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Title: Ecosystem Metabolism as an Early Warning Indicator of Lake Algal Blooms

Authors: [1]Spencer J. Tassone, [1]Brendan M. Foster, [1]Carly M. Maas, [1]John D. Jastram

Affiliations: [1]U.S. Geological Survey, Virginia-West Virginia Water Science Center, Richmond, VA

Corresponding Author: Spencer J. Tassone (stassone@usgs.gov)

ORCID iD:
Spencer J. Tassone - https://orcid.org/0000-0002-9340-7170
Brendan M. Foster - https://orcid.org/0000-0003-3029-9923
Carly M. Maas - https://orcid.org/0000-0001-8050-4070
John D. Jastram - https://orcid.org/0000-0002-9416-3358

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All authors conceived of the study. SJT conducted the analyses and wrote the initial manuscript draft. BMF, CMM, and JDJ contributed to manuscript revision.

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Data Availability Statement

All data used in this analysis are available from publicly available data repositories: the U.S. Geological Survey (USGS) Water Data for the Nation (WDFN; U.S. Geological Survey, 2026; https://doi.org/10.5066/F7P55KJN) and the National Ecological Observatory Network (NEON; https://data.neonscience.org/data-products/explore). Metabolism model inputs, outputs, and associated R scripts are provided in Tassone (2026; https://doi.org/10.5066/P13AKNWB).

Abstract

Algal blooms represent ecosystem state shifts that degrade drinking water, restrict recreation, threaten public health, and lower property values. Detecting blooms in advance on management relevant timescales of days to weeks can support proactive intervention. Early warning statistics derived from indicator time series offer a framework for detecting state shifts, but the use of lake metabolic estimates (gross primary production, ecosystem respiration, and net ecosystem production) in this context has been limited. Here, we modeled lake metabolism using water-quality monitoring data from eight U.S. lakes spanning a trophic gradient to test the hypothesis that metabolic estimates serve as effective early warning indicators of algal blooms. Time series of early warning statistics were analyzed using the conventional Kendall's tau approach and a complementary threshold-based approach. The threshold-based approach yielded higher bloom detection rates, longer early warning lead times, and fewer false alarms than the Kendall's tau approach. Across lakes, metabolic metrics detected 86% of blooms, with the strongest early warning signals in oligotrophic, eutrophic, and hypereutrophic systems. However, directly measured water-quality parameters, particularly water temperature and chlorophyll concentration, were the primary early warning indicators of blooms. Overall, these results demonstrate that metabolic estimates can provide early warning signals of bloom development but are secondary to directly measured water-quality parameters, indicating a complementary rather than primary role in early bloom detection.

Keywords

Lake, Metabolism, Production, Respiration, Early Warning, Algal Bloom

Introduction

Algae are the base of the aquatic food web; however, rapid and often non-linear increases in algae biomass, termed algal blooms, can impair water resources and lead to environmental, social, public health, and economic challenges. The progression and impact of algal growth to nuisance or harmful status has been studied globally, spanning the freshwater-marine continuum (Paerl 1988; Griffith and Gobler 2020; Feng et al. 2024). Management of blooms in inland waters has historically relied on reactive strategies aimed at mitigating impacts after a bloom has occurred (Anantapantula and Wilson 2023). However, advances in sensor technologies and methodologies have increased attention toward detecting early warning signals indicative of impending bloom formation to support proactive bloom management (Almuhtaram et al. 2021; Carey et al. 2022; Xiao et al. 2024).

As ecosystems approach a transition, such as shifting from a non-bloom to a bloom condition (Batt et al. 2013a; Ortiz et al. 2020), variability and autocorrelation within indicator time series should theoretically increase and enable the early detection of impending state change (Carpenter 2003; Scheffer et al. 2009; Scheffer et al. 2012). In lakes, experimental studies have provided evidence to support this concept of early warning signals preceding state change (Carpenter et al. 2011; Pace et al. 2017; Wilkinson et al. 2018; Buelo et al. 2022), albeit inconsistently in non-experimental settings (Gsell et al. 2016; Ortiz et al. 2020; O'Brien et al. 2023). Aquatic metabolism, encompassing rates of gross primary production (GPP), ecosystem respiration (ER) and their difference (net ecosystem production [NEP] = GPP - ER), have been proposed as early warning indicator (EWIs) of algal bloom development due to close associations with nutrient concentrations and algal biomass (Batt et al. 2013b; Corman et al. 2023). However, Batt et al. (2013b) provided evidence from a mesotrophic lake with an experimentally manipulated food web, that water-quality parameters related to ecosystem metabolism (e.g., dissolved oxygen [DO], pH, chlorophyll) were more effective EWIs of state change than metabolic parameters. In non-eutrophic lakes (i.e., oligotrophic, mesotrophic), low biotic activity relative to abiotic processes can make it challenging to constrain metabolic estimates (Staehr et al. 2010; Richardson et al. 2017; Jankowski et al. 2021). In contrast, eutrophic and hypereutrophic lakes, characterized by greater nutrient (nitrogen and phosphorous) availability and biotic activity, exhibit stronger metabolic signals and are more prone to algal blooms (Paerl and Paul 2012; Tigli et al. 2025). Consequently, the ability to use metabolic estimates as EWIs of algal blooms may vary systematically among trophic groups (i.e., oligotrophic, mesotrophic, eutrophic, and hypereutrophic).

In this study, we revisit lake metabolism metrics (i.e., GPP, ER, NEP) as potential EWIs by evaluating their effectiveness in detecting algal blooms before their onset across multiple lakes spanning the oligotrophic to hypereutrophic gradient. We hypothesized that metabolism-based parameters would be effective EWIs of blooms along the lake trophic gradient, particularly in eutrophic and hypereutrophic lakes where blooms are more frequent, prolonged, and/or severe. We further compared the abilities of metabolism-based indicators and directly measured *in situ* water-quality parameters to identify early warning signals of impending bloom formation. To compare metabolism and water-quality parameters among trophic groups, we evaluated two complementary analytical approaches for detecting early warning signals in lakes: a conventional Kendall's tau–based method and a novel threshold-based approach.

Methods

Site Description & Data Collection

Lake Anna (ANNA) is an 83 km^2 reservoir in Spotsylvania, Orange, and Louisa Counties, Virginia, that was constructed in 1972 by damming the North Anna River (Eric Adams and Wells 1984). The reservoir is a popular destination for swimming, boating, and fishing; however, since 2018, the riverine-lake transition zone in the western section of the reservoir has experienced algal blooms exceeding recreational advisory thresholds (Hanlon et al. 2022). The Virginia General Assembly appropriated funds to support investigations into Lake Anna algae blooms and the U.S. Geological Survey (USGS), in partnership with the Virginia Department of Environmental Quality installed water-quality and meteorological monitoring equipment at Red House Point near Ellisville, VA (USGS site no: 01670144; U.S. Geological Survey, 2026). Concurrent monitoring spanned November 2023 through December 2024. Water-quality observations were continuously monitored using a YSI Inc. (Yellow Springs, OH) EXO3 Multiparameter Water-Quality Sonde with a sampling frequency of 15-minutes. Algal pigment concentration time series were collected using a bbe-Moldaenke (Schwentinental, Germany) PhycoProbe that differentiated each 15-minute chlorophyll observation into algal groups including cyanobacteria, diatoms, and green algae. All water quality and algal pigment time series were collected from a dock 10 m from the shoreline at a fixed depth of 1.25 m above the sediment surface. Wind speed and direction were monitored from the Red House dock from a height of 3 m at a sampling frequency of 5 minutes. All monitoring and data quality control followed standard USGS practices (Wagner et al. 2006; Turnipseed and Sauer 2010; Foster et al. 2022).

The National Ecological Observatory Network (NEON) collects high-frequency water-quality and meteorological observations from seven lakes across the Northern Plains, Great Lakes, Southeast, and Tundra ecoclimatic domains of the United States (https://www.neonscience.org/field-sites). Of the seven lakes, six were paired, including Prairie Lake (PRLA) and Prairie Pothole (PRPO) in North Dakota (11 km apart), Crampton Lake (CRAM) and Little Rock Lake (LIRO) in Wisconsin (29.5 km), Suggs Lake (SUGG) and Lake Barco (BARC) in Florida (1.6 km), and Toolik Lake, Alaska (TOOK). Watershed area ranges between 0.6-67.6 km^2 and maximum lake depth ranges between 3.2-27 m. All water-quality observations were collected using a buoy-mounted YSI EXO2 Multiparameter Water-Quality Sonde above the deepest section of the lake at a sampling frequency of 5-minutes. Water temperatures at various depths were recorded from the buoy at a sampling frequency of 1 minute while meteorological observations were measured from fixed heights above the buoy every 2 minutes. NEON lake buoys were removed during winter except at SUGG and BARC. Time series observations were quality assured and controlled by NEON's data quality program, and only approved data were used which encompassed January 2018 through June 2024. All NEON time series were accessed using the *neonUtilities* R package (R Core Team, 2025; Lunch et al. 2024; SI Table 1).

Lake Trophic Status & Algae Bloom Classification

There are many ways to classify the trophic status of inland waters (Meyer et al. 2025). In this study, we use the term *trophic group* to refer specifically to four trophic classes—oligotrophic, mesotrophic, eutrophic, and hypereutrophic. The trophic classification of all eight lakes (NEON + ANNA) were based on their median chlorophyll concentration according to the U.S. Environmental Protection Agency National Lake Assessment (U.S. Environmental Protection Agency 2024) as oligotrophic (≤ 2 μg L^{-1}), mesotrophic (2-7 μg L^{-1}), eutrophic (7-30 μg L^{-1}), or hypereutrophic (> 30 μg L^{-1}). BARC (median = 1.8 μg L^{-1}) and ANNA (46.1 μg L^{-1}) were oligotrophic and hypereutrophic, respectively; TOOK, LIRO, and CRAM were mesotrophic (2.4, 3.0, and 3.8 μg L^{-1}, respectively) while PRPO, SUGG, and PRLA were eutrophic (14.4, 14.8, 21.2 μg L^{-1}, respectively).

There is no standard quantitative definition of an algal bloom, though definitions often share commonality in using thresholds of an algal parameter (i.e., pigment concentration, cell counts), above which a system is in a bloom state (Smayda 1997; WHO 2003; Stackpoole et al. 2024). Here, blooms were defined using site-specific thresholds calculated as the median of the high-frequency chlorophyll concentration time series plus one standard deviation, such that bloom conditions represent periods of elevated chlorophyll relative to typical conditions within each lake. A lake was classified as being in a bloom state when the daily mean chlorophyll concentration exceeded this threshold. This approach emphasizes within-site anomaly detection rather than cross-site comparability and was selected in part for its ability to delineate bloom and non-bloom periods at the site with the shortest time series (ANNA), where a single, large-magnitude, long-duration bloom event was observed. We acknowledge that this threshold is statistically derived and may not correspond to management-defined bloom conditions; however, this threshold provides a pragmatic framework for identifying blooms within non-experimental lakes with differing baseline conditions. When a bloom was observed, bloom duration was calculated as the difference in days between the bloom end and start date and bloom magnitude as the maximum daily average chlorophyll concentration during the bloom.

Metabolism Model

Daily average metabolic estimates were modeled with a Bayesian model structure using the R package *lakeMetabolizer* (Winslow et al. 2016). Photosynthetically active radiation was estimated for each site using the *calc_light* function from the R package *streamMetabolizer* (Appling et al. 2018a). Likewise, gas transfer velocity was estimated using wind speed and sensor height according to Cole and Caraco (1998) and converted to a gas- and temperature-specific transfer velocity according to Raymond et al. (2012) using *lakeMetabolizer*'s *k.cole.base* and *k600.2.kGAS.base* functions, respectively. Thermocline depth time series were estimated for the NEON lakes using water temperature observations at various depth and the R package *rLakeAnalyzer* (Winslow et al. 2019), with a metalimnion minimum density gradient cutoff of 0.1 kg m^{-3} m^{-1}. At ANNA, water temperature observations from multiple depths, collected October 2024 through January 2025, indicated no stratification. Lacking a concurrent thermocline depth time series and personal observations of regular wake boat activity in the vicinity of the Red House dock during the growing season, the thermocline depth was set equal to the maximum lake depth from where the observations were collected, 1.8 m. Confidence in each lake's metabolic model was assessed based on the percentage of biologically unrealistic estimates of GPP and ER (i.e., negative GPP and positive ER; Appling et al. 2018b). All GPP estimates < 0 but ≥ -0.5 and ER estimates > 0 but ≤ 0.5 g O_2 m^{-2} d^{-1} were converted to 0 (Appling et al. 2018b), and all days with a biologically unrealistic estimate were excluded from analysis (Bernhardt et al. 2022; Tassone 2026).

Early Warning Statistics

Several early warning statistics (EWS) exist (Dakos et al. 2012); however, studies from ecological systems, including lakes, have provided support for the use of standard deviation (SD) and lag-1 autocorrelation (AR1) calculated over rolling windows (Batt et al. 2013b; Burthe et al. 2015; Pace et al. 2017; Wilkinson et al. 2018; Ortiz et al. 2020; Buelo et al. 2022). To determine the sensitivity of our results to multiple rolling windows, we calculated SD and AR1 over 7-, 14-, and 21-day windows for each lake using daily averages of metabolism (GPP, ER, NEP) and water-quality parameters (water temperature, pH, DO, turbidity, and log-transformed chlorophyll and specific conductance; hereafter, both metabolism and water-quality parameters are collectively referred to as water-quality parameters) with the R package *tvsews* (Buelo et al. 2022). These rolling window widths were selected based on previous early warning lake algal bloom studies (Wilkinson et al. 2018; Ortiz et al. 2020) that have provided evidence for them being long enough to detect signals in EWIs while minimizing false alarms.

In EWS time series analysis, a common approach for assessing increases in SD and AR1 is the non-parametric Kendall's tau (τ) coefficient, where a positive and statistically significant τ (p-value < 0.05), calculated as the rank correlation between EWS values and time indicates an increase in variability consistent with an impending bloom (Dakos et al. 2012; Gsell et al. 2016; Pace et al. 2017; Buelo et al. 2022). When calculating τ, window widths of 7-, 14-, and 21-days were used to assess the sensitivity of results to the choice of window width. When a bloom was detected early, the early warning lead time for each parameter was calculated as the difference between the date the early warning was detected and the date the bloom started. False alarms were defined as instances when τ was positive and significant but did not overlap the start of a bloom.

Given the multiple EWS (SD and AR1), EWS window widths, and τ-window widths, a sensitivity analysis was conducted. For each scenario (2 EWS * 3 EWS window widths * 3 τ-window widths = 18 scenarios), three key performance indicators (KPI) were calculated for each trophic group: 1) the fraction of correctly identified blooms (hereafter, detection rate), 2) the median number of early warning days, and 3) the fraction of false alarms. To identify the top performing scenario, KPIs were summed across trophic groups within each scenario. However, because a lower false alarm ratio indicates better performance, the inverse of this KPI was calculated prior to summing. To identify the top performing water-quality parameter for each scenario and trophic group, KPIs were normalized and summed as follows:

$$Normalized\ KPI_i = D_i + L_i + F_i$$

where i represents a unique water-quality parameter for each scenario and trophic group. The detection rate (D_i) was min-max normalized such that the highest fraction of correctly identified blooms (x) had a value of one, the lowest had a value of zero and all others were scaled between zero and one.

$$D_i = \frac{x - \min(x)}{\max(x) - \min(x)}$$

The early warning lead time (L_i) was binarized such that scenarios with an early warning lead time ≥ 7 days were assigned a value of one, and those < 7 days a value of zero. A 7-day threshold was selected to represent a management-relevant response window, though results were robust when using a 3-day threshold. Lastly, the false alarm ratio (F_i) was inverse min-max normalized, such that lower false alarms ratios received higher scores. Normalized KPIs were equally weighted to avoid imposing subjective priorities among detection rates, early warning lead times, and false alarm rates.

A complementary, threshold-based approach for analyzing EWI time series was evaluated to assess potential improvements in KPI performance (i.e., a higher detection rate, longer early warnings, and fewer false alarms) relative to the conventional τ-approach. This approach provides an alternative framework for identifying increases in EWI variability that may precede bloom development in non-experimental systems. Rather than assessing temporal trends in EWI with the τ-coefficient, this alternative approach defined a fixed, site- and parameter-specific statistical threshold, above which a system may be entering a period of instability that could be indicative of impending bloom formation (Figure 1). Two definitions of this potential instability threshold (PIT) were explored, the mean and median of the EWI time series. These distribution-based PITs were selected because they characterize the central tendency of the EWI time series, enabling the identification of periods when EWIs were elevated relative to baseline conditions. If an EWI exceeded the PIT for a continuous period but dropped below the threshold for one week or less before exceeding the PIT again, that dip below the PIT was considered part of the same early warning event rather than indicating the end of one event and the start of another event.

False alarms were identified as instances when the PIT was exceeded but no bloom occurred during the exceedance or within one week following the return below the PIT. Because multiple EWS metrics, window widths, and PIT definitions were evaluated, a sensitivity analysis analogous to the τ-based approach described above was conducted for the threshold-based approach. All modelling, statistical analyses, and visualizations were conducted in the R environment for statistical computing (R Core Team 2025).

Results

Algal Blooms

Among the eight lakes, there were 89 algal blooms with a median (25^{th}-75^{th} percentile) duration of 6 (3-17) days and range of 1 and 80 days. The median bloom magnitude was 35.7 (13.1-58.8) $\mu g\ L^{-1}$ and ranged between 4.8 and 319 $\mu g\ L^{-1}$ (SI Figure 1). ANNA, with the shortest time series, had one bloom while the NEON lakes had between 6 and 22 blooms (PRLA and SUGG, respectively; Figure 2).

Metabolism

The range in metabolic estimates generally increased with trophic status, apart from eutrophic and hypereutrophic groups which were similar. GPP ranged between 4.8, 9.3, 36.8, and 31.1 $g\ O_2\ m^{-2}\ d^{-1}$ for oligotrophic, mesotrophic, eutrophic, and hypereutrophic, respectively (Figure 2). Likewise, ER ranged between 5.7, 14.9, 32.7, and 33 $g\ O_2\ m^{-2}\ d^{-1}$ for oligotrophic, mesotrophic, eutrophic, and hypereutrophic, respectively. Daily occurrences of autotrophy (NEP > 0) were observed across all lakes; however, heterotrophy (NEP < 0) was predominant in five lakes, with ANNA, CRAM, and TOOK being predominantly autotrophic (55%, 57%, and 54% days of autotrophy, respectively; Figure 2).

Early Warning Detection

KPIs from the two sensitivity analyses, one based on Kendall's tau (SI Figure 2) and the other on the EWS threshold (Figure 3), indicated that the threshold approach generally achieved higher detection rates, longer early warning lead times, and fewer false alarms across lake trophic groups regardless of EWS metric, window width, or τ window width. For the Kendall's tau, the detection rates ranged between 0 to 78% with false alarm rates ranging between 90 and 100% (SI Figure 2). When blooms were detected early, median early warning lead times ranged from 1 to 22 days. In contrast, the threshold-based approach yielded detection rates between 46 and 100%, with false alarm rates between 69 and 89% and median early warning lead times of 9 to 57 days (Figure 3).

Among the threshold-based scenarios, the scenario with the largest normalized KPI score used AR1 calculated over a 7-day rolling window with the PIT set to the mean (Figure 3). Under this scenario, and across trophic groups, bloom detection rates ranged from 88 to 100%, median early warning lead times ranged from 25 to 54 days, and false alarm rates ranged from 69 to 82%. Within this top performing scenario, median detection rates across water-quality parameters increased from 90% (80-100%) to 100% along the oligotrophic to hypereutrophic gradient, with water temperature and log-transformed chlorophyll both achieving median detection rates of 100% (98-100%; Figure 4). These two parameters also exhibited the longest median early warning lead times, at 40 days (16-77 days) for water temperature and 36 days (13-66 days) for log-transformed chlorophyll. Water temperature produced the lowest false alarm rates for the oligotrophic, mesotrophic, and eutrophic groups at 44, 23, and 32%, respectively. In the hypereutrophic group, the false alarm rates were elevated (> 50%) across all water-quality parameters but were lowest for log-transformed chlorophyll at 67%. Overall, given high detection rates, long early warning lead times, and relatively low false alarm rates, water temperature had the largest normalized KPI among water-quality parameters for bloom early warning in the oligotrophic, mesotrophic, and eutrophic groups, whereas log-transformed chlorophyll had the largest normalized KPI in the hypereutrophic group.

Across the 12 threshold-based sensitivity scenarios, the most influential water-quality parameter was identified within each trophic group based on the largest normalized KPI score (Figure 5). Metabolism metrics (GPP, ER, NEP) had the largest normalized KPI in at least one scenario across all trophic groups except for mesotrophic. Across the oligotrophic, eutrophic, and hypereutrophic groups, metabolic metrics had the largest normalized KPI among water-quality parameters in 33 to 58% of scenarios. When aggregated across trophic groups (12 scenarios * 4 trophic groups = 48 trophic-specific scenarios), water temperature was most frequently identified as having the largest normalized KPI (n = 10), followed by GPP (n = 9; SI Figure 3).

Discussion

Algal blooms were observed across all trophic groups, and early warning signals derived from metabolic estimates were capable of detecting blooms across trophic groups, although detection rates varied among groups. When bloom detection was successful, metabolic indicators preceded blooms at management-relevant timescales, typically days to weeks but up to five months in advance. However, metabolic parameters were not the most influential indicators, based on normalized KPI scores, in the threshold-based scenario with the strongest early-warning results and did not emerge as the most influential indicator in any of the mesotrophic scenarios. Their reduced early-warning capacity in mesotrophic lakes may indicate weaker coupling between algal biomass and ecosystem metabolism, where abiotic drivers such as mixing and light availability can obscure biologically driven signals (Staehr et al. 2010; Richardson et al. 2017; Jankowski et al. 2021; Farruggia et al. 2026). Additionally, the mesotrophic lakes in this study were located at northern latitudes (e.g., Wisconsin and Alaska), where seasonal ice cover required removal of buoy-deployed monitoring equipment. Consequently, bloom events occurring during ice-impacted periods may have been missed (Salmi and Salonen 2016; Reinl et al. 2023). Overall, these results indicate that while metabolic estimates can provide actionable early warning signals, particularly in oligotrophic, eutrophic, and hypereutrophic systems, their normalized KPI scores were generally secondary to directly measured water-quality parameters, indicating a complementary rather than primary role in early bloom detection.

Broadly, our results align with prior studies demonstrating that water-quality parameters can provide early warning of impending ecosystem state change in lakes, including algal blooms (Wilkinson et al. 2018; Ortiz et al. 2020; Buelo et al. 2022). The secondary role of derived metabolic estimates relative to the directly measured water-quality parameters in mesotrophic lakes is consistent with Batt et al. (2013b) who observed similar patterns in a single, experimentally manipulated mesotrophic lake. Further, results from the Kendall’s tau sensitivity analysis were consistent with prior studies that have highlighted challenges in the application of early warning signals in non-experimental lakes

(Gsell et al. 2016; O’Brien et al. 2023). These challenges may indicate limitations in the trend-based approach, which can be insensitive to abrupt or non-monotonic changes in early warning signals. In contrast, our results suggest that a threshold-based approach, applied to the same underlying EWI time series used in the trend-based approach, may increase algal bloom detection and reduce false alarm rates in non-experimental lakes. Lastly, our results support growing recognition of aquatic metabolism as an informative suite of metrics for environmental management (Jankowski et al. 2021).

False alarm rates were elevated for both analytical approaches but were lower (< 50%) for certain combinations of trophic groups (i.e., oligotrophic, mesotrophic, and eutrophic) and water-quality parameters (i.e., water temperature) using the threshold-based approach. False alarms may arise from asynchronous bloom dynamics within the algal community (George et al. 2023). For instance, in Lake Anna, a spring green-algae bloom triggered an early warning signal despite its low magnitude relative to the total chlorophyll concentration. Additionally, while this study utilized relatively simple and transferable distribution-based approaches to defining algal blooms and potential instability thresholds across multiple lakes, studies have used other thresholds (Stackpoole et al. 2024). Lowering thresholds may improve detection rates but also increase false alarms, highlighting a tradeoff between early warning sensitivity and specificity. This tradeoff demonstrates a broader challenge in proactive water-quality management—acting on an early warning signal that turns out to be a false alarm or failing to act during the early stages of a real event. Although responding to false alarms can strain limited resources, it can also reinforce management preparedness, analogous to fire drills, by maintaining readiness to intervene during early bloom development before ecological and socioeconomic impacts escalate. Future efforts could adjust thresholds to align with management needs to improve the reliability and efficacy of EWS frameworks as a lake management bloom-detection tool (Biggs et al. 2009; Scheffer et al. 2012; George et al. 2023). Management-specific thresholds integrated with spatial water-quality monitoring programs or spatially explicit predictive water-quality models could be utilized to evaluate the effectiveness of ecosystem metabolism as a spatial, intra-lake EWI (Buelo et al. 2022; Caballero et al. 2025). Likewise, 73% of bloom events were detected by multiple water-quality parameters, indicating redundancy among EWIs and utility in ensemble early warning systems that integrate multiple indicators of change rather than relying on a single indicator (Gsell et al. 2016; Almuhtaram et al. 2021; Laitinen and Lahti 2022).

This study demonstrates that across diverse trophic conditions and a broad geographic range, estimates of aquatic ecosystem metabolism detected a substantial proportion of blooms (86%), though their normalized KPI scores were generally lower than those of directly measured water-quality parameters, particularly in mesotrophic systems. Given the rapid, non-linear growth of algae during the onset of blooms, early detection provides opportunities for water-quality management intervention before blooms escalate to nuisance or harmful levels (Biggs et al. 2009; Crépin et al. 2012; Pace et al. 2017). However, these windows of intervention were typically open for days to weeks, so resource monitoring programs with a low sampling frequency may fail to capture them. This study highlights the importance of high-frequency water-quality monitoring and the utility of coordinated monitoring networks in supporting early warning systems.

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Tables and Figures

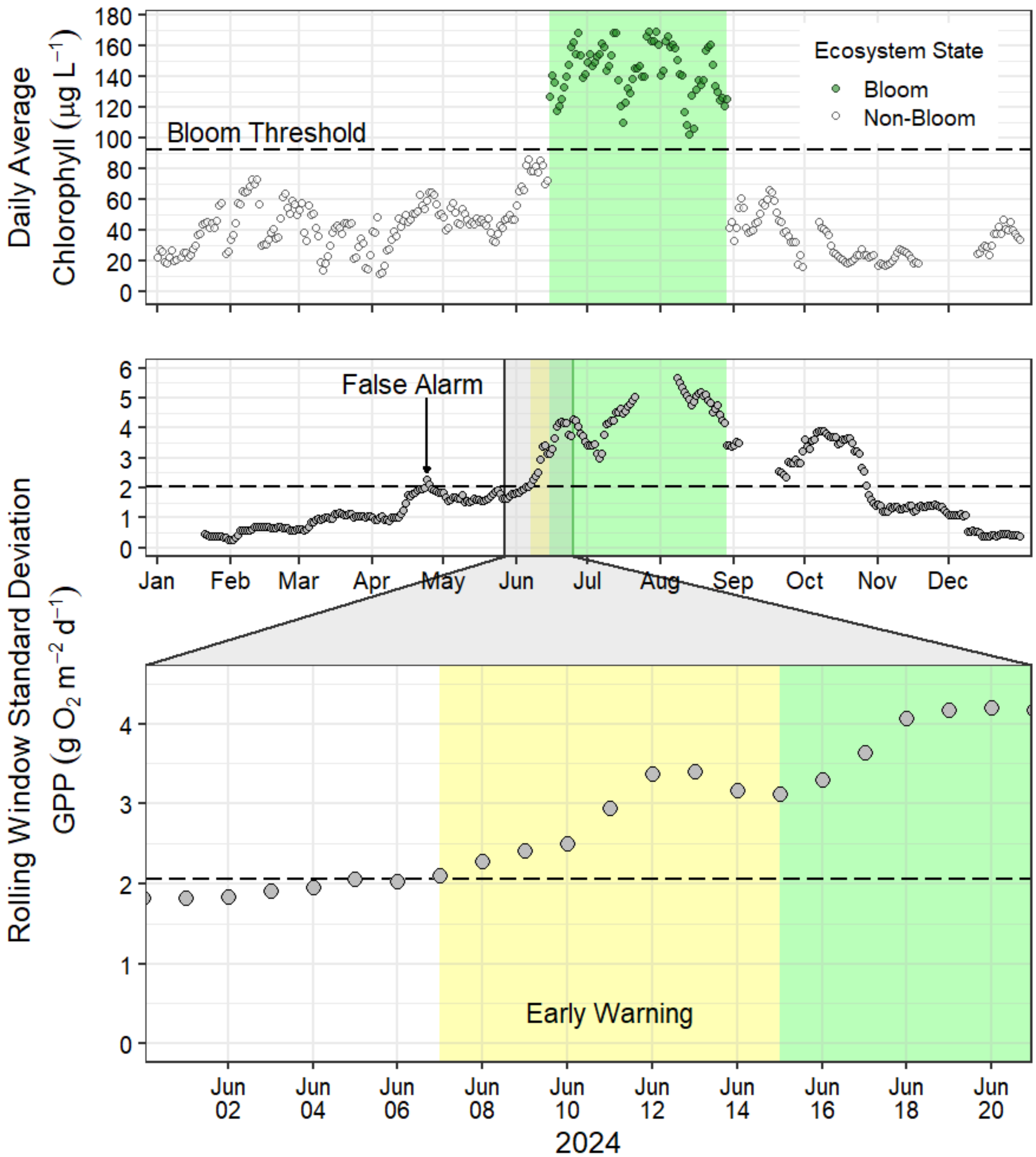


Figure 1. Example from Lake Anna, VA of using a rolling window standard deviation of gross primary production (GPP) to detect an algae bloom before it occurs. Daily average chlorophyll time series with the dashed line representing the fixed site-specific algae bloom threshold (top). Chlorophyll concentrations above the threshold indicate bloom conditions, while concentrations below indicate non-bloom conditions. The shaded green region indicates the duration of the bloom. The middle and bottom time series are the rolling window standard deviation for GPP, with the dashed line representing the site- and parameter-specific fixed potential instability threshold (PIT). The shaded yellow region represents the early warning lead time when the rolling window standard deviation exceeds the PIT prior to a bloom. False alarms occur when the rolling window standard deviation exceeds the PIT without bloom development within one week of return below the PIT.

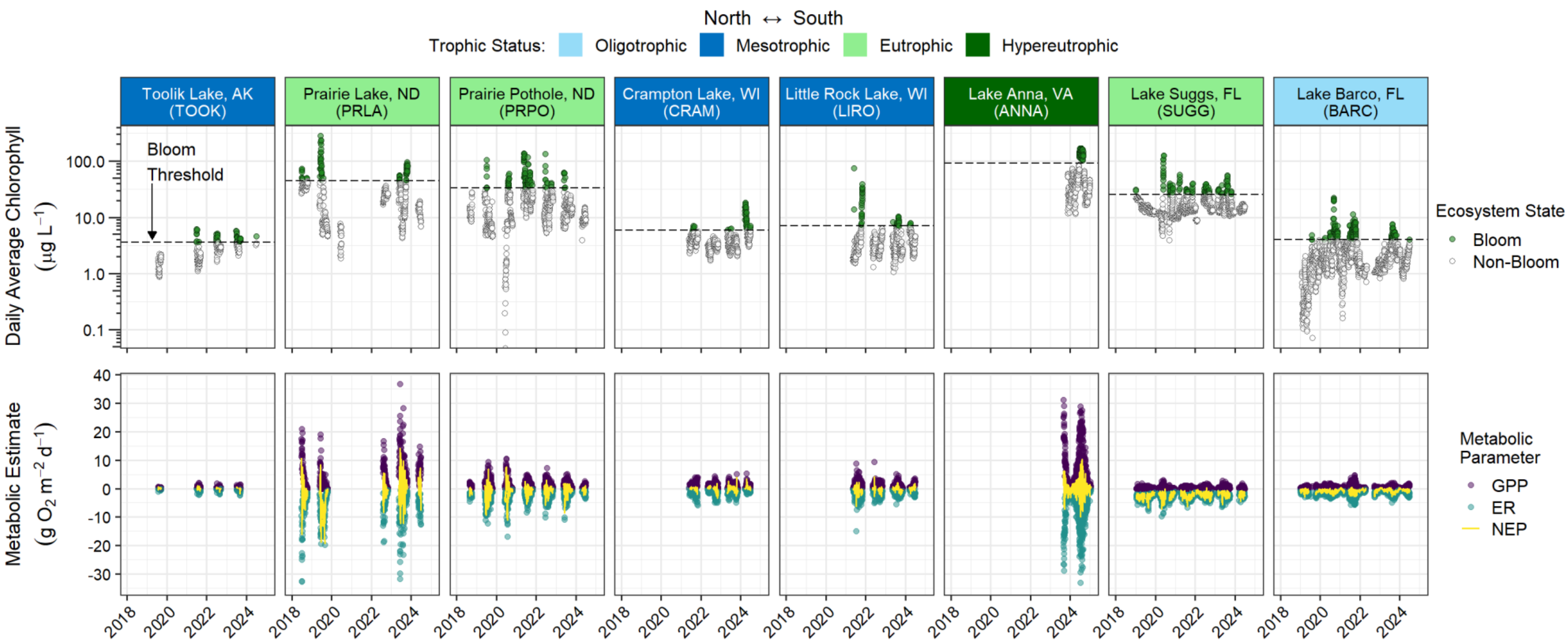


Figure 2. Time series of daily average chlorophyll concentrations (top row) and ecosystem metabolism (bottom row) for eight lakes, arranged geographically from north to south. Lake names are color-coded according to trophic status. Horizontal dashed lines mark the site-specific algal bloom thresholds, defined as the median chlorophyll concentration plus one standard deviation. Concentrations above the threshold are shown in green (indicating bloom conditions), while those below the threshold are white (non-bloom conditions). Metabolism metrics include gross primary production (GPP, purple points), ecosystem respiration (ER, teal points), and net ecosystem production (NEP, yellow lines).

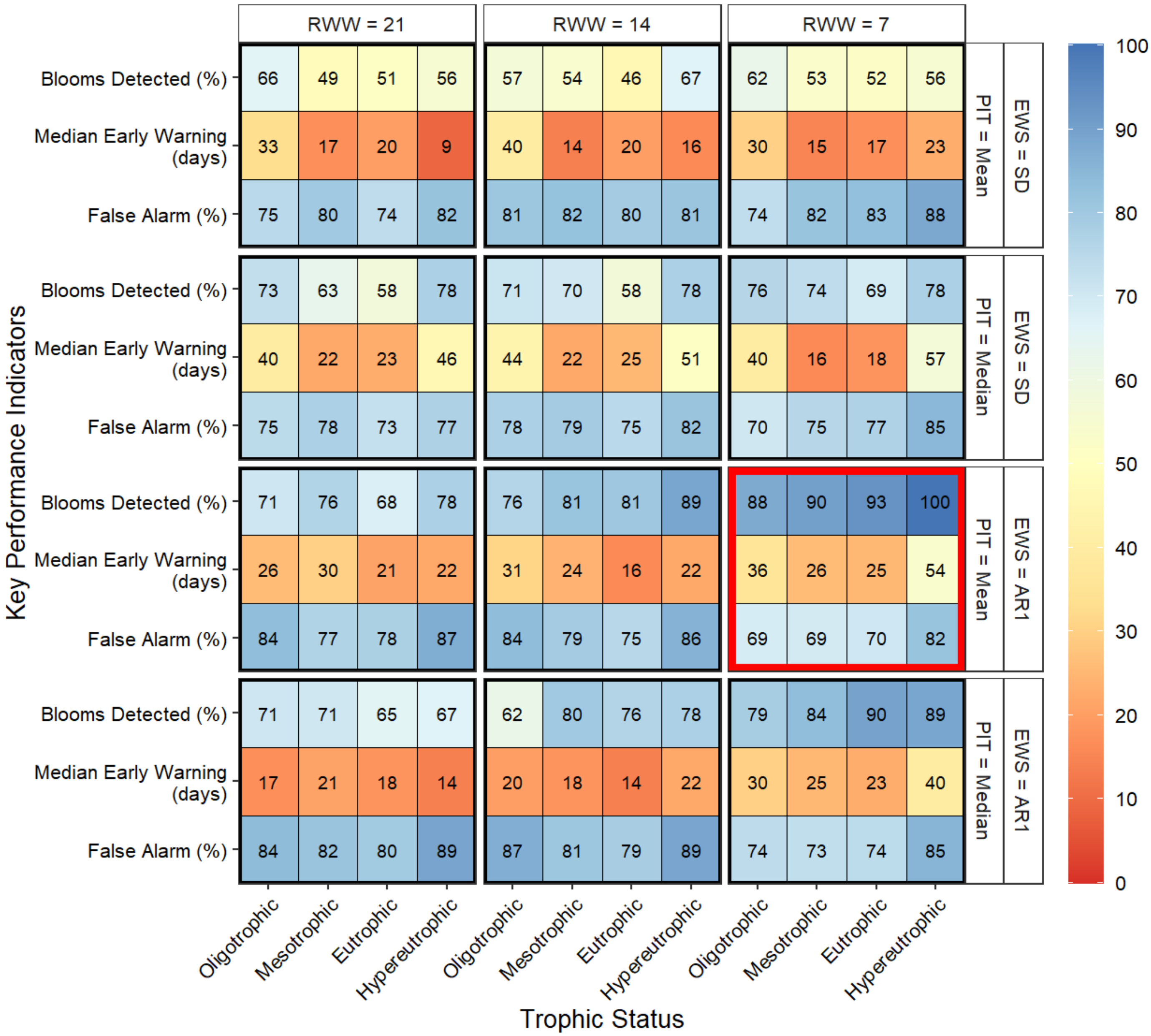


Figure 3. Results of the threshold-based sensitivity analyses for each lake trophic group as they relate to the three key performance indicators (KPI). Twelve scenarios were tested corresponding to each combination of early warning statistic (EWS = SD or AR1), EWS-rolling window width (RWW = 7, 14, 21-days), and potential instability threshold (PIT = mean or median of the site- and parameter-specific EWS). The bolded red scenario involving the AR1 EWS, 7-day RWW, and mean PIT was the scenario with the highest summed KPI values (with false-alarm rate inversely scaled because lower values indicate better performance) across lake trophic groups.

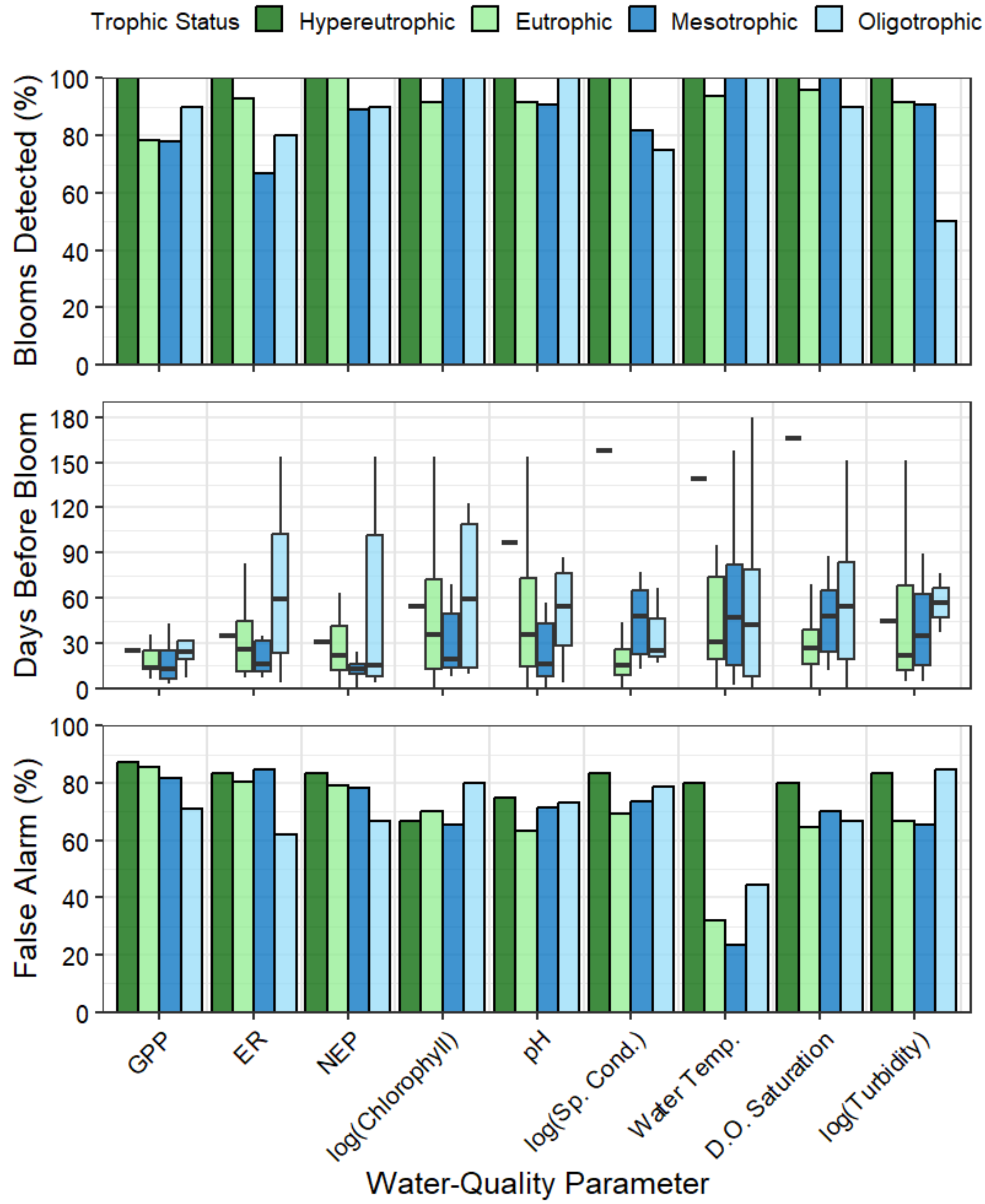
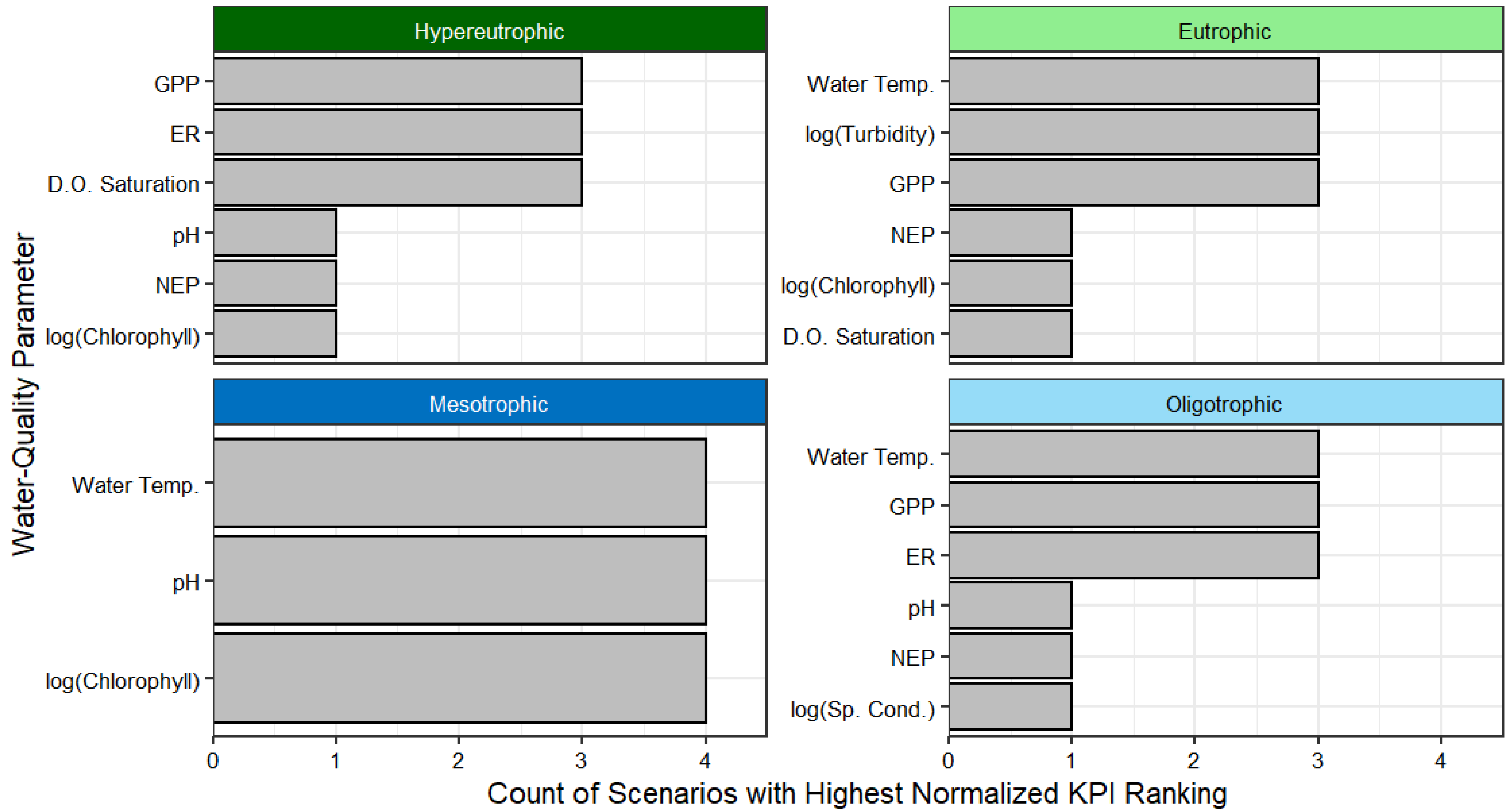


Figure 4. Key performance indicators (bloom detection rate [top], early warning lead time [middle], and false alarm rate [bottom]) for each trophic group across all metabolism and water-quality parameters. Results represent the threshold-based sensitivity analysis corresponding to the scenario with the highest summed KPI values. The hypereutrophic boxplots appear as a line because there was only one bloom for this trophic group. The upper and lower hinges of the boxplot represent the 75th and 25th percentiles, the horizontal line represents the median, and the whiskers represent 1.5 times the range between the 75th and 25th percentiles.

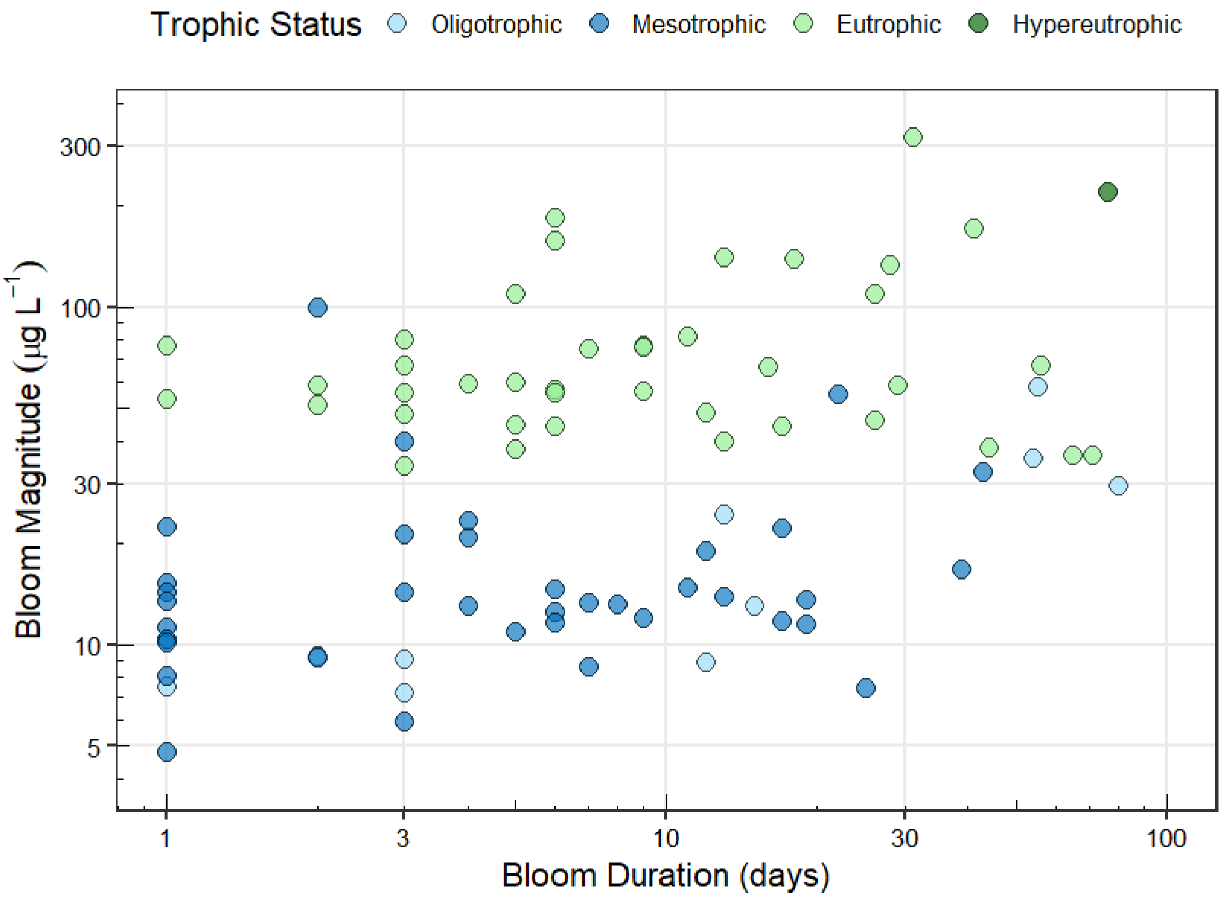


619 Figure 5. Counts of top-performing metabolism and water-quality parameters, based on the highest normalized KPI score, for
620 each of the 12 threshold-based sensitivity-analysis scenarios by trophic groups.

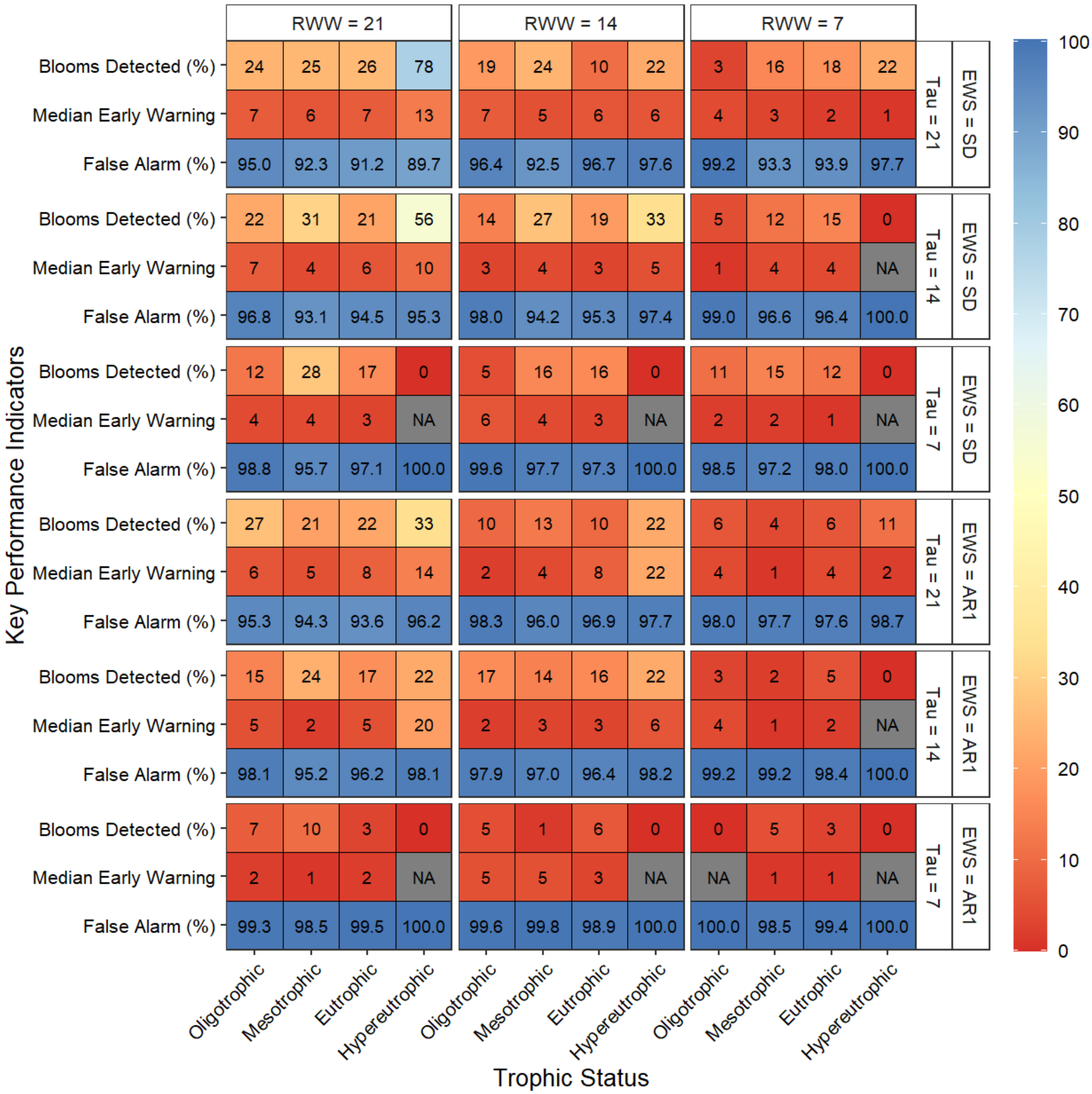
Supplemental Information

SI Table 1. National Ecological Observatory Network (NEON) datasets used in this study.

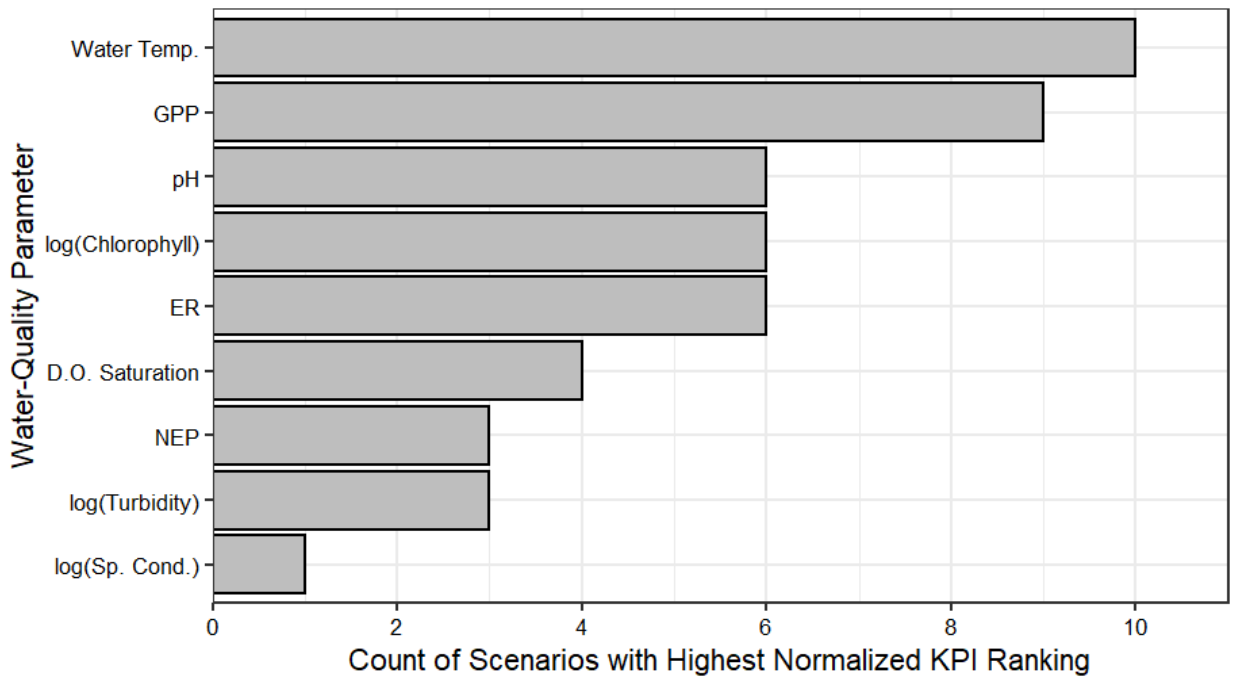
Parameter	Unique Identifier	Citation
Water quality	DP1.20288.001	NEON (National Ecological Observatory Network). Water quality (DP1.20288.001), RELEASE-2025. https://doi.org/10.48443/03mj-t174. Dataset accessed from https://data.neonscience.org/data-products/DP1.20288.001/RELEASE-2025 on June 13, 2025.
Temperature at specific depth in surface water	DP1.20264.001	NEON (National Ecological Observatory Network). Temperature at specific depth in surface water (DP1.20264.001), RELEASE-2025. https://doi.org/10.48443/06xg-mz55. Dataset accessed from https://data.neonscience.org/data-products/DP1.20264.001/RELEASE-2025 on June 18, 2025.
Windspeed and direction above water on-buoy	DP1.20059.001	NEON (National Ecological Observatory Network). Windspeed and direction above water on-buoy (DP1.20059.001), RELEASE-2025. https://doi.org/10.48443/w72m-nx46. Dataset accessed from https://data.neonscience.org/data-products/DP1.20059.001/RELEASE-2025 on June 17, 2025.
Photosynthetically active radiation at water surface	DP1.20042.001	NEON (National Ecological Observatory Network). Photosynthetically active radiation at water surface (DP1.20042.001), RELEASE-2025. https://doi.org/10.48443/rerd-cr90. Dataset accessed from https://data.neonscience.org/data-products/DP1.20042.001/RELEASE-2025 on June 17, 2025.
Barometric pressure above water on-buoy	DP1.20004.001	NEON (National Ecological Observatory Network). Barometric pressure above water on-buoy (DP1.20004.001), RELEASE-2025. https://doi.org/10.48443/aym4-6h05. Dataset accessed from https://data.neonscience.org/data-products/DP1.20004.001/RELEASE-2025 on June 17, 2025.



624 SI Figure 1. Algal bloom magnitude, defined as the maximum daily mean chlorophyll during
625 an active bloom, as a function of bloom duration across lake trophic groups.



SI Figure 2. Results of the Kendall's tau-based sensitivity analysis for each lake trophic group as they relate to the three key performance indicators (KPI).



SI Figure 3. Counts of the top-performing metabolism and water-quality parameters based on the highest normalized KPI score, for each of the 12 threshold-based sensitivity-analysis scenarios summed across trophic groups.