inventory to quantify the relative proportion of lakes and reservoirs that were able to be assessed in the region using the assembled *in situ* and remote sensing datasets. The target population of lakes and reservoirs included: 1) waterbodies greater than 1 hectare in size and 2) were dominated by open water habitats. We took steps to explicitly exclude agricultural ponds, because they can be typically large enough in size contain enough open water to be initially categorized as a lake in many databases.

To identify the total number of lakes and reservoirs in the CV region, we used GIS to merge the National Hydrology Plus Dataset (NHDplus) maintained by US Geological Survey (USGS) as a base, then added additional waterbodies from the National Hydrology Dataset (NHD) and National Wetland Inventory maintained by US Fish and Wildlife Service. Additional metadata was added from the Beneficial Use GIS database from the Basin Plan GIS Library hosted by the California Water Boards. A preliminary match between the lake inventory and *in situ* waterbodies was done to manually draw polygons for waterbodies with *in situ* data compiled for this project that were lacking polygons. These waterbodies were manually inspected using Google Earth imagery to confirm that the data was from a waterbody in our target population. Polygons were classified as greater than 8 hectares or between 1 and 8 hectares. Polygons less than 8 hectares that were overlapping a greater than 8-hectare polygon were removed. To further consolidate, polygons were dissolved in GIS with adjacent polygons to form a singular larger polygon. If lake polygons were merged, then new resulting polygon surface area was the sum of all the merged polygons surface areas and was assigned the metadata of the dominant polygon. Since lake polygons maybe have multiple recorded surface areas from different datasets, the largest surface area was chosen. Polygons smaller than 1 hectare were removed.

Following these initial filtering steps, the remaining polygons were evaluated against the 2021 National Land Cover Database (NLCD) to remove waterbodies that were not identified as lakes, ponds or reservoirs in the available metadata, because not all polygons greater than 1 hectare had assigned waterbody type designations. The land use inside each of the polygons was evaluated and assigned the following categories: 1) High certainty perennial lake = 75th percentile open water level (this level was chosen to account for fluctuating lake levels during drought); 2) Medium certainty perennial lake = 50th percentile open water level; 3) Low certainty perennial lake = 10th percentile open water level; 4) Potential agricultural pond = >10th percentile agricultural land use; 5) potential intermittent lake/wetland = >50th percentile wetland and water are < 10th percentile open water level; and 6) Flagged polygons = < 50^{th} percentile wetland or <10^{th} percentile open water level. Polygons assigned categories 4, 5, and 6 were removed unless *in situ* data existed for that waterbody. Due to the quantity of waterbody polygons, a full manual inspection was not conducted, but a randomized spot check was done on each category to confirm that each category was appropriate.

Following this procedure, the waterbodies for which data were available (see below) were compared against the waterbody inventory. A small number of waterbodies required additional data management to appropriately match with the lake inventory due to inaccurate *in situ* lake coordinates or misaligned polygons. The final inventory consisted of 4499 CV lakes, ponds, and reservoirs that are within the target population for the assessment. We acknowledge that the finalized waterbody inventory may still include non-target or exclude desired waterbodies.

Compilation of Existing Data

Three principal data sources were used for the assessment: 1) *In situ (*field) data, 2) remotely sensed satellite data processed for eutrophication indicators and 3) geographic information system data, specifically land use/land cover and shapefiles designated disadvantaged communities.

In situ field data

Multiple agencies have conducted water quality sampling of nutrient and biological indicators throughout the CV region; however, a majority of efforts were limited in scope either spatially or temporally. We targeted data collected between 2000-2022 with the goal of obtaining observations of as many eutrophication relevant indicators from as many lakes and reservoirs as possible in the region. *In situ* data were collated from two principal sources: 1) National Lakes Assessment (NLA) observations in the region from the surveys conducted in 2007, 2012 and 2017 and 2) CV region relevant data from publicly accessible databases. The queried databases included the Department of Water Resources (DWR), Water Quality Program Database (for federally funded data; WQP); Surface Water Ambient Monitoring Program (SWAMP) and California Environmental Data Exchange Network (CEDEN).

Data were downloaded based on search criteria corresponding to the targeted indicators (Figure 1), including laboratory-based measurements of chlorophyll-a and the forms of nutrients that alone or together could comprise the assessment of total nitrogen (TN) and total phosphorus (TP) for water grab samples. We ultimately only included direct measurements of TN and TP because there was rarely enough co-occurring measures of individual forms of nitrogen or phosphorus, respectively, to calculate estimates of the total fraction. Other collateral data that provided context or quality assurance support included water temperature, dissolved organic carbon and turbidity were compiled, but not assembled in the final dataset. A summary of the final dataset, including the analytical methodologies used for each of the *in situ* analytes in the final dataset is described in Supplemental Table 1.

From the initial suite of downloaded data, several data quality control procedures were taken. First, duplicate data entries across databases were also eliminated. These measures included removal of data based on incompatible measures, sampling locations, laboratory analytical procedures, and through outlier identification. All parameters were plotted and manually inspected for extreme values. It was expected that some parameters such as chlorophyll a may yield some extreme values due to biological variability, however, values well beyond reasonable limits were manually removed. After the removal of extreme values, data points which were three standard deviations from the mean were removed.

Remotely sensed satellite imagery data

In addition to *in situ* data, we also utilized remotely sensed cyanobacterial abundance derived from satellite imagery as an additional line of evidence of eutrophication and to widen expand the number of lakes and reservoirs that could be assessed. We used data collected by the Ocean and Land Colour Instrument (OLCI) onboard the Sentinel-3A and Sentinel-3B satellites, which provides a near-continuous time series of surface water observations. The OLCI sensor has a 300-meter by 300-meter (~22 acres) pixel resolution, though factors including cloud cover, sun glint, snow, and ice can limit image availability during satellite overpass.

OLCI imagery data processed by the Cyanobacterial Assessment Network (CyAN) project were downloaded from the online data portal (https://oceancolor.gsfc.nasa.gov/about/projects/cyan/; Version 5 data following May 2023 processing procedures). Level 3 mapped data were downloaded for the years of 2017-2023 in order to only consider years where the full calendar year of data were available. These data underwent several processing steps by the CyAN project which will be briefly described. The imagery was geolocated, converted to an Albers Equal Area projection, and corrected for top-of-atmosphere reflectance to remove the spectral contribution of Rayleigh scattering. Data flags were applied to pixels that were identified by the processing algorithm as containing clouds, land, and mixed land-water pixels. CI-cyano values were calculated for remaining pixels. The CI-cyano value is a proxy of cyanobacteria specific Chl-a absorption and estimates the cyanobacterial biomass using a distinct spectral shape signature that allows for the differentiation of cyanobacterial biomass from other eukaryotic algae and reflective matter present in water (Lunetta et al. 2015; Wynne et al. 2018). The CI-cyano value was calculated using established spectral shape algorithms that utilize the spectral bands centered at 665 nm, 681 nm, and 709 nm to estimate bloom biomass and the spectral bands centered at 620 nm, 665 nm, and 681 nm to differentiate between cyanobacterial and non-cyanobacterial biomass. A detailed description of the CI-cyano calculations can be found in Lunetta et al. (2015) and Wynne et al. (2010, 2008).

For our analyses, we utilized 7-day maximum temporal composite images. These imagery composites were generated by compositing the maximum pixel value observed within a 7-day period for all resolvable pixels within that timeframe. This helps to mitigate the loss of data from interfering factors like clouds and also capture the highest observed cyanobacterial biomass within that timeframe. Composites from 2017 only represent imagery collected by Sentinel-3A, while composites from May 2018-present represent merged Sentinel-3A and 3B imagery, meaning that the number of available images to composite within a 7-day period effectively doubled following this addition. We utilized the resolvable lakes inventory developed by the CyAN project to extract data from lakes present in the CV regional lakes (Clark et al. 2017). The inventory included only lakes with a unique COMID and a minimum of 3 resolvable pixels within the lake surface. Ultimately a total of 47 lakes were identified in the CV Region (Figure 1; see Supplementary Table 1 for individual lake summaries).

We then conducted additional post-processing steps on downloaded data. All satellite pixels flagged for clouds, land, and mixed land-water pixels by CyAN processing procedures were masked and discarded. We took additional steps to remove pixels potentially containing ice or snow or pixels that may intermittently overlap with the shoreline with variable lake levels following the approaches described in Urquhart and Schaeffer et al. (2020) to ensure only pixels with a high degree of confidence were included in later analysis. Pixels containing ice and snow can sometimes wrongly appear as cyanobacteria by the CI-cyano algorithm. To avoid incidences of false positives due to interference from ice and snow, these pixels were removed. Following the approach described in Urquhart and Schaeffer (2020), pixels where ice might have been present were masked. In brief, daily snow and ice cover in the Northern Hemisphere were downloaded from the National Snow and Ice Data Center (https://nsidc.org/data/G02156/versions/1). Snow and ice cover data were composited into weekly maps of maximal ice extent in the state, which was determined from daily 4 km resolution Iterative Multisensor Snow and Ice Mapping System Northern Hemisphere Snow and Ice Analysis data. These maps were used to flag and mask any pixels containing ice and snow. An additional 1-pixel buffer of the nearshore region of a waterbody was applied to reduce interference related to adjacency effects (Bulgarelli et al. 2014) or mixed pixels that were missed by the processing algorithm, again following the approaches described in Urquhart and Schaeffer et al. (2020).

Landscape context: land use and disadvantaged communities

We compared eutrophication risk and evidence against developed and agriculture land use group percentages using the National Land Cover Dataset (NLCD; database available at https://www.mrlc.gov/) and against the geographic distribution of disadvantaged communities to provide context for the findings of our eutrophication assessment.

To achieve this, the major land use categories for each lake or reservoir in the lake inventory were calculated for the HUC12 watershed area. Within the NLCD, there are 16 unique land use categories but for the purposes of these analyses we consolidated these categories into developed lands (4 categories of developed lands spanning a range of impervious surfaces from <20% to >80%), undeveloped lands (barren land, 3 forest types, shrubland, grassland/herbaceous cover and 2 types of wetlands), and agricultural lands (cultivated crops and pasture/hay). We excluded land identified as open water and perennial ice/snow from all statistical comparisons. All statistical comparisons were made within similar ecoregions within the CV regional bounds to account for areas with known ecological similarities (see Statistical Analyses section below). Collectively, there are six Level-3 EPA ecoregions (Omernik and Griffith 2014) within the bounds of the CV Regional Water Board and these were consolidated due to small sample sizes within individual ecoregions into a combined mountain ecoregion (containing Level-3 ecoregions 4, 5, 6, 9, 78) and valley ecoregion (containing Level-3 ecoregion 7).

Disadvantaged communities were determined using the 2020 California Division of Water Rights disadvantaged community (DAC) Mapping Tool (https://gis.water.ca.gov/app/dacs/). The i16 Census Track layer summarizing data from 2016-2020 was used. This tool identified if a census tract was a DAC based on median household income data derived from the American Community Survey. *In situ* and remotely sensed lakes centroids were used to determine if the lake was located inside or outside a DAC.

Eutrophication Assessment Framework

Terminology

An assessment framework (AF) is a quantitative scheme intended to classify aquatic waterbody segments in tiers representing a gradient in ecological condition, from very high ecological condition to very low, based on risk of potential adverse effects of eutrophication (Sutula et al. 2014), similar to the construct of a biological condition gradient (BCG) model (Davies and Jackson, 2005). This concept has its roots in ecological risk assessment (EPA 1998), in which multiple ecological response indicators (e.g., chlorophyll-a, cyanobacterial biomass, cyanotoxins) are assessed in combination with causal factors that represent the risk of eutrophication (e.g., total nitrogen and total phosphorus).

In this document, we define “thresholds” as the endpoints that define break between categories; these thresholds should not be mistaken as recommendations for policy or regulatory assessment endpoints as those are not the intended product of this study.

Selection of priority indicators and categorical thresholds

There is a rich literature of scientific approaches to assess eutrophication and investigate its causal drivers, particularly in lakes, dating from the mid-20th century (Carlson 1977; Davis et al. 2019; Zhang et al. 2021; USEPA 2021). For that reason, we did not create a new framework, but rather reviewed and adapted as needed from existing approaches and frameworks, based on what was most suitable for this non-regulatory application. The eutrophication assessment framework consisted of three categories: 1) risk of eutrophication (as indicated by total nitrogen (TN) and total phosphorus concentrations (TP)), 2) evidence of eutrophication (as indicated by *in situ* chlorophyll-a or satellite remotely sensed cyanobacterial biomass) and 3) eutrophication impact (as indicated by cyanobacterial toxin concentrations). Thresholds that were used to assign lakes into categories were derived from various sources. The categories for this assessment were based on the five trophic states described in the Trophic State Index (TSI) are summarized in **Table 1**, while the final selected thresholds for each trophic state are described in **Table 2**.

For eutrophication evidence and risk, we based the classification on the work of Carlson (1977), who developed the TSI for lakes and reservoirs. TSI is a numerical scale based on the weight of living biological material (biomass) at a specific place and time. It has been used and adapted by several states to assess eutrophication. Within this framework, there is a continuum of trophic states including oligotrophic, mesotrophic, eutrophic 1, eutrophic 2, and hypereutrophic (**Table 1**) that represents a biological condition gradient in response to eutrophication. The original TSI (Carlson 1977) uses three different indicators to define these trophic states, including chl-a, TP, and Secchi depth, a measure of water clarity. These indicators are all statistically related and thus the application of any combination of these indicators may result in the same trophic classification for a waterbody, but total phosphorus and total nitrogen represent eutrophication potential or risk, while chlorophyll-a represents the expression of eutrophication. Since the TSI was introduced, others have adapted it to include total nitrogen (Hopkinson et al. 1997).

We evaluated nutrients through a risk-based lens given the fact that over enrichment with nutrients does not always result in eutrophication effects. We combined observations of TN and total phosphorus (TP) into an assessment of eutrophication risk based on nutrient concentrations. The categories for this assessment were based on the five trophic states described in the TSI (**Table 1**). The thresholds for each trophic state are described in **Table 2**. The TP thresholds are from the Carlson TSI (Carlson 1977) and the TN thresholds are based on the EPA modeling effort as adjusted by Sutula et al. 2025.

Eutrophication evidence was evaluated using the two biomass indicators, *in situ* measured chlorophyll-a and counts of cyano-bloom occurrences from remotely sensed cyanobacterial biomass. In order to combine *in situ* chlorophyll-a concentrations and mean number of cyano-bloom occurrences via remote sensing imagery, the EE assessment had a binary output of either no evidence or evidence. A summary of the thresholds and indicators for this component of the framework are described in **Table 2**.

For eutrophication impact, we scoped the use of cyanotoxins as the principal metric, which includes three classes of cyanotoxins: 1) microcystin, 2) anatoxin-a, and 3) cylindrospermopsin. Initial compilation of data identified major data gaps which presented an impediment to using cyanotoxin data in this first assessment. Observations of anatoxin-a and cylindrospermopsin were extremely rare (< 40 observations total); microcystin was more abundant but nearly 2/3 of the observations were from a single lake (Clear Lake). For this reason, although there is an intent on including eutrophication impact over the long term, we chose not to create categorical thresholds time. Instead, the relationship between microcystin concentrations relative to eutrophication evidence and risk are presented in Appendix 1 (**Supplemental Figure 1**). Future iterations of this assessment should include that component as this major data gap is addressed.

Table 1. Trophic state definitions, modified from Carlson (1977), convey a narrative description of how the gradient of trophic state translates to use support.

Trophic State	Description/definition
Oligotrophic	Clear water, low algae and nutrient concentrations, usually blue in color. Oxygen is typically present throughout the year in the hypolimnion. Salmonid fisheries dominate, particularly in deep colder water lakes.
Mesotrophic	Moderate algae and nutrients and moderate water clarity. Increasing probability of hypolimnetic anoxia during summer. Iron, manganese, taste, and odor problems worsen. Raw water turbidity requires filtration. Hypolimnetic anoxia results in partial loss of salmonids in cold water lakes. Warm water fisheries are preserved.
Eutrophic 1	High algae and nutrients, low water clarity, usually green in color. Anoxic hypolimnion, macrophyte problems possible. Salmonid fisheries lost in cold water; loss of some warm water fisheries diversity.
Eutrophic 2	Similar to Eutrophic 1, slightly higher of algae and nutrients, similar green color Blue-green algae dominate, algal scums and macrophyte problems. Episodes of severe taste and odor possible. Nuisance macrophytes, algal scums, and low transparency may discourage swimming and boating.
Hypereutrophic	High algae and nutrients, low to no water clarity, water color green. Higher severity of dense algae and macrophytes. Warm water pollution tolerant fish only.

For our use, we employed the chl-a and TP classification scheme of the TSI but added TN, because nitrogen availability is an important risk factor for biomass accumulation and on the formation of cyanoHABs (Wurtsbaugh et al. 2019; Paerl et al. 2016). We chose not to utilize the TSI index itself but preferred to leave the individual metrics unaggregated to look at agreement among combined lines of evidence. We excluded the measurement of water clarity via Secchi depth, for example, as it can be reduced by non-biological turbidity (Xu et al. 2015).

To this suite of traditional trophic state metrics, we chose to add one metric related to cyanoHABs: cyanobacterial biomass, measured as CI-cyano via satellite remote sensing (see compilation of existing data for details).

For total nitrogen as well as CI-cyano measures, additional science was used to determine thresholds associated with trophic state. Evidence for total nitrogen thresholds that correspond to chl-a trophic classifications came from statistical models originally developed by US EPA, then modified for California lakes and reservoirs by Sutula et al. (2025). As brief context, US EPA has recently provided national statistical stress-response models that link beneficial uses to ecoregional thresholds of chl-a, TN and TP in lakes and reservoirs (US EPA 2021). Sutula et al. (2025) refined these models, augmenting them with CA-relevant ecoregional data sources, including available data from the CV Regional Water Board jurisdiction. We utilized the Sutula et al. (2025) model identify the TN concentrations associated with the chlorophyll-a thresholds that defines the boundary between each trophic state described by Carlson (1996). In order to derive these values, the US EPA-adapted statistical model requires the inputs of dissolved organic carbon concentration and statistical confidence required in achieving the predicted chl-a endpoint. Per the methods of Sutula et al. (2025), we applied dissolved organic carbon levels of 3.9 mg/L, 4.4 mg/L, 5.9 mg/L, and 8.1 mg/L as the inputs for mesotrophic, eutrophic 1, eutrophic 2, and hypereutrophic, respectively. We utilized an 80% confidence level in achieving the targeted chl-a threshold, which is the default recommendation of the US EPA (2021). This was translated to suite of TN thresholds corresponding to each chlorophyll-a threshold per trophic state boundary captured in Table 2. R script and associated data for calculating these thresholds are provided at https://github.com/SCCWRP/CA_Biostim_Lakes_2021. Detailed information on model development is provided in US EPA (2021), with model updates and documentation in Sutula et al. (2025).

Table 2. Total phosphorus and total nitrogen concentrations associated with each of the five trophic states that comprise the eutrophication risk categories.

Type	Indicator	Trophic State				
		Oligotrophic	Mesotrophic	Eutrophic 1	Eutrophic 2	Hypereutrophic
Evidence	*In situ* Chl-a (µg/L)	< 0.95	2.6- 7.3	7.3- 20	20-56	>56
	Cyano-bloom occurrence via imagery	< 3 years with 3 blooms at the 7 µg/L cyanobacterial chl-a intensity		≥ 3 years with 3 blooms at the 7 µg/L cyanobacterial chl-a intensity	≥ 3 years with 3 blooms at the 20 µg/L cyanobacterial chl-a intensity	≥ 3 years with 3 blooms at the 56 µg/L cyanobacterial chl-a intensity
Risk	TP (mg/L)	<0.012	0.012 - 0.024	0.024 - 0.048	0.048 - 0.096	> 0.096
	TN (mg/L)	<0.277	0.277 - 0.393	0.393 - 0.651	0.651 - 1.129	> 1.129

Our satellite imagery metric mimics the satellite imagery impairment framework described in Davis et al. (2019) for Lake Erie that examines the estimated lake area exceeding a bloom intensity threshold within a set time period. For remotely sensed biomass thresholds, we utilized the cyanobacterial bloom occurrence metric (hereafter called cyano-bloom occurrence). For this metric, a cyano-bloom is defined as a binary occurrence (e.g., a cyano-bloom is or is not present) based on the percentage of pixels in the lake (e.g., the spatial bloom area) at or above a given cyanobacterial concentration threshold from a 7-day maximum temporal imagery composite (Coffer et al. 2020).

Here, we applied a spatial threshold of 10%, meaning that for a lake to be considered as experiencing a cyano-bloom, at least 10% of the total number of detectable pixels must be at a specific pixel intensity threshold. We selected the 10% spatial threshold based on the recommendations of Coffer et al. (2020) because in their analysis it reduced the variance in occurrence across differently sized lakes. We used three different pixel intensity thresholds to define blooms that correspond with an estimated cyanobacterial chl-a concentration of 7 µg/L, 20 µg/L, and 56 µg/L, using the conversion equation for CI-cyano to cyanobacterial chl-a described in Seegers et al. (2022) and aligning with the chl-a levels associated with the trophic state eutrophic 1, eutrophic 2, and hypereutrophic, respectively (Table 2). Cyanobacterial chl-a concentrations of <7 µg/L were not reliably differentiated by Seegers et al. (2022), thus we did not calculate the number of cyano-bloom occurrences at concentrations below this level. We then counted how many years between 2017-2023 had at least 3 blooms at each cyano-bloom intensity threshold. A lake was placed lakes into a trophic state if at least 3-years had a minimum of 3 blooms at a given intensity (Table 2). If less than 3-years were observed, the lake was placed into a combined oligotrophic/mesotrophic category, similar to the trophic state grouping applied in Seegers et al. (2022).

Data inclusion criteria and data calculations

We developed a rule set for evaluating data that was designed to be flexible in nature to accommodate a varied dataset for lakes that may have one or more of the priority indicators. In recognition that our indicators included both direct measures of nutrient concentrations as well as measures of algal or cyanobacterial biomass we created distinctive evaluation assessments that synthesized each group of indicators within the framework.

We set a minimum observation requirement of three observations of at least one indicator from eutrophication risk or evidence scoring for a lake to be included in the assessment. This minimum observation requirement was included to help ensure representativeness and avoid making a risk or evidence status based on a single observation. We then considered several types of descriptive statistics to use for making the scoring assignment including the mean, median, maximum and 90th percentile. We tested these statistics using model dataset of 2 lakes in the region (H.V. Eastman Lake and Hensley Lake) for which there was a spatial and temporally comprehensive dataset of both *in situ* and remotely sensed observations over two years (Huie et al, *in prep*). When looking at the time series data for individual lake systems, the trophic state (as indicated by either nutrient concentrations or by biomass) was not a constant state over time and each lake shifted between trophic state categories multiple times over the observational period. Thus, we ultimately opted to use the mean in the assessment framework in order to understand the central tendency of the observations, while still considering the entire distribution of available data for a given indicator.

The mean of the observations for a given indicator was then used for comparison against the thresholds for the respective assessment elements (TN, TP, or biomass). A trophic state was assigned for each indicator available within a given waterbody. If multiple indicators are available for a given lake, then the “worst case” trophic state was then used for each element of the framework where data was available.

We note that the assessment covered a mix of cold water (salmonid) and warm water lakes, and that the assessment framework categorization marks the degradation of cold-water fisheries support at mesotrophy, while for warm-water fisheries that occurs at categories of eutrophic 1 and beyond. Our assessment did not attempt to benchmark each lake in their reference state (e.g., cold versus warm water), as that was beyond the scope of this study.

Statistical Analyses

Land Use

Due to extreme differences in sample size between the total inventory of CV lakes and reservoirs and assessed lakes and reservoirs, statistical differences between land use between these two groups were not able to be calculated. Instead, the mean percentage and standard deviation of land use within each of the three main land use categories was calculated for the HUC12 watershed area of each lake or reservoir in the lake inventory by ecoregion. The means and standard deviations were compared, looking for overlaps in ranges of standard deviations to identify any notable differences in land use characteristics of the HUC12 watersheds between the two groups.

We compared eutrophication risk and evidence against developed, undeveloped and agriculture land use group percentages using the NLCD (see Landscape Context section above for details). To achieve this, the percentage of land use within each of the three main categories was calculated for the HUC12 watershed area of each lake or reservoir in the lake inventory. Comparisons were made within similar ecoregions within the CV regional bounds to account for areas with known ecological similarities. For all groupings, Shapiro–Wilk test and Levene's test were done to check for normality and equal variances, respectively. Due to nonnormality, the Wilcoxon ranked sum test was selected to determine median differences for all comparisons. For some comparisons, there was unequal variance which lowers the power of the test and only allowed for comparison of differences but not the magnitude of differences (Mann and Whitney 1947). Statistically significant differences were determined at $p<0.05$. All statistical tests were conducted using R statistical software (R Core Team 2024).

Remotely sensed satellite imagery data time series analysis

Annual and interannual variations in cyano-bloom occurrence were explored to investigate how temporal variation might influence assessment results, due to the high temporal resolution of satellite imagery data (e.g., weekly observations). Seasonality within was explored within the 7 µg/L cyano-bloom occurrences timeseries. A regional climatology was calculated using the average number of weekly cyano-bloom occurrences across the seven years of available satellite observations and was compared to the seasonal patterns observed within each year to assess interannual variations in cyano-bloom patterns. Each week was assigned a corresponding season to examine which seasons experienced the most frequent cyano-bloom occurrences during the timeseries. For this analysis, spring was defined as weeks 10-22 out of 52 in a year; summer was defined as weeks 23-35; autumn was defined as weeks 36-48; and winter was defined as weeks 1-9 and 49-52.

Annual variations in regional bloom occurrence were also examined in relation to hydrologic conditions by comparing regional mean cyano-bloom occurrences to the annual water year hydrologic classification index for the Sacramento and San Joaquin Valley developed by the California Department of Water Resources (https://cdec.water.ca.gov/reportapp/). Water year classifications are determined based on measured, unimpaired runoff for the basin. The California Department of Water Resources defines unimpaired runoff as the natural water production of a river basin, unaltered by upstream diversions, storage, export of water to or import of water from other basins. For the years considered, the designations were the same for the Sacramento Valley and the San Joaquin Valley.

RESULTS

Lake and Reservoir data availability and distributions in the Central Valley region

A total of 91 lakes and reservoirs in the region had *in situ* data relevant for assessment and 47 lakes had data with remotely sensed imagery data (**Table 3**). After considering assessment inclusion criteria described below (requirement of at least 3 repeated observations of an indicator), this resulted in the ability to assess 86 distinct lakes and reservoirs in the region. The lakes were distributed throughout the region (**Figure 2**). Overall, the most common indicator within the database was total phosphorus with a total of 3103 observations within the database, with just over a third of those observations collected from Clear Lake. Observations of total nitrogen were the least common, with a total of 314 observations (**Table 3**).

Table 3. Summary counts of lakes and reservoirs in the Central Valley region with data relevant to the eutrophication assessment framework.

	Lakes with at least one observation	Lakes with three or more observations	Total number of observations	Lake with the greatest number of observations
In situ assessment data for any indicator	90	61	3842	Clear Lake (1252)
Total phosphorus observations	85	46	3103	Clear Lake (1186)
Total nitrogen observations	60	24	314	H.V. Eastman Lake (59)
In situ Chlorophyll-a observations	49	30	425	Clear Lake (66)
Remotely sensed imagery observations	47	47	Not applicable	Not applicable
Microcystin observations	35	17	865	Clear Lake (662)

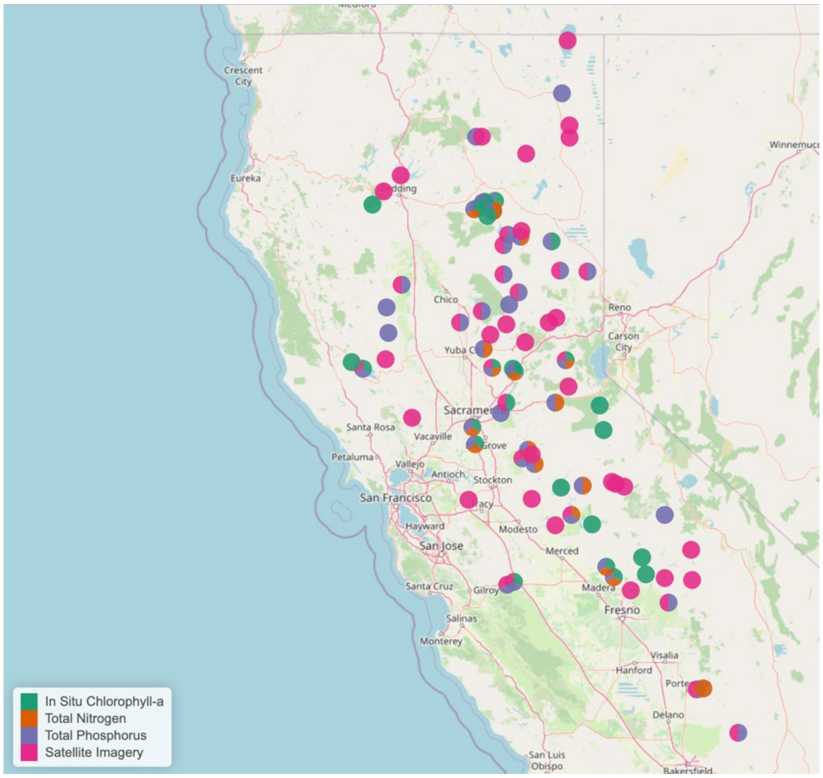

Figure 2. Maps of the Central Valley region of California showing the geographic distributions of waterbodies with assessment data. Points indicate locations with framework indicator data, both *in situ* and remotely sensed. Data type is indicated by the colors of the points. Locations with more than one type of indicator present are indicated with wedges that are colored by the types of indicators present. This data is available in tabular format in Supplemental Table 2.

A wide range of nutrient and biomass concentrations are observed across the lakes and reservoirs across the region (**Table 4**). The mean concentrations of total phosphorus and total nitrogen were at the eutrophic 1 and eutrophic 2 risk levels, respectively, however, the standard deviation for each indicator highlights the wide variance in concentrations observed for these indicators (**Table 4**). Similarly, *in situ* chlorophyll-a concentrations indicate that extreme and widely variable levels of algal biomass have been observed in some lakes within the region with the mean of all observations exceeding the hypereutrophic levels (**Table 4**). Imagery based estimates of cyano-blooms indicate that 26 resolvable lakes experienced cyanobacterial blooms at least 3 or more weeks per year, on average in the last seven years (**Table 4, Supplemental Figure 2**).

Table 4. Data distributions and summary statistics from the assembled dataset. Standard deviation was calculated including non-detect values which were set to zero.

Indicator	Range	Average	Median	Standard deviation
Total nitrogen (mg/L)	0 – 8.2	0.661	0.273	0.969
Total phosphorus (mg/L)	0 – 2.2	0.088	0.03	0.145
Chlorophyll-a (μg/L)	0 - 7121	111	4.7	469
Annual 7 μg/L intensity cyano-bloom occurrences (n)	0-35	2.8	1	6.0
Total Microcystin (μg/L)	0-5554	19.9	0	266

Application of eutrophication assessment framework in the Central Valley region

Eutrophication Risk

There were 47 lakes that had enough data to meet the inclusion criteria for the assessment of eutrophication risk. Of these 47 lakes, 46 were able to be scored based on TP concentrations, while 24 were able to be scored based on TN concentrations (**Figure 3**). Assessable lakes were distributed throughout the region (**Figure 4, Supplemental Table 2**).

When scoring individually based on TP concentrations, 44% of assessed lakes were at risk of being in eutrophic state (43.5%), with 10.9%, 15.2% and 17.4% of lakes being ranked with risk of eutrophic 1, eutrophic 2 or hypereutrophic state conditions, respectively. Conversely, 55.3% of assessed lakes were not at risk of a eutrophic state (**Figure 3A**). Different distribution of eutrophication risk was observed using TN concentrations. The majority (66.7%) of assessed lakes were likely in an oligotrophic condition based on TN concentrations (**Figure 3B**). A smaller proportion of assessed lakes were ranked as being at risk of a eutrophic state (20.9%) when considering TN concentrations. Importantly, however, a smaller number of lakes (n = 45) had TN data that met the assessment inclusion criteria than for eutrophication risk assessment via TP.

Overall, the findings indicate a slightly lower percentage of lakes at risk of being in a eutrophic state (44.7%) than being ranked as oligotrophic or mesotrophic (55.3%). Additionally, within the spectrum of eutrophic conditions, lakes were nearly evenly distributed across eutrophic categories (e.g., eutrophic 1, eutrophic 2 and hypereutrophic) (**Figure 3C**).

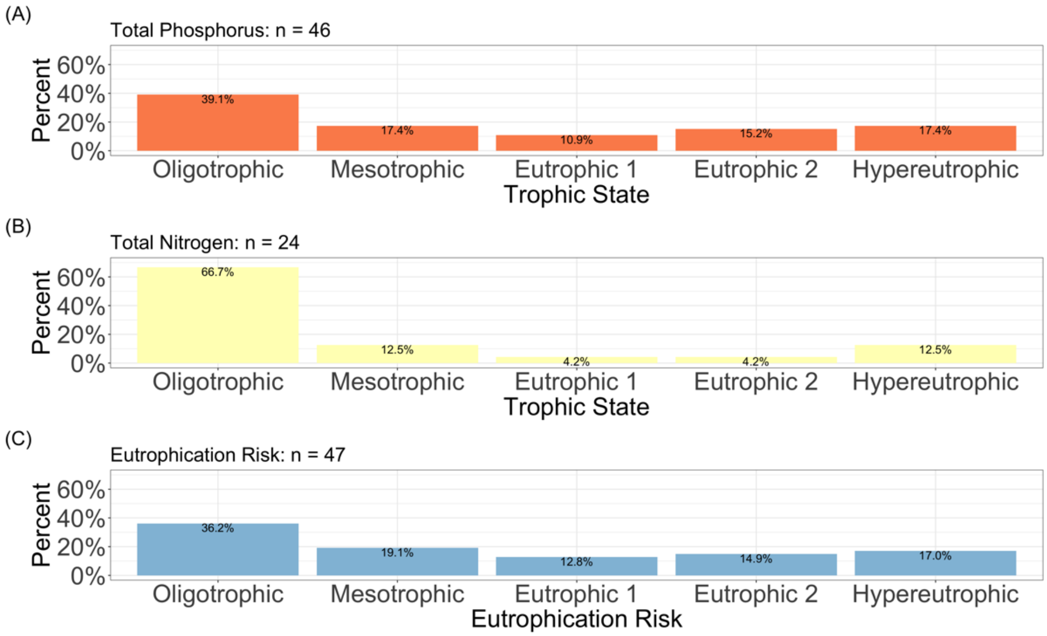

Figure 3. Percentage of lakes with each trophic risk state observed based on total phosphorus (A) and total nitrogen (B) thresholds and measurements. Panel C shows the breakdown of overall risk scores for all lakes with nutrient measurements meeting the assessment inclusion criteria of at least 3 or more observations.

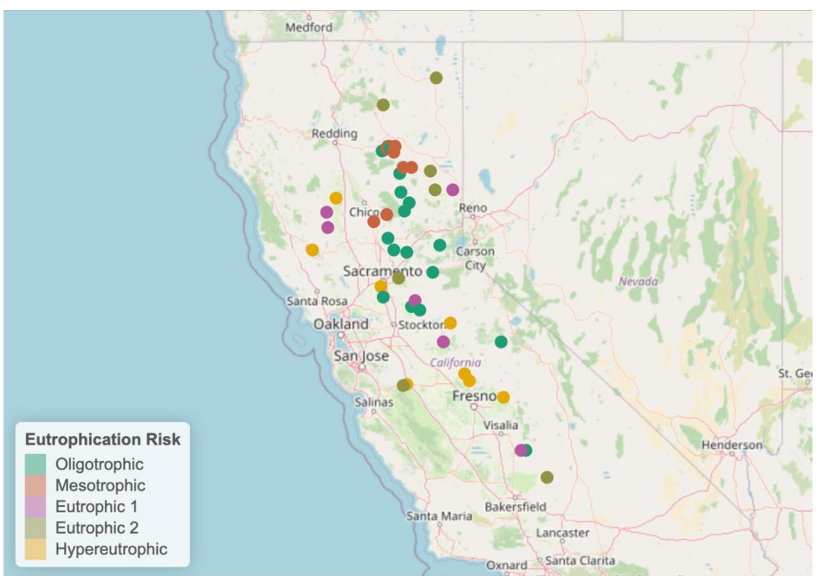

Figure 4. Map of lakes and their overall eutrophication risk levels.

Eutrophication Evidence

A total of 71 lakes met the data inclusion criteria to assess evidence of eutrophication. A total of 30 waterbodies were assessable based on available *in situ* chlorophyll-a measurements. Remotely sensed imagery more than doubled the number of assessable waterbodies by adding 41 additional lakes and reservoirs that did not otherwise have *in situ* chlorophyll-a measurements. (**Figure 5**, **Supplemental Table 2**).

When scoring individually based on chlorophyll-a concentrations, 46.7% of assessed lakes had evidence of eutrophic or hypereutrophic state based on mean chlorophyll-a concentrations of >7.3 μg/L. Of these, a majority had evidence of hypereutrophic conditions with mean chlorophyll-a concentrations exceeding 56 μg/L (**Figure 5A**). A larger proportion of lakes (60%) were scored as being in an oligotrophic or mesotrophic state based on remotely sensed cyano-bloom occurrence, but notably, most of these lakes (89%) did not have paired *in situ* observations (**Figure 5B**). When the individual metrics were combined, a similar split was observed between lakes with evidence for a eutrophic or hypereutrophic state (38%) and lakes with evidence of an oligotrophic or mesotrophic state (62%; **Figure 5C**).

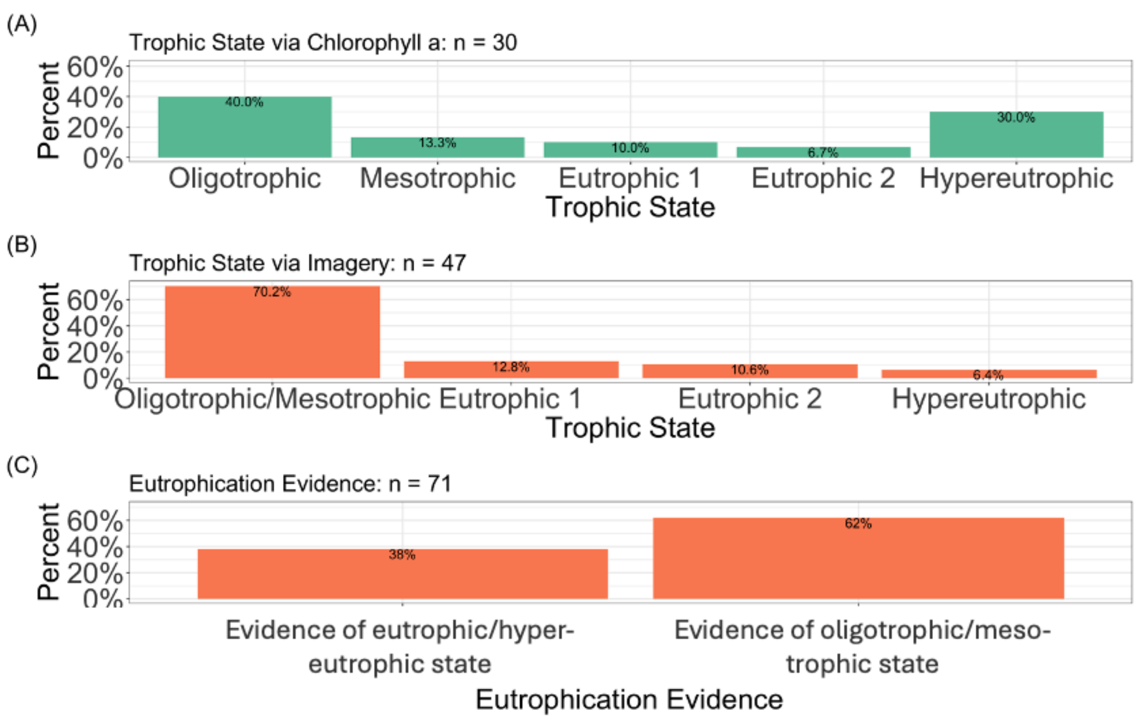

Figure 5. Percentage of lakes with eutrophication evidence indicators. Panel A shows the chlorophyll-a based metric, panel B shows the percentage of lakes in each trophic category derived from remotely sensed imagery data (note that the oligotrophic and mesotrophic categories are combined due to the decreased sensitivity at lower cyanobacterial biomass levels making it difficult to differentiate these categories) and panel C shows the integrated evidence of eutrophication.

Seasonal and Interannual Trends in the Central Valley Region

In situ datasets tend to be limited over time due to the expense of sample collection which limits our ability to assess temporal variations in response to variations in large scale environmental conditions such as climate and seasonality. Remote sensing via satellite imagery allows for a comprehensive temporal trend assessment for larger lakes and reservoirs. We have seven years of routine observations of satellite imagery measuring cyanobacterial biomass which we analyzed to determine the number cyano-bloom occurrences during this timeframe. The analysis revealed clear seasonal and interannual variations in cyano-bloom occurrences across the CV region (**Figure 6**). Cyano-bloom occurrences typically occurred in the summer and fall for most lakes and reservoirs, however many lakes in the CV region also experienced blooms in the winter and spring (**Figure 6A**). Interestingly, cyano-bloom occurrences were the least common during the spring season in the CV region.

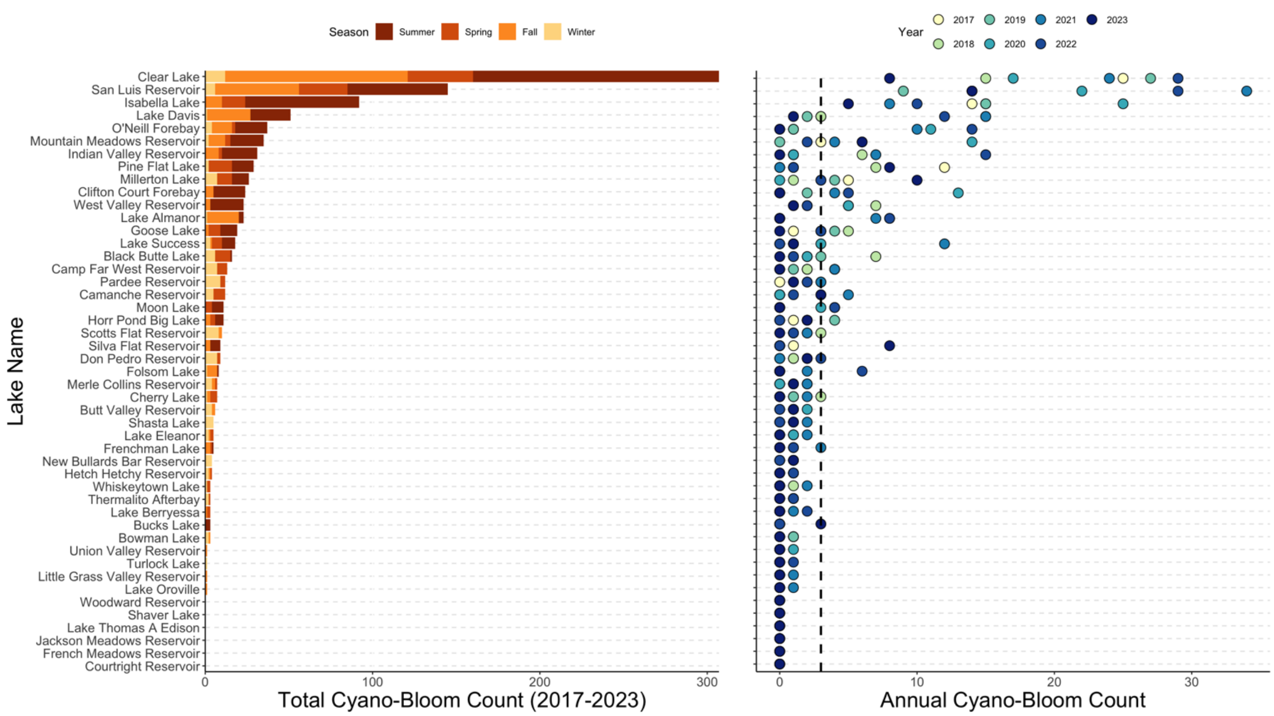

Figure 6. (A) Summary of total annual weekly cyano-bloom occurrence counts at the 7 µg/L cyanobacterial chl-a intensity between 2017-2023 from remote sensing imagery observations, colored by season. The season during which blooms were detected throughout the year are indicated in the legend. (B) Annual total count of cyano-blooms per year for each lake plotted by year between 2017-2023, which each point colored by year. The black dashed line (n=3) indicates the number of weeks used within the assessment framework to identify a given lake as eutrophic. Lakes with a minimum of 3 years with 3 blooms were identified as eutrophic 1 or greater.

Some lakes and reservoirs, such as Clear Lake and San Luis Reservoir, experienced multiple years with 20 or more weeks with cyano-blooms (**Table 2**, **Figure 6B**), indicating a chronic issue with cyanobacterial blooms. Most lakes and reservoirs, however, demonstrated clear interannual variability in the number of cyano-bloom occurrence detected each year. When looking at the broader regional patters in cyano-bloom occurrence, we can see that the within lake variation in cyano-blooms often matches a broader regional trend in the weekly counts of cyano-blooms in the region (**Figure 7**). Precipitation patterns may be one important factor in interannual differences in biomass accumulation. In our time series of annual cyano-bloom occurrences, we observed that median cyano-bloom occurrences were generally higher in drier years than in wetter years across the region (**Figure 8**). For example, the years 2017 and 2023 (wet years) both show lower weekly counts of cyano-bloom occurrences for a majority of the year when compared to the seven-year average count of blooms for the region (e.g., the colored lines in the 2017 and 2023 panels both fall below the black line denoting the long-term average for the region). Similarly, 2021 and 2022 (critically dry years) show routinely higher counts of weekly cyano-bloom occurrences for the region (**Figure 7, Figure 8**).

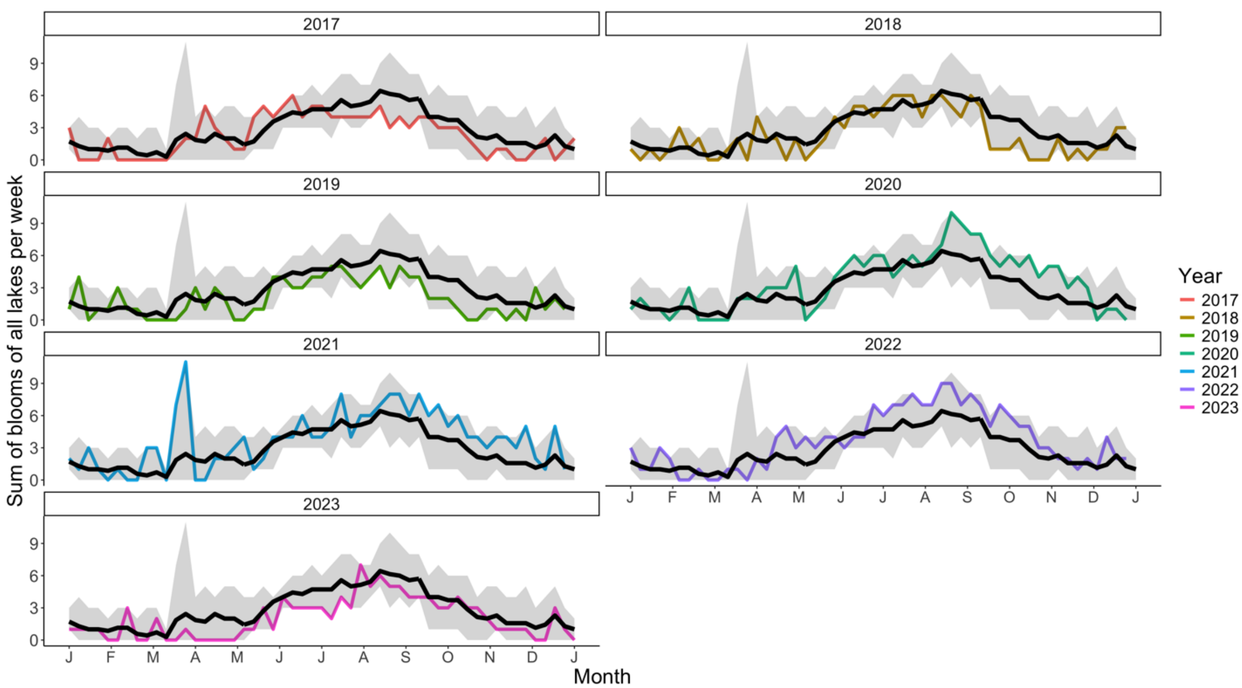

Figure 7. Annual time series of weekly cyano-bloom occurrences at the 7 µg/L cyanobacterial chl-a intensity detected via satellite remote sensing across the Central Valley. The colored line in each panel shows the count of blooms in all resolvable lakes each week for that specific year. The black solid line is the average number of blooms per week across all seven years, providing a 'typical' bloom climatology for the resolvable lakes in the region. The grey intervals show the maximum and minimum weekly count of cyano-blooms observed between 2017 and 2023.

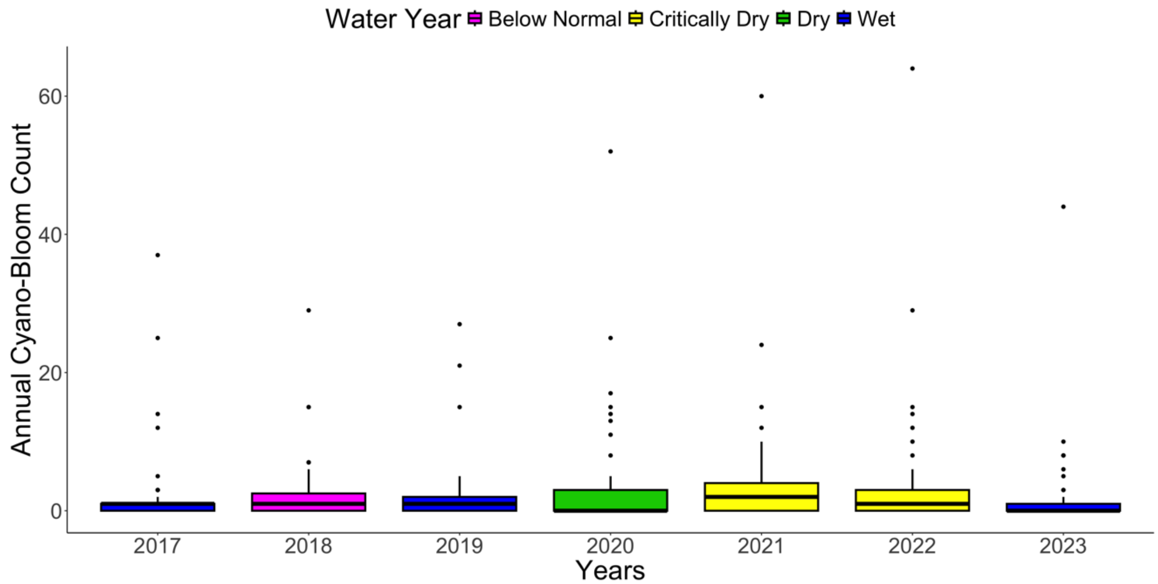

Figure 8. Box plot of average weekly cyano-bloom occurrence counts at the 7 µg/L cyanobacterial chl-a intensity by year for each lake assessed by satellite imagery. Boxes are colored based on the Water Year Hydrologic Classification Indices for the Sacramento and San Joaquin Valley conducted by the California Department of Water Resources to indicate if the year was designated as a wet water year (wet, indicated in purple), below normal water year (below normal, indicated with red), dry water year (dry, indicated with aqua) or critically dry water year (critically dry, indicated with green) based on the historical climate of the region.

Spatial Characteristics and Representativeness of Assessment

Land Use

Despite only having sufficient data to assess a small percentage (~2%) of the CV region's estimated 4490 lakes and reservoirs, the ecoregional distribution and land use characteristics of the assessed waterbodies were generally representative of the larger lake and reservoir population (**Table 5, Supplemental Table 2**). A majority of the region's lakes and reservoirs were located within the mountain ecoregion grouping (80%), and a much smaller percentage were located within the valley ecoregion (20%). The spatial distribution of assessed lakes and reservoirs mimicked the overall regional pattern with 87.2% of assessed lakes located in the mountain ecoregional group and 12.8% located in the valley ecoregion. As expected, our analysis showed that major land uses within the HUC12 watersheds of the total inventory of lakes and reservoirs were distinctive between the mountain and valley ecoregion groups, thus comparisons between watershed land uses were conducted by ecoregional group.

Undeveloped land uses were the most dominant category of the mountain ecoregion grouping, while agricultural uses were the most dominant land uses in the valley ecoregion (**Supplemental Table 3**). Within the mountain ecoregion grouping, similar percentages undeveloped land uses were observed with overlapping standard deviations. Similar overlapping standard deviations were observed for agricultural and developed land uses, but these land uses are a much smaller proportion of the overall land used within lake and reservoir watersheds of the mountain ecoregion group (**Table 5**). A larger difference between watershed land uses of total inventory and the assessed waterbodies were observed in the valley ecoregion for agricultural and undeveloped land uses, but ultimately standard deviations overlapped. Mean developed land use percentages within the valley ecoregion, however, were relatively similar (**Table 5**).

Table 5. Data count and mean watershed land use percentages from the total inventory of Central Valley lakes and reservoirs and of assessed lakes and reservoirs separated by ecoregion groups.

Analysis	**Total Inventory**	**Assessed Waterbodies**
Waterbodies in Mountain Ecoregion group (*n*)	3594	76
Agricultural Watershed Area in Mountain Ecoregion Group (Mean % ± Standard Deviation)	3.8±6.0	1.6±3.8
Developed Watershed Area in Mountain Ecoregion Group (Mean % ± Standard Deviation)	1.5±1.2	2.8±3.9
Undeveloped Watershed Area in Mountain Ecoregion Group (Mean % ± Standard Deviation)	74.4±36.8	88.9±15.8
Waterbodies in Valley Ecoregion (*n*)	895	10
Agricultural Watershed Area in Valley Ecoregion Group (Mean % ± Standard Deviation)	49.5±26.1	24.0±25.5
Developed Watershed Area in Valley Ecoregion Group (Mean % ± Standard Deviation)	16.5±12.5	21.6±28.6
Undeveloped Watershed Area in Valley Ecoregion Group (Mean % ± Standard Deviation)	27.6±22.1	48.2±27.9

Given the similarities of the assessed waterbodies to the larger population of lakes and reservoirs in the CV region, we investigated if there were significant differences in watershed land use class percentages between lakes based on their eutrophication risk and eutrophication evidence status. Overall, however, significant differences were not observed for either assessment component in either ecoregion for any land use category for pairwise comparisons, with most p-values indicating non-significant results (**Table 6**).

Table 6. Wilcoxon test results comparing eutrophication risk with no eutrophication risk and evidence of a eutrophic/hypereutrophic state with evidence of an oligotrophic/mesotrophic state for the different land use categories and ecoregions.

Ecoregion Group	Land Use Category	Comparison	p-value
Mountain	Ag	Eutrophication Risk Status	1
Valley	Ag	Eutrophication Risk Status	0.229
Mountain	Developed	Eutrophication Risk Status	0.218
Valley	Developed	Eutrophication Risk Status	0.786
Mountain	Undeveloped	Eutrophication Risk Status	0.119
Valley	Undeveloped	Eutrophication Risk Status	1
Mountain	Ag	Eutrophication Evidence Status	0.520
Valley	Ag	Eutrophication Evidence Status	0.400
Mountain	Developed	Eutrophication Evidence Status	0.038
Valley	Developed	Eutrophication Evidence Status	1
Mountain	Undeveloped	Eutrophication Evidence Status	0.063
Valley	Undeveloped	Eutrophication Evidence Status	0.571

Distribution of Assessed Lake Across Disadvantaged Communities

Numerous disadvantaged communities are located within the CV region (**Figure 9, Supplemental Table 2**) and of the assessed lakes and reservoirs, 60.4% of those assessed for eutrophication risk and 50.7% of those assessed for eutrophication evidence were located within these communities. Our assessment, though numerically limited, showed that of the waterbodies ranked as experiencing eutrophication risk (**Table 7, Supplemental Figure 3**), a slightly larger percentage of these waterbodies are located within a disadvantaged community (52.2%) than in non-disadvantaged communities (47.8%). Similarly, a larger percentage of waterbodies ranked as having evidence of eutrophication (**Table 7, Supplemental Table 2**) are also located with disadvantaged communities (61.8%) than in non-disadvantaged communities (38.2%). Given the overall small sample size, however, it is difficult to determine if these results are broadly applicable.

Table 7. Count of lakes in disadvantaged communities based on the trophic risk and eutrophication evidence. The presence of an assessed waterbody in a DAC was determined based on if the lake or reservoir was located directly within the geographic area designated as a DAC. Note that lakes and reservoirs assessed for eutrophication risk do not fully overlap with those assessed for eutrophication evidence.

Assessment Status	Count of waterbodies within a disadvantaged community (*n*)	Count of waterbodies outside a disadvantaged community (*n*)
Eutrophication risk observed	13	8
Eutrophication risk not observed	16	10
Insufficient data to assess eutrophication risk	15	24
Evidence of eutrophic/hypereutrophic state	17	10
Evidence of oligotrophic/mesotrophic state	18	26
Insufficient data to assess eutrophication evidence	9	6

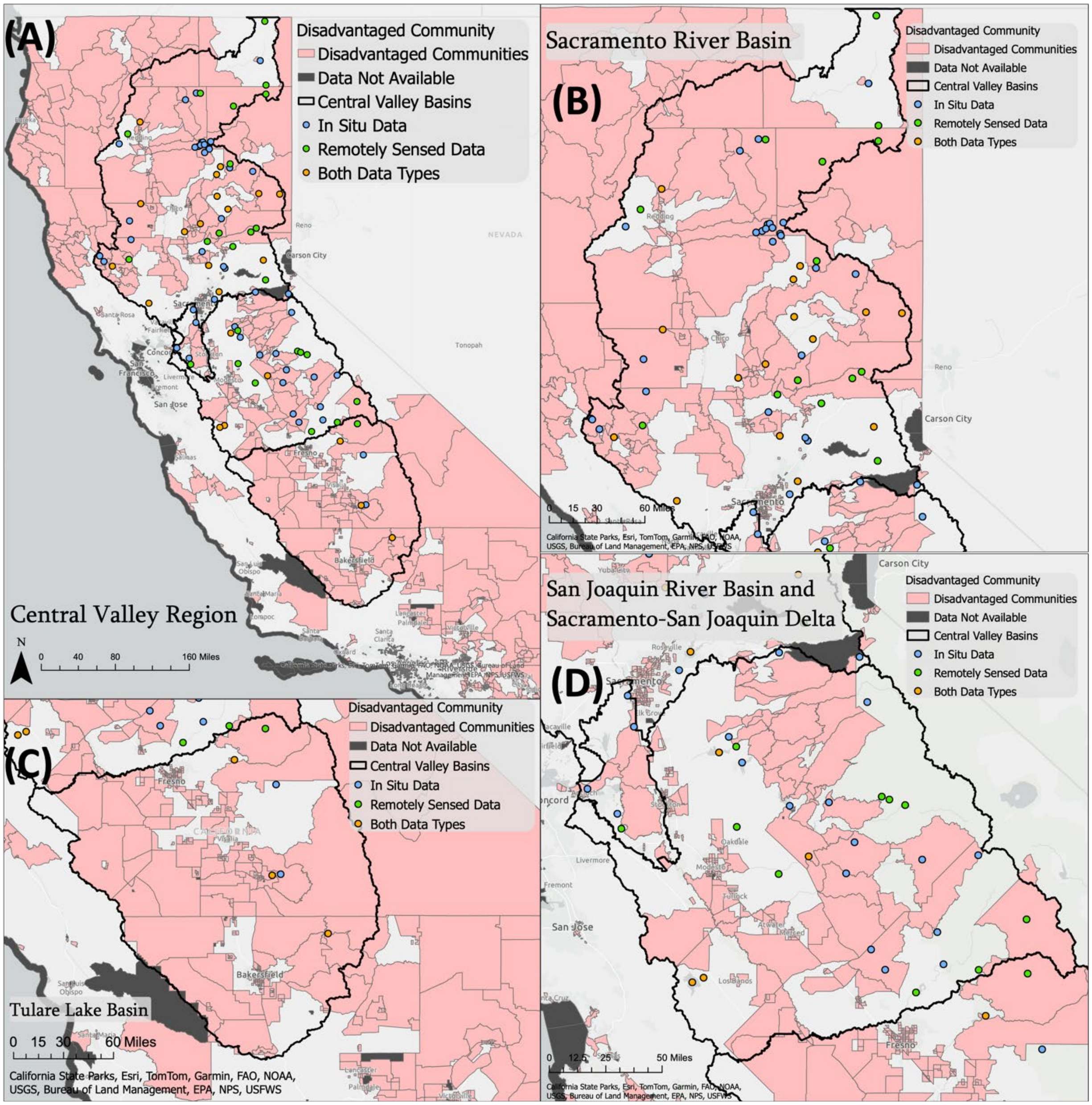

Figure 9. Map of disadvantaged communities and the 86 assessed lakes and reservoirs within the Central Valley region. Panel A shows a synoptic view of the entire region outlined in with a dark black line, Panel B shows a zoomed view of the Sacramento River Basin subregion, Panel C shows a zoomed view of the Tulare Lake Basin subregion, and Panel D shows a zoomed in view of the San Joaquin River Basin and the Sacramento-San Joaquin Delta. Shaded areas with grey outlines are individual census tract areas and are colored based on light pink if the track is identified as a disadvantaged community, light grey if not identified as a disadvantaged community and dark grey if data is not available for that tract. Points indicate locations of the assessed lakes and the point colors are based on the data sources available to conduct the assessment.

Discussion

This study adapted and applied a framework, based on a combination field and remote sensing data, to create the first regional assessment of eutrophication in California's CV Region. The framework utilized an innovative combination of remote sensing and *in situ* field data to assessment both the evidence of eutrophication (based on algal biomass) and risk of eutrophication based on TN and TP. About 40% of the lakes and reservoirs for which data were available were found to have evidence of eutrophication, with some ranging up to hypertrophy. Slightly higher numbers had evidence of eutrophication, based on thresholds for TN and TP. A proportion of waterbodies at risk for or experiencing evidence of eutrophication were in disadvantaged communities. However, our sample size was small and more observations would be needed for this analysis to be robust. However, it does point to the utility of this eutrophication assessment framework to help prioritize monitoring effort and management support actions in the future.

Forty Percent of Central Valley Lakes and Reservoirs Show Evidence or Risk of Eutrophication

In this study, we gathered sufficient data to evaluate 86 lakes and reservoirs in the CV region. Of these, 47 lakes met the criteria for assessing eutrophication risk, while 71 qualified for an evaluation of eutrophication evidence. The results revealed a slightly lower percentage of lakes were at risk of eutrophication (44.7%), while 55.3% fell below the risk threshold. Similarly, 38% of the lakes showed biomass-based evidence of waterbodies experiencing a eutrophic or hypereutrophic state, while 62% showed no such evidence. The results indicate that eutrophication is prevalent in many water bodies, with observable impacts on water quality and ecosystem health. This underscores the need for proactive monitoring and mitigation efforts, where the framework can serve as a valuable tool for guiding decision-making and policy development.

A variety of factors that vary on seasonal, annual, or multiannual timescales contribute to excessive biomass accumulation. These factors are multiple and include variations in the nutrient levels within individual lakes and reservoirs due to shifts in internal and external nutrient loading dynamics, changes to the biological communities within lakes, or changes in climate such as temperature regimes or precipitation patterns (Lau et al. 2002, Liu et al. 2010, Jones and Brett 2014). The region has previously been reported to experience public reports of algal blooms throughout the calendar year (Jang and Otim 2023), however our analysis shows that while this is true in some lakes, blooms in the region most typically occur during the summer and fall. Our findings mirror the typical bloom phenology observed in many other studies (Coffer et al. 2020, Jang and Otim 2023). This is an important consideration for any future sampling efforts, as the timing of sample collection may predispose the dataset to either see higher or lower instances of high algal biomass depending on the timing selected for sampling. As currently applied, our framework considers data collected throughout the annual cycle, however this decision was made to maximize the number of waterbodies we could assess. This does risk the underestimation or overestimation of potential biomass accumulation observed depending on when samples were collected and if they were all collected in a single season. We attempted to offset this effect through averaging at least three observations of biomass from a waterbody to understand the central tendency of the data, however we also did not consider the timing of sample collection. It might be appropriate to limit the temporal scope of data included in the assessment in the future depending on the nature of future data collection efforts.

One important factor that modulates biomass accumulation in lakes and reservoirs is changes in precipitation and the cascade of impacts this may have on biomass accumulation dynamics within an individual waterbody (Ho and Michalak 2020). In our study, we found evidence that cyanobacterial blooms, as detected by satellite remote sensing, were more frequent and occurred in more waterbodies during drier years than in wetter years. Cyanobacterial blooms may be more frequent and intense in years with low precipitation due to reduced water inflow, longer water residence times, and increased water temperature (Paerl and Otten 2013). Lower precipitation leads to decreased flushing of lakes and reservoirs, allowing nutrients to accumulate and remain available for cyanobacterial growth. Additionally, reduced cloud cover and higher solar radiation in dry years can enhance water column stratification, creating stable, warm surface layers that favor cyanobacterial dominance (Paerl and Huisman 2009; O'Neil et al. 2012). In contrast, years with high precipitation typically experience increased water exchange, dilution of nutrients, and stronger mixing, which can disrupt stratification and limit conditions favorable for bloom formation. The duration of our timeseries is somewhat limited (seven years) and not currently able to fully resolve the influence of these factors on biomass accumulation within the CV, but this analysis points to the importance of considering how multiple factors influence biomass accumulation. It also points to the value of collecting repeated observations over time to ensure that the eutrophication assessment is not heavily influenced by years with higher or lower than typical cyano-bloom counts.

The CV region is large and encompasses a range of ecoregions and land uses. These landscape level characteristics are an important factor in modulating eutrophication and also might be predictive of where waterbodies might be at an increased risk of eutrophication related impacts. Based on our analysis, the waterbodies we were able to assess, albeit limited, were located in watersheds with land use characteristics that were similar to the large lake and reservoir population. Watershed level characteristics have previously been modeled and were able to successfully predict the eutrophication status of thousands of unsampled lakes throughout the continental United States (Hill et al. 2018). Given the large number of lakes and reservoirs in the CV, we attempted to derive similar risk-based predictive relationships based on our assessment data since this would provide a valuable tool for guiding future sampling efforts. Unfortunately, our dataset was not robust enough to develop regionally specific relationships of this nature. To move towards this ability, future sampling efforts should strategically consider the ecoregions and land use characteristics when selecting which lakes and reservoirs to target for sample collection.

We attempted to understand if eutrophication disproportionately impacted the disadvantaged communities within the CV region. Our high-level analysis suggested that a larger proportion of waterbodies at risk for or experiencing evidence of eutrophication were in disadvantaged communities. However, our sample size was small and more observations would be needed for this analysis to be robust. Additionally, more work is needed to understand the specific impact pathways of eutrophication that are meaningful to these communities and the appropriate mitigation approaches (Fernandez-Bou et al. 2021).

Eutrophication Assessment as a Decision Support Tool for Prioritizing Monitoring

The eutrophication assessment framework utilized in this study represents an important advance in an important advancement in understanding and managing eutrophication in the CV region. Rather than creating a new framework, we reviewed and adapted existing approaches based on their suitability for this non-regulatory application. This process ensured that the framework remains grounded in established methodologies while being tailored to provide practical and actionable insights. Designed to be broadly applicable, the framework can be used in other regions to assess eutrophication risk and inform management decisions. In the CV region, it serves as a foundational tool for future assessments, with the potential to be refined as additional data become available. By synthesizing complex ecological data into an accessible format, the framework offers a clear indication of eutrophication risk, which can directly inform lake and reservoir management strategies.

Scientific Data Gaps and Management Recommendations

Our assessment did not have a comprehensive enough dataset to conduct statistical analyses to conclusively determine if there are statistically significant relationships between eutrophication and land use or if disadvantaged communities are disproportionally impacted by eutrophication. Strategic collection of data is needed to more quantitively address these questions including strategic collection of data from within lakes and reservoirs within different ecoregions, with diverse watershed land uses and from within and outside of disadvantaged communities. These analyses are important to support strategic monitoring and risk management in the future.

We highlighted that seasonal and interannual variations in biomass accumulation are present in many lakes across the region. This is clearly observed though the variations in the number of cyano-bloom occurrences via remote sensing between 2017-2023 (Figure 6B). This dynamic has also been observed *in situ* in routinely sampled lakes in the Central Valley (Huie et al, *in prep*) and in lakes in the Los Angeles area (Smith et al. 2023b). The factors driving this variation are multiple and include large scale dynamics such as regional precipitation factors. These factors almost certainly influence assessment results, particularly when looking at biomass accumulation indicators. Future studies and data collection efforts should carefully consider the timing and frequency of observations as well as the larger environmental factors such as climatology and precipitation. Special studies should also be considered to untangle the effects of large-scale drivers like precipitation and climate on the eutrophication status of the region's lakes and reservoirs.

Table 8. Sensitivity comparison of trophic state assignments based on eutrophication risk nutrient indicators and eutrophication evidence biomass indicators for the 32 lakes and reservoirs where data were available for each type of assessment.

		Eutrophication Evidence			
		Oligotrophic/Mesotrophic	Eutrophic 1	Eutrophic 2	Hyper-eutrophic
Eutrophication Risk	Oligotrophic/ Mesotrophic	9	2	0	7
	Eutrophic 1	3	0		
	Eutrophic 2	1	0	1	2
	Hyper-eutrophic	1	0	4	2

A total of 32 were able to be assessed using all the indicators we selected in our framework (**Table 8**). We saw general agreement amongst assessment results where multiple indicators were available within the same waterbody (agreement for 18 or 56.3% of waterbodies with multiple indicators). A total of 12 (37.5%) waterbodies had full agreement between the risk and evidence indicators and 6 (18.8%) of waterbodies both placing a waterbody into a eutrophic or hypereutrophic category. A mismatch was observed in 5 (15.6%) waterbodies where risk indicators suggested the waterbody was in an oligotrophic/mesotrophic state and evidence indicators indicated a eutrophic 1 status, or vice versa. Larger mismatches where one component of the assessment suggested an oligotrophic/mesotrophic state and the other suggested a state of eutrophic 2 or hypereutrophic occurred in 9 (28.1%) waterbodies. Overall, the instances of multiple data types from the same waterbody were rare enough that we were not able to fully understand the cross comparability of indicators or the relationship between waterbodies ranked with eutrophication risk and eutrophication evidence. The reasons for the observed mismatches could be multiple and include that we did not have a strict requirement that all observations be co-located in time or space. Thus, observations of risk and evidence indicators could be significantly staggered in time and/or space within a given waterbody. Future efforts should focus on co-locating nutrient and biomass measures temporally and spatially to better understand cross comparability of indicators.

Overall, standardized operating procedures for combined harmful algal bloom and eutrophication assessments are needed for lakes and reservoirs to generate the datasets that allow for more robust assessments in the future. Additionally, integration of satellite remote sensing technologies into future assessment efforts should also be prioritized as they show great promise in supporting broader assessment than would otherwise be possible with *in situ* sampling efforts alone.

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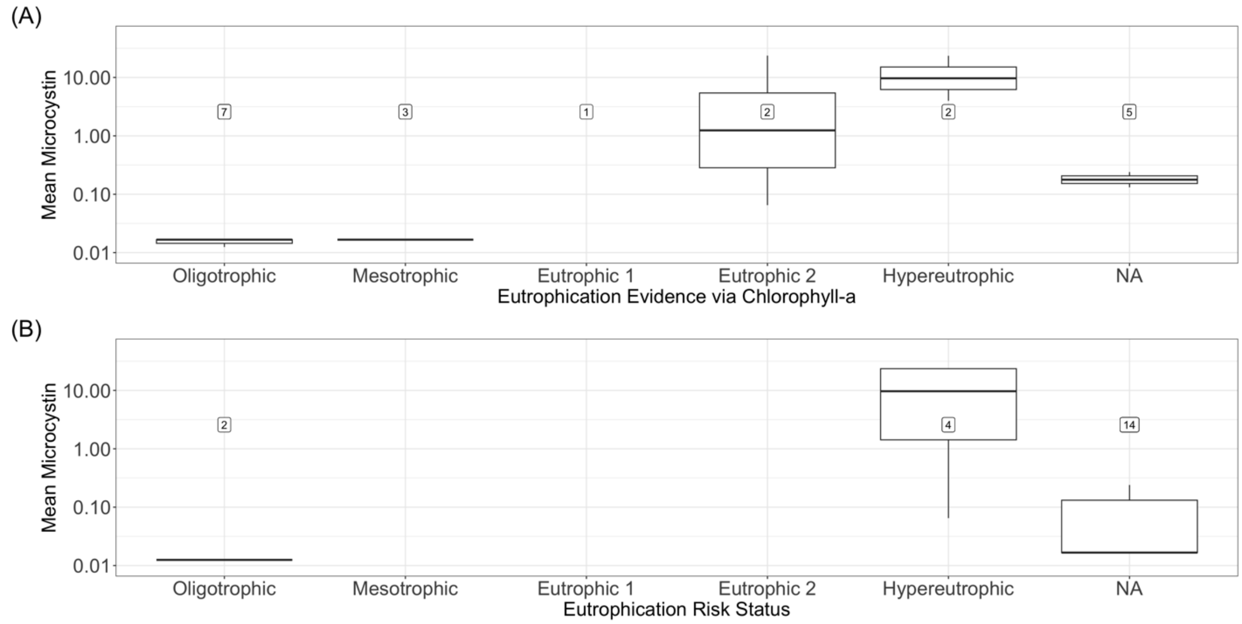
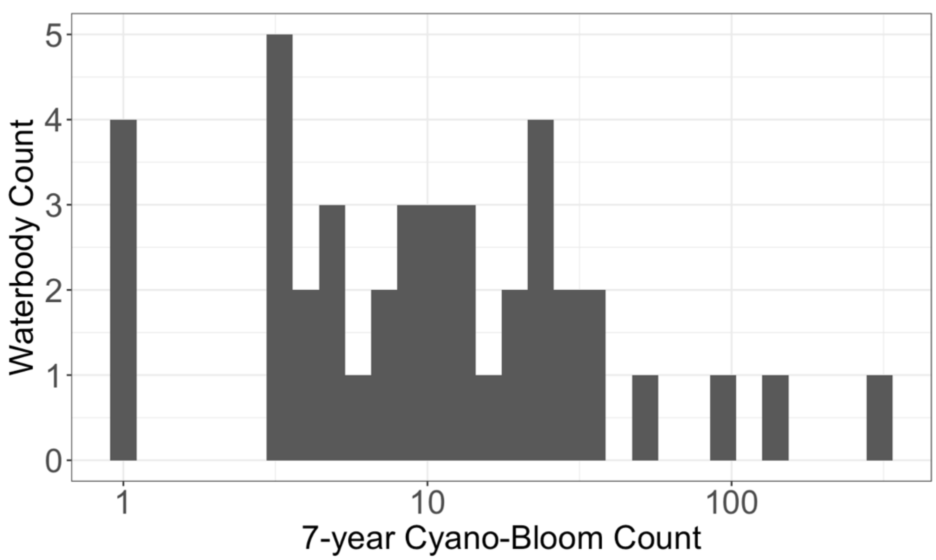
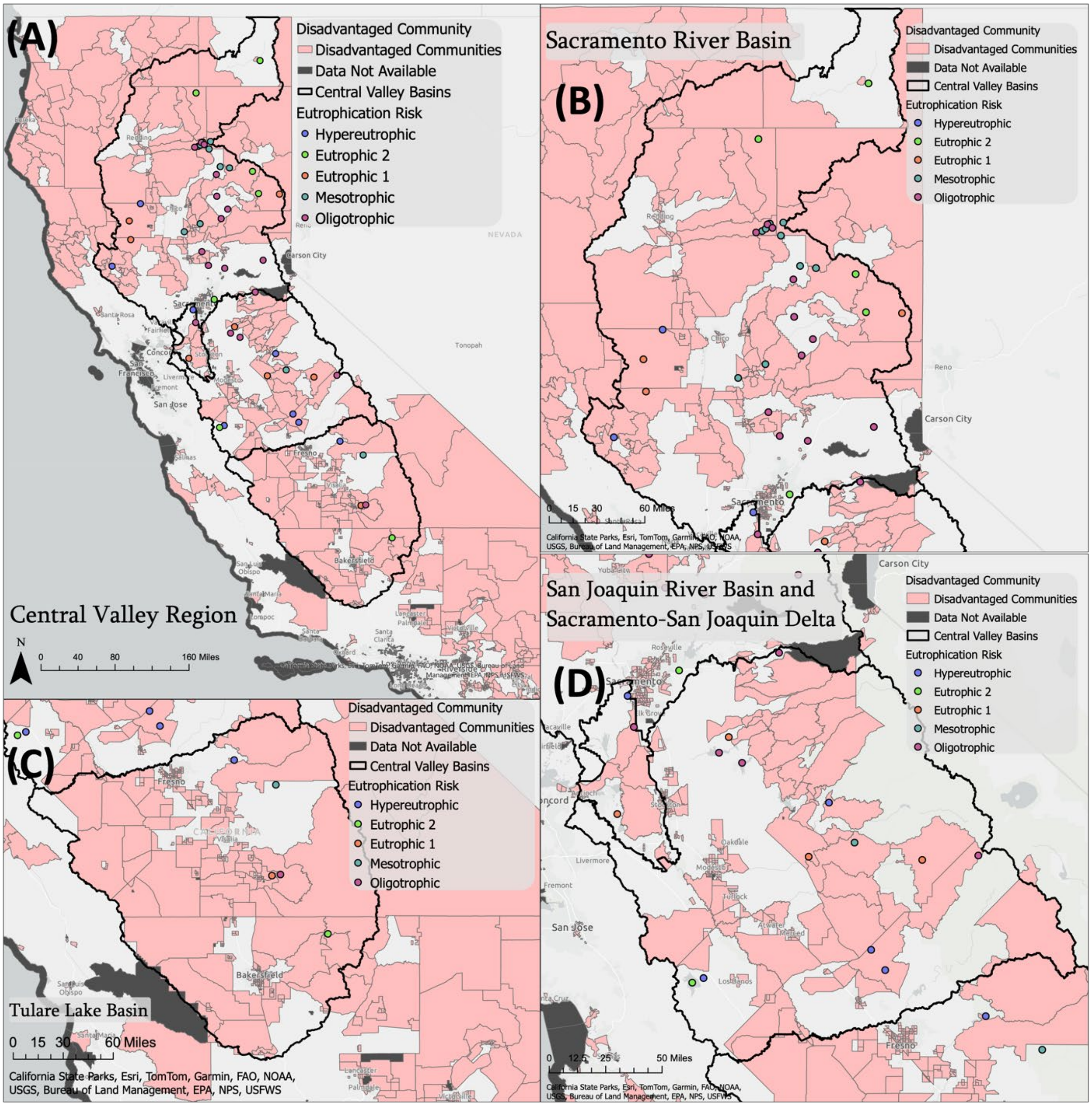
Appendix A. Supplementary Materials



Supplemental Figure 1. Box plot of comparison of mean microcystins concentrations (µg/L) for a given lake to the corresponding (A) *in situ* chlorophyll-a based evidence status and (B) eutrophication risk status. The NA box represents lakes or reservoirs for which total microcystin observations were available but data to assess trophic status were not.



Supplemental Figure 2. Histogram of the count cyano-bloom occurrences between 2017-2023 at the 7 µg/L cyanobacterial chl-a intensity in resolvable lakes based on remotely sensed imagery data.



Supplemental Figure 3. Map of disadvantaged communities and the 48 lakes and reservoirs assessed for eutrophication risk within the Central Valley region. Panel A shows a synoptic view of the entire region outlined in with a dark black line, Panel B shows a zoomed view of the Sacramento River Basin subregion, Panel C shows a zoomed view of the Tulare Lake Basin subregion, and Panel D shows a zoomed in view of the San Joaquin River Basin and the Sacramento-San Joaquin Delta. Shaded areas with grey outlines are individual census tract areas and are colored based on light pink if the track is identified as a disadvantaged community, light grey if not identified as a disadvantaged community and dark grey if data is not available for that tract. Points indicate locations of the assessed lakes, and the point colors are based on the eutrophication risk status of that lake.

Supplemental Table 1. Summary of data analysis methods for each *in situ* parameter included in the assessment framework. Table includes the parameters, the reporting agency(s), and the methods used to collect the data. Analysis methods were reported according to the available agency metadata. In some cases, observations were reported as unknown methods (generally less than 8% of observations). All observations were derived from water grab samples. Data source abbreviations indicate U.S. Geological Survey (USGS), Department of Water Resources (DWR), National Park Service Water Resources Division (NPSWRD), California State Water Boards (CWBs), Aquatic Pesticide Monitoring Program (APMP), Big Valley Rancheria EPA (BVR), Hensley and Eastman HABs Study (HEHAB), National Lakes Assessment (NLA), Tuolumne Band of Me-Wuk Indians Monitoring (TMTC), U.S. Army Corps of Engineers (USACE), and U.S. Forest Services (USFS).

Assessment Element	Parameter	Reporting Agencies	Analysis Methods
Eutrophication Evidence	Chlorophyll-a	APMP, CWBs, DWR, HEHAB, NLA, NPSWRD, USGS	EPA 445.0, SM 10200 H, SM 10200 Hb, Unspecified fluorometric
Eutrophication Risk	Total Nitrogen	APMP, CWBs, HEHAB, NLA, NPSWRD, TMTC, USFS, USGS	SM 4500 NO3 and SM 4500 with modifications, QC 10107062E, Unknown
Eutrophication Risk	Total Phosphorus	APMP, BVR, CWBs, DWR, HEHAB, NLA, NPSWRD, TMTC, USACE, USFS, USGS	EPA 365.1 with modifications, EPA 365.3 and 365.3 with modifications , EPA 365.4 and 365.4 with modifications, SM 4500-P E, QC 10115011D, Unknown
Eutrophication Impact	Total Microcystins	BVR, CWBs, HEHAB, NLA	ELISA, LC-MS

Supplemental Table 2: Summary of all assessable lakes showing what data types were available, the eutrophication risk status, and eutrophication evidence status.

Lake Name	Lat	Long	Chl-a	TP	TN	Remote Sensing	Eutro Risk	Eutro Evidence	DAC20
Alder Creek	38.636	-121.206	NA	X	NA	NA	Eutrophic 2	NA	N
Antelope Lake	40.180	-120.607	X	X	NA	NA	Eutrophic 2	Oligo/Meso	Y
Bass Lake	37.313	-119.551	X	NA	NA	NA	NA	Oligo/Meso	N
Black Butte Lake	39.794	-122.358	NA	X	NA	X	Hypereutrophic	Oligo/Meso	Y
Bowman Lake	39.452	-120.636	NA	NA	NA	X	NA	Oligo/Meso	Y
Bucks Lake	39.882	-121.165	NA	X	NA	X	Oligotrophic	Oligo/Meso	N
Butt Valley Reservoir	40.143	-121.172	NA	X	NA	X	Oligotrophic	Oligo/Meso	N
Camanche Reservoir	38.223	-120.950	NA	X	X	X	Oligotrophic	Oligo/Meso	N
Camp Far West Reservoir	39.048	-121.295	X	X	X	X	Oligotrophic	Oligo/Meso	Y
Cherry Lake	38.001	-119.907	NA	NA	NA	X	NA	Oligo/Meso	N
Clear Lake	39.039	-122.800	X	X	NA	X	Hypereutrophic	Hypereutrophic	N
Cliff Lake	40.477	-121.455	X	X	X	NA	Mesotrophic	Hypereutrophic	Y
Clifton Court Forebay	37.838	-121.576	NA	NA	NA	X	NA	Eutrophic 1	N
Costa Ponds	36.087	-118.839	NA	NA	X	NA	Oligotrophic	NA	Y
Courtright Reservoir	37.102	-118.972	NA	NA	NA	X	NA	Oligo/Meso	Y
Crystal Lake	40.459	-121.291	X	NA	NA	NA	NA	Oligo/Meso	Y
Don Pedro Reservoir	37.698	-120.375	NA	X	X	X	Eutrophic 1	Oligo/Meso	Y
Dorris Reservoir	41.488	-120.490	NA	X	NA	NA	Eutrophic 2	NA	N
East Park Reservoir	39.361	-122.509	NA	X	NA	NA	Eutrophic 1	NA	Y
Eastman Lake	41.108	-121.489	NA	X	NA	NA	Eutrophic 2	NA	Y
Folsom Lake	38.728	-121.133	X	NA	NA	X	NA	Oligo/Meso	N
French Meadows Reservoir	39.112	-120.442	X	X	X	X	Oligotrophic	Oligo/Meso	N
Frenchman Lake	39.908	-120.186	NA	X	NA	X	Eutrophic 1	Oligo/Meso	Y

Lake Name	Lat	Long	Chl-a	TP	TN	Remote Sensing	Eutro Risk	Eutro Evidence	DAC20
Goose Lake	41.947	-120.419	NA	NA	NA	X	NA	Eutrophic 1	N
H. V. Eastman Lake	37.225	-119.975	X	X	X	NA	Hypereutrophic	Hypereutrophic	Y
Hensley Lake	37.121	-119.885	X	X	X	NA	Hypereutrophic	Eutrophic 2	Y
Hetch Hetchy Reservoir	37.958	-119.757	NA	NA	NA	X	NA	Oligo/Meso	N
Homer Lake	40.221	-120.967	NA	X	X	NA	Mesotrophic	NA	Y
Horr Pond Big Lake	41.106	-121.425	NA	NA	NA	X	NA	Oligo/Meso	Y
Indian Valley Reservoir	39.122	-122.540	NA	NA	NA	X	NA	Eutrophic 2	Y
Isabella Lake	35.670	-118.427	NA	X	NA	X	Eutrophic 2	Hypereutrophic	Y
Jackson Meadows Reservoir	39.499	-120.552	NA	NA	NA	X	NA	Oligo/Meso	Y
Jenkinson Lake	38.724	-120.565	NA	X	X	NA	Oligotrophic	NA	N
Kerckhoff Lake	37.149	-119.511	X	NA	NA	NA	NA	Oligo/Meso	N
Lake Almanor	40.236	-121.111	NA	X	NA	X	Mesotrophic	Eutrophic 1	N
Lake Alpine	38.476	-120.000	X	NA	NA	NA	NA	Oligo/Meso	N
Lake Amador	38.302	-120.887	NA	X	X	NA	Eutrophic 1	NA	N
Lake Berryessa	38.589	-122.230	NA	NA	NA	X	NA	Oligo/Meso	N
Lake Combie	39.014	-121.041	X	X	X	NA	Oligotrophic	Oligo/Meso	N
Lake Davis	39.915	-120.513	NA	X	NA	X	Eutrophic 2	Eutrophic 2	Y
Lake Eleanor	37.986	-119.858	NA	NA	NA	X	NA	Oligo/Meso	N
Lake Greenhaven	38.508	-121.535	X	X	X	NA	Hypereutrophic	Eutrophic 2	N
Lake Helen	40.467	-121.510	X	X	X	NA	Oligotrophic	Hypereutrophic	Y
Lake McClure	37.612	-120.135	X	NA	NA	NA	NA	Oligo/Meso	Y
Lake near Tuolumne Meadows	37.704	-119.289	NA	X	NA	NA	Oligotrophic	NA	Y
Lake of the Pines	39.036	-121.063	X	NA	NA	NA	NA	Oligo/Meso	N
Lake Oroville	39.552	-121.425	NA	X	NA	X	Mesotrophic	Oligo/Meso	Y
Lake Success	36.079	-118.913	NA	X	NA	X	Eutrophic 1	Oligo/Meso	Y

Lake Name	Lat	Long	Chl-a	TP	TN	Remote Sensing	Eutro Risk	Eutro Evidence	DAC20
Lake Thomas A Edison	37.378	-118.979	NA	NA	NA	X	NA	Oligo/Meso	Y
Little Bear Lake	40.523	-121.406	X	X	X	NA	Oligotrophic	Hypereutrophic	Y
Little Grass Valley Reservoir	39.727	-120.995	NA	X	NA	X	Oligotrophic	Oligo/Meso	N
Merle Collins Reservoir	39.339	-121.317	NA	NA	NA	X	NA	Oligo/Meso	N
Millerton Lake	37.005	-119.687	NA	NA	NA	X	NA	Eutrophic 1	N
Moon Lake	41.095	-120.401	NA	NA	NA	X	NA	Eutrophic 1	Y
Mountain Meadows Reservoir	40.270	-120.961	NA	NA	NA	X	NA	Eutrophic 1	Y
New Bullards Bar Reservoir	39.439	-121.132	NA	NA	NA	X	NA	Oligo/Meso	Y
New Hogan Lake	38.172	-120.802	NA	X	X	NA	Oligotrophic	NA	N
New Melones Lake	37.954	-120.497	X	NA	NA	NA	NA	Oligo/Meso	N
O'Neill Forebay	37.081	-121.049	X	X	NA	X	Hypereutrophic	Eutrophic 2	N
Pardee Reservoir	38.253	-120.839	NA	NA	NA	X	NA	Oligo/Meso	N
Pine Flat Lake	36.886	-119.241	NA	X	NA	X	Hypereutrophic	Eutrophic 2	N
Pond in Yuba Goldfields	39.216	-121.398	NA	X	X	NA	Oligotrophic	NA	Y
Rainbow Lake	40.508	-122.694	X	NA	NA	NA	NA	Oligo/Meso	N
San Luis Reservoir	37.057	-121.121	X	X	NA	X	Eutrophic 2	Hypereutrophic	N
Scotts Flat Reservoir	39.277	-120.918	NA	NA	NA	X	NA	Oligo/Meso	N
Shasta Lake	40.767	-122.368	NA	NA	NA	X	NA	Oligo/Meso	Y
Shaver Lake	37.121	-119.286	NA	NA	NA	X	NA	Oligo/Meso	N
Silva Flat Reservoir	40.954	-120.909	NA	NA	NA	X	NA	Oligo/Meso	Y
Silver Lake	40.529	-121.386	X	X	X	NA	Mesotrophic	Hypereutrophic	Y
Sly Creek Reservoir	39.614	-121.097	NA	X	NA	NA	Oligotrophic	NA	N
Stone Lake	38.352	-121.495	X	X	X	NA	Oligotrophic	Eutrophic 1	Y
Stony Gorge Reservoir	39.586	-122.532	NA	X	NA	NA	Eutrophic 1	NA	Y
Summit Lake	40.493	-121.422	X	X	X	NA	Mesotrophic	Hypereutrophic	Y

Lake Name	Lat	Long	Chl-a	TP	TN	Remote Sensing	Eutro Risk	Eutro Evidence	DAC20
Swan Lake	40.499	-121.362	X	X	X	NA	Oligotrophic	Hypereutrophic	Y
Thermalito Afterbay	39.456	-121.673	NA	X	NA	X	Mesotrophic	Oligo/Meso	Y
Thomas Pond Behind Fire Station	37.972	-120.245	NA	X	X	NA	Hypereutrophic	NA	Y
Turlock Lake	37.609	-120.568	NA	NA	NA	X	NA	Oligo/Meso	N
Twin Lakes Reservoir	38.702	-120.049	X	NA	NA	NA	NA	Oligo/Meso	N
Union Valley Reservoir	38.872	-120.407	NA	NA	NA	X	NA	Oligo/Meso	N
Unnamed LAVO Lake 1135 4	40.446	-121.285	NA	X	X	NA	Mesotrophic	NA	Y
Unnamed NLA12 Lake 141	39.096	-122.932	X	NA	NA	NA	NA	Eutrophic 1	Y
West Valley Reservoir	41.201	-120.400	NA	NA	NA	X	NA	Eutrophic 2	N
Whiskeytown Lake	40.626	-122.560	NA	NA	NA	X	NA	Oligo/Meso	N
Widow Lake	40.535	-121.263	X	X	X	NA	Mesotrophic	Hypereutrophic	Y
Willow Lake	40.404	-121.359	X	NA	NA	NA	NA	Oligo/Meso	Y
Woodward Reservoir	37.848	-120.836	NA	NA	NA	X	NA	Oligo/Meso	N

Supplemental Table 3: Summary of all assessable lakes showing the percentages of agricultural, developed, and undeveloped land uses in the HUC12 watershed of the lake.

Lake Name	Ecoregion	Agricultural Land Uses (%)	Developed Land Uses (%)	Undeveloped Land Uses (%)
Antelope Lake	Mountain	NA	2.3	97.7
Bass Lake	Mountain	NA	4.0	93.1
Bowman Lake	Mountain	NA	0.8	94.7
Bucks Lake	Mountain	NA	1.1	93.3
Butt Valley Reservoir	Mountain	NA	1.3	91.2
Camanche Reservoir	Mountain	0.5	5.4	75.0
Camp Far West Reservoir	Mountain	NA	5.0	93.4
Cherry Lake	Mountain	NA	0.0	93.1
Clear Lake	Mountain	NA	2.3	2.5
Cliff Lake	Mountain	NA	0.3	99.7
Costa Ponds	Mountain	0.9	5.4	93.5
Courtright Reservoir	Mountain	NA	0.0	95.5
Crystal Lake	Mountain	NA	0.6	97.4
Don Pedro Reservoir	Mountain	NA	3.6	71.9
Dorris Reservoir	Mountain	14.3	1.7	81.5
East Park Reservoir	Mountain	NA	4.3	93.7
Eastman Lake	Mountain	7.5	1.9	86.6
Folsom Lake	Mountain	NA	17.8	73.5
French Meadows Reservoir	Mountain	NA	0.0	97.0
Frenchman Lake	Mountain	NA	0.6	96.6
Goose Lake	Mountain	0.1	0.0	99.7
H. V. Eastman Lake	Mountain	0.1	0.7	96.3
Hensley Lake	Mountain	NA	1.3	95.9

Lake Name	Ecoregion	Agricultural Land Uses (%)	Developed Land Uses (%)	Undeveloped Land Uses (%)
Hetch Hetchy Reservoir	Mountain	NA	0.0	91.9
Homer Lake	Mountain	NA	0.2	87.8
Horr Pond Big Lake	Mountain	7.5	1.9	86.6
Indian Valley Reservoir	Mountain	NA	0.7	96.5
Isabella Lake	Mountain	0.3	3.3	92.7
Jackson Meadows Reservoir	Mountain	NA	1.0	92.2
Jenkinson Lake	Mountain	NA	5.5	90.5
Kerckhoff Lake	Mountain	NA	3.2	96.1
Lake Almanor	Mountain	NA	0.3	7.9
Lake Alpine	Mountain	NA	2.2	95.7
Lake Amador	Mountain	0.0	4.3	94.1
Lake Berryessa	Mountain	NA	1.8	69.7
Lake Combie	Mountain	NA	18.8	79.6
Lake Davis	Mountain	NA	2.7	87.9
Lake Eleanor	Mountain	NA	0.0	93.6
Lake Helen	Mountain	NA	1.8	98.2
Lake McClure	Mountain	NA	1.1	96.4
Lake near Tuolumne Meadows	Mountain	NA	NA	98.5
Lake of the Pines	Mountain	NA	18.8	79.6
Lake Oroville	Mountain	NA	6.5	78.4
Lake Success	Mountain	0.3	3.1	91.1
Lake Thomas A Edison	Mountain	NA	0.0	95.4
Little Bear Lake	Mountain	0.0	1.4	98.4
Little Grass Valley Reservoir	Mountain	NA	0.8	91.7
Merle Collins Reservoir	Mountain	0.3	5.0	91.6
Millerton Lake	Mountain	NA	0.5	89.9

Lake Name	Ecoregion	Agricultural Land Uses (%)	Developed Land Uses (%)	Undeveloped Land Uses (%)
Moon Lake	Mountain	NA	NA	86.4
Mountain Meadows Reservoir	Mountain	NA	0.2	87.8
New Bullards Bar Reservoir	Mountain	NA	1.2	91.4
New Hogan Lake	Mountain	0.0	1.4	88.0
New Melones Lake	Mountain	0.0	5.3	72.1
Pardee Reservoir	Mountain	0.0	1.8	86.0
Pine Flat Lake	Mountain	NA	0.0	97.3
Rainbow Lake	Mountain	NA	1.7	98.1
San Luis Reservoir	Mountain	0.0	1.6	73.8
Scotts Flat Reservoir	Mountain	NA	5.5	89.4
Shasta Lake	Mountain	NA	1.7	78.4
Shaver Lake	Mountain	NA	2.1	88.9
Silva Flat Reservoir	Mountain	NA	1.1	98.9
Silver Lake	Mountain	0.0	1.4	98.4
Sly Creek Reservoir	Mountain	NA	1.0	96.7
Stony Gorge Reservoir	Mountain	NA	2.4	96.7
Summit Lake	Mountain	NA	0.6	97.4
Swan Lake	Mountain	NA	NA	97.2
ThomasPondBehindFireStation	Mountain	0.0	13.3	86.6
Twin Lakes Reservoir	Mountain	NA	2.0	94.5
Union Valley Reservoir	Mountain	NA	1.6	89.7
Unnamed LAVO Lake 11354	Mountain	NA	0.3	99.7
Unnamed NLA12 Lake 141	Mountain	1.4	5.8	92.1
West Valley Reservoir	Mountain	NA	0.0	98.2
Whiskeytown Lake	Mountain	NA	3.9	86.3
Widow Lake	Mountain	NA	0.4	99.0

Lake Name	Ecoregion	Agricultural Land Uses (%)	Developed Land Uses (%)	Undeveloped Land Uses (%)
Willow Lake	Mountain	NA	0.0	99.8
Alder Creek	Valley	0.4	56.9	40.8
Black Butte Lake	Valley	NA	0.5	94.1
Clifton Court Forebay	Valley	17.2	4.6	61.9
Lake Greenhaven	Valley	2.1	88.6	6.4
O'Neill Forebay	Valley	0.1	6.9	75.2
Pond in Yuba Goldfields	Valley	26.5	5.4	62.4
Stone Lake	Valley	59.3	17.0	23.2
Thermalito Afterbay	Valley	3.8	14.0	58.6
Turlock Lake	Valley	62.4	19.8	13.0
Woodward Reservoir	Valley	44.3	2.8	46.7