Long-term trends in productivity across Intermountain West lakes provide no evidence of widespread eutrophication

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Key Points:

- Remote sensing imagery captures long-term trends in lake productivity across the Intermountain West
- The majority of lakes observed in this dataset were not exhibiting shifts in trophic status from 1984-2019
- The incorporation of fine-scale lake climate data from new deep learning datasets results in substantial improvement to model accuracy

Abstract

Eutrophication represents a major threat to freshwater systems and climate change is expected to drive further increases in freshwater primary productivity. However, long-term in-situ data is available for very few lakes and makes identifying trends and drivers of eutrophication challenging. Using remote sensing data, we conducted a retrospective analysis of long-term trends in trophic status across the Intermountain West, a region with understudied water quality trends and limited long-term datasets. We found that most lakes (55%) were not exhibiting shifts in trophic status from 1984-2019. Our results also show that increases in eutrophication were rare (3% of lakes) during this period, and that lakes exhibiting negative trends in trophic status were more common (17% of lakes). Lakes that were not trending occupied a wide range of lake and landscape characteristics, whereas lakes that were becoming less eutrophic tended to be in more heavily developed catchments. Our results highlight that while there are well-established narratives that climate change can lead to more eutrophication of lakes, this is not broadly observed in our dataset, with more lakes becoming more oligotrophic than lakes becoming eutrophic.

Plain Language Summary

Lakes are often classified by their productivity. Low productive lakes generally represent deep lakes with low amounts of algae. Whereas lakes with high levels of productivity support more plant growth and have higher amounts of algae. The accumulation of nutrients in freshwater systems often results in increases in productivity and can lead to the development of algal blooms. Algal blooms are a major concern due to their threat to ecosystem health, recreation, and drinking water sources. Yet the lack of long-term field data across large scales has resulted in a limited understanding of 1) what factors are driving productivity trends and the development of algal blooms across regions, and 2) are increasing trends representative of widespread

intensification or an increase in awareness and reporting. Therefore, there is a pressing need to effectively monitor and understand these trends in order to inform management actions that address their frequency and intensity. Here, we use data obtained from satellite imagery from 1984 - 2019 to document lake productivity trends in 1,169 lakes across the Intermountain West. We show that substantial increases in productivity were rare, and that the majority of lakes have not undergone widespread change.

1 Introduction

Widespread eutrophication is a global phenomenon that threatens water quality, recreational industries, and ecosystem function (Paerl et al., 2001; Gatz, 2020; Amorim and Moura, 2021). A common outcome of eutrophication is an increase in the biomass of phytoplankton, both algae and cyanobacteria, in freshwater, transitional, and ocean environments (Anderson et al., 2008; Hudnell, 2010; Wurtsbaugh et al, 2019). In many cases, this rapid and excessive growth can become severe and lead to the development of Harmful Algal Blooms (HABs) (Smith, 2003; Heisler et al. 2008). HABs are of particular concern due to the threats they pose to human health and drinking water sources (Fleming et al., 2002; Falconer and Humpage et al., 2005; Christensen and Khan, 2020). Thus, the wide-ranging effects that eutrophication and HABs have on aquatic systems and their threat to human health have highlighted the need to understand the factors which drive them.

Generally, eutrophication and algal blooms are attributed to excessive loading of nitrogen (N) and phosphorus (P) as well as high water temperatures (Rejmankova and Komarkova, 2005; Paerl and Paul, 2012; Gobbler et al. 2016; Beaver et al. 2018). However, in shallow lakes, warmer temperatures and higher light absorption have been found to be more significant drivers of productivity (Kosten et al., 2012). In other words, the combination of factors that drive rapid increases in lake productivity may differ between individual water bodies or geographic regions, hence smaller and more focused state and regional scale studies may be more useful in describing changes in lake productivity dynamics (Oleksy et al., 2022).

Large scale studies have highlighted that water quality trends are context dependent and vary across regions (Beaver et al., 2018). However, some regions with unique landscape features remain understudied regarding lake productivity trends. For example, the Intermountain West region (including the US states Colorado, Idaho, Montana, Utah, and Wyoming) has very different hydrological dynamics and landscape features compared with other regions, yet water quality trends remain mostly undocumented. The region undergoes quick wet-dry seasonal transitions, with most of the streamflow generated by snowmelt (Bales et al., 2006). Higher gradients in temperature and precipitation with elevation make hydrologic processes significantly different compared with low-elevation regions (Bales et al., 2006). Land use in this region also differs, with substantial amounts of grassland pasture and range contributing to increased organic nutrient loading to streams and rivers (Agouridis et al., 2005).

An increase in awareness and reporting of HABs in the Intermountain West suggests that lakes in the region may be becoming more eutrophic, yet our understanding of lake productivity trends is very limited. As nation-wide research and understanding of HABs has grown, so have management and sampling plans, educational materials, and overall public awareness (Hudnell et al. 2010). However, this increase in awareness and reporting has the potential to create a perception that blooms are already increasing in intensity and frequency (Hallegraeff et al., 2021). Recent work in the region highlights that lakes are experiencing roughly equal trends of changing from blue to green or changing green to blue, indicating there is not overwhelming evidence that they are getting more eutrophic, where eutrophic lakes are generally more green

(Oleksy et al., 2022). It remains unclear whether this is a result of representative increases in intensity or a result of heightened monitoring. Therefore, retrospective data analyses and long-term monitoring are needed to identify consistent productivity trends (Hudnell, 2008), particularly in understudied regions like the Western US.

Remote sensing and long-term satellite imagery create opportunities to address key research gaps surrounding what factors are driving freshwater productivity across regions. In-situ sampling methods are often limited by resources such as time and funding. Therefore, in-situ water quality data tends to be focused on relatively large lakes (> 20 ha) and long-term records tend to be rare (Stanley et al. 2019). Importantly, leveraging remote sensing data can address water quality dynamics over large spatial and temporal scales where in situ data is lacking (Topp et al. 2020). Remote sensing data with high spatial and temporal coverage are also useful to understand how global change is affecting productivity and bloom dynamics (Harvey et al. 2015; Ho et al., 2017; Seegers et al. 2021). These tools can be used to determine water quality parameters in freshwater systems such as chlorophyll-a (Boucher et al., 2018; Kuhn et al., 2019; Papenfus et al., 2020), suspended sediments (Pavelsky and Smith, 2009), and organic matter (Kutser et al., 2005; Slonecker et al., 2016).

In this study, we address two gaps in our understanding of lake productivity dynamics in the Intermountain West. Specifically, we aimed to identify 1) the historical prevalence of eutrophic lakes and whether this is an increasing trend of eutrophication, and 2) the drivers and spatial distribution of changes in trophic state. We use remote sensing imagery and in-situ chlorophyll-a data, covering 1984-2019, to predict chlorophyll-a and lake trophic state based solely on satellite imagery. This approach allowed us to document productivity trends in 1,169 lakes over 35 years. By increasing the level of understanding of historical trends in lake productivity and their drivers in this region, our analysis can also shed light on the intensification of algal blooms in lakes and provide important information for water quality management.

2 Materials and Methods

2.1 Data Sources and Processing

Our analysis used various remote sensing, water quality, lake and landscape features, and climate datasets. We opted for a machine-learning approach that uses paired satellite reflectance from Landsat observations and in-situ water quality data. We acquired Landsat data and in-situ chlorophyll-a samples for model training from the AquaSat dataset (Ross et al., 2019). AquaSat joins Landsat Tier 1 surface reflectance to water quality samples from the Water Quality Portal (Read et al. 2017) and LAGOS-NE (Soranno et al. 2017) that occurred ± 1 day of a Landsat observation. We filtered AquaSat to only include observations over the Intermountain West region and with Landsat scenes with less than 50% cloud cover. The resulting dataset included 1,340 observations across 249 lakes in the region. Reflectance values across the three different Landsat satellites used (5, 7, and 8) were standardized using the methodology outlined in Gardner et al. (2021). We then identified various open-source datasets that captured environmental drivers we hypothesized might be important for predicting chlorophyll-a. We merged Lake characteristics and catchment level metrics to our training dataset from the LakeCat (Hill et al., 2018) and LAGOS-US (Cheruvelil et al., 2021), and HydroLAKES (Messager at al., 2016) datasets. Initially we joined lakes in the training set to corresponding lake polygons included in NHDPlusV2. LakeCat, LAGOS-US, and HydroLAKES datasets were then added through common NHD identifiers. We selected metrics that were derived from these datasets based on their potential to impact water quality (Table S1).

Daily surface water temperature and corresponding weather data (wind speed) were also included in our model development. We extracted daily water temperature from Willard et al. (2022), which includes estimated daily surface water temperature for 185,549 lakes across the US. In addition to daily surface temperature, we calculated prior 14-day mean temperatures for all 1,340 observations included in our training set. Then, we joined 14-day mean temperature and meridional wind speed to our training set using common NHD identifiers and the date of observation.

Using the same methods, we built our prediction dataset using LimnoSat-US (Topp et al., 2021). LimnoSat-US includes Landsat Collection 1, Tier 1 surface reflectance for lakes greater than 10 hectares in the U.S. spanning 1984 – 2020. Surface reflectance values represent the median surface reflectance of a 120-meter buffer of the "deepest point" of a lake polygon. This "deepest point" can be defined as the center of the largest circle that can fit within a lake polygon. We joined the lake characteristics, catchment level metrics, and climate data described above to our prediction dataset, resulting in 1,264,355 observations across 2,596 lakes in the Intermountain West.

Lastly, we defined categories for three trophic states based on the following chlorophyll-a thresholds: oligotrophic (0 - 2.6 ug /L), mesotrophic (2.7 – 7 ug / L), and eutrophic (> 7 ug / L). These thresholds were inspired by the criteria outlined in the National Lakes Assessment (U.S. Environmental Protection Agency, 2009). This categorical approach was taken because predicting chlorophyll-a concentrations in freshwater systems with remote sensing has been notably challenging, particularly with Landsat imagery (Salem et al., 2017; Smith et al. 2021). Landsat bands are relatively broad with a low signal-to-noise ratio, often resulting in predictions of chlorophyll-a with high levels of uncertainty (Matthews, 2011). Furthermore, the accurate prediction of chlorophyll-a is affected by complex optical conditions in various waterbodies with higher levels of turbidity (Ruddick et al. 2001; Alvain et al. 2005). These challenges were addressed by focusing on broad, trophic level predictions of chlorophyll-a.

2.2 Model Development

We developed an Extreme Gradient Boosting (XgBoost) model to classify categories of chlorophyll-a. These models build on machine learning concepts such as decision trees and ensemble learning (Cheng and Guesterin, 2016). Decision trees represent a supervised learning approach where training features are split into internal nodes and evaluated to form homogeneous groups (terminal nodes) (Kotsiantis, 2013). Decision trees can comprise a single univariate classifier or the combination of multiple classifiers, known as an ensemble classifier. Gradient boosting is a method of ensemble learning where a series of models are built with weights assigned to misclassified observations. Misclassified observations from the previous model are used as training data for the next, and the result is an ensemble classifier that represents an aggregation of individual classifiers and minimizes overall error (Pal, 2007).

We used a combination of optical and climatic variables to build a predictive model for chlorophyll-a. Specifically, we calculated multiple band ratios that have been shown to explain variation in phytoplankton blooms (Ho et al., 2017). We used a 14-day average of lake surface temperature and daily meridional wind speed as additional predictor variables. We explored the addition of static predictor variables (such as lake elevation or watershed land use) yet refrained from including these in our final model because recent studies have shown that static predictor variables can act as ‘identifiers’ and lead to overfitting and over-optimistic evaluation metrics

(Meyer et al., 2018). Thus, we selected only continuous predictor variables that we would not expect to lead to substantial overfitting (Table 1).

Table 1. Predictor variables used for model training.

Predictor variable	Description
Blue	Surface reflectance of blue band
Dwl	Dominant wavelength
Nir	Surface reflectance of Nir band
Swir2	Surface reflectance of Swir2 band
Red / Blue	Red / Blue
Red / Nir	Red / Nir
Nir / Red.	Nir / Red
Green / Blue	Green / Blue
Nir Sac	(Nir – 1.03) * Swir1
Nir – Red	Nir - Red
Red - Green	Red - Green
EVI	2.5*((Nir – Red)/(Nir + ((6*Red) – (7.5*Blue)) + 1))
GCI	Nir / (Green – 1)
Mean 14-day Temp	14- day average surface water temperature (deg. C)
Wind	Meridional wind speed (m/s)

We partitioned our training set to reserve 20% for model testing and evaluation and 80% for model training and parameter tuning. XgBoost models include a wide range of hyperparameters and are one of the main tools used to reduce model variance. Hyperparameters were tuned by first establishing a grid of conservative values (to prevent overfitting) and then extracting the hyperparameters that resulted in the lowest validation loss. After training the final model with these hyperparameters, model performance was evaluated through a confusion matrix which shows the relative accuracy of predictions across different categories.

2.3 Data Analysis

To summarize lake trends and capture long-term changes in chlorophyll-a, we analyzed the percent occurrence of trophic state observations. First, lakes included in our trend analysis had to have at least two summer observations (June – September) for each year (1984-2019). More conservative filtering criteria, such as at least 5 observations per year, was explored yet had negligible effects on overall results and resulted in fewer lakes being included in our analysis. We specifically focused our analysis on summer observations to limit the effect that snow and ice may have on our results. As a result, 1,169 lakes were included in our analysis based on these criteria. For each summer, the percent occurrence of each trophic state observation was recorded. Then, the average percent occurrence for each trophic state was recorded across two time periods: 1984 – 2004; and 2005 – 2019. Lastly, lakes were grouped into the following categories based on the shift (if any) in trophic state during these two time periods:

1) **No trend:** Change in % oligotrophic, % mesotrophic, and % eutrophic was less than 10% across all three categories (Figure 1A)
2) **Increasing in % Eutrophic:** Number of eutrophic observations increased by 10% or more while the number of oligotrophic observations decreased by 10% or more (Figure 1B)
3) **Increasing in % Oligotrophic:** Number of oligotrophic observations increased by 10% or more while the number of eutrophic observations decreased by 10% or more (Figure 1C).

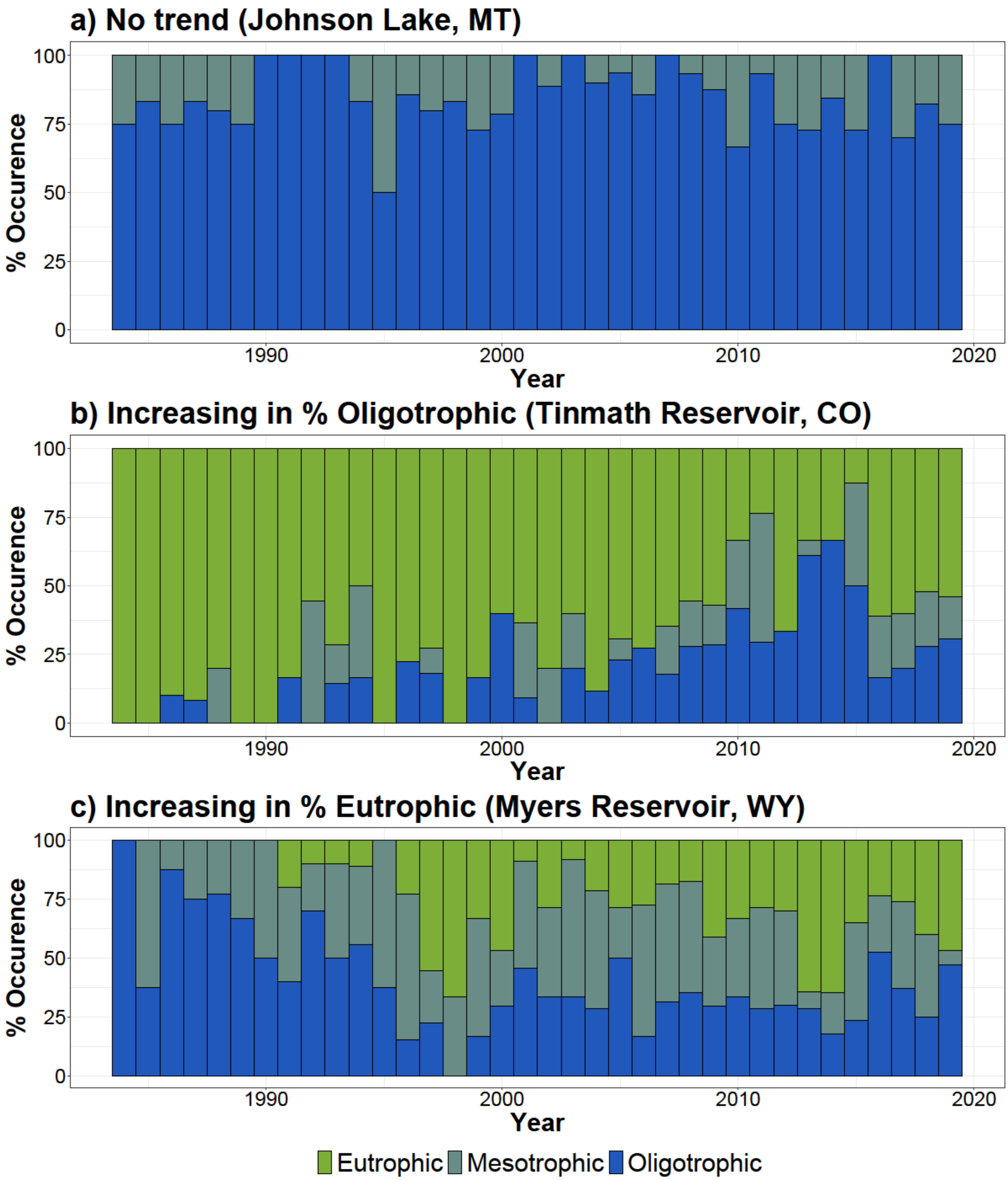

Figure 1. Examples of three possible trend categories based on the trends in % occurrence of oligotrophic, mesotrophic, and eutrophic observations. Each panel included in this plot represents the trends observed across three different lakes.

Lastly, trend-specific drivers were examined by determining how lake catchment, hydrologic, and climate metrics explained differences across trends. We calculated variable importance across trend categories by applying a random forest model using the randomForest package in R (Liaw and Wiener, 2002). With this approach, we were able to classify the reduction in accuracy that occurred across all three responses when certain variables were excluded. All data processing, model development, statistical analysis, and visualizations were done in Program R (R Core Team, 2022).

3 Results

3.1 Model Performance

Model performance was evaluated through a confusion matrix as well as various accuracy and error metrics (Table 2, Figure 2). In the range of oligotrophic values (0 - 2.6 ug/L), observations had a balanced accuracy of 78% and only 7% of these observations were misclassified as eutrophic (Table 2). Mesotrophic observations (2.7 - 7 ug/L) represented the range of values with the lowest prediction accuracy. Our model reported a balanced accuracy of 69% for mesotrophic classifications (Table 2). The most common misclassification among mesotrophic predictions was with observed classes that were oligotrophic (30%) (Figure 2). Lastly, eutrophic observations (> 7 ug/L) represented the class with the highest prediction accuracy (85%) (Table 2). In addition, there was relatively low prediction error with oligotrophic classes (6%). Overall, our model reported a global accuracy of 70% with a 95% confidence interval of between 63% and 76% (Table S2).

Table 2. Model evaluation metrics for each predicted class.

Statistic	Oligotrophic	Mesotrophic	Eutrophic
Sensitivity	0.7500	0.5397	0.8426
Specificity	0.8167	0.8440	0.8912
Neg Pred Value	0.8235	0.8041	0.9291
Pos Pred Value	0.7412	0.6071	0.7460
Prevalence	0.4118	0.3088	0.2794
Balanced Accuracy	78.33%	69.18%	85.79%

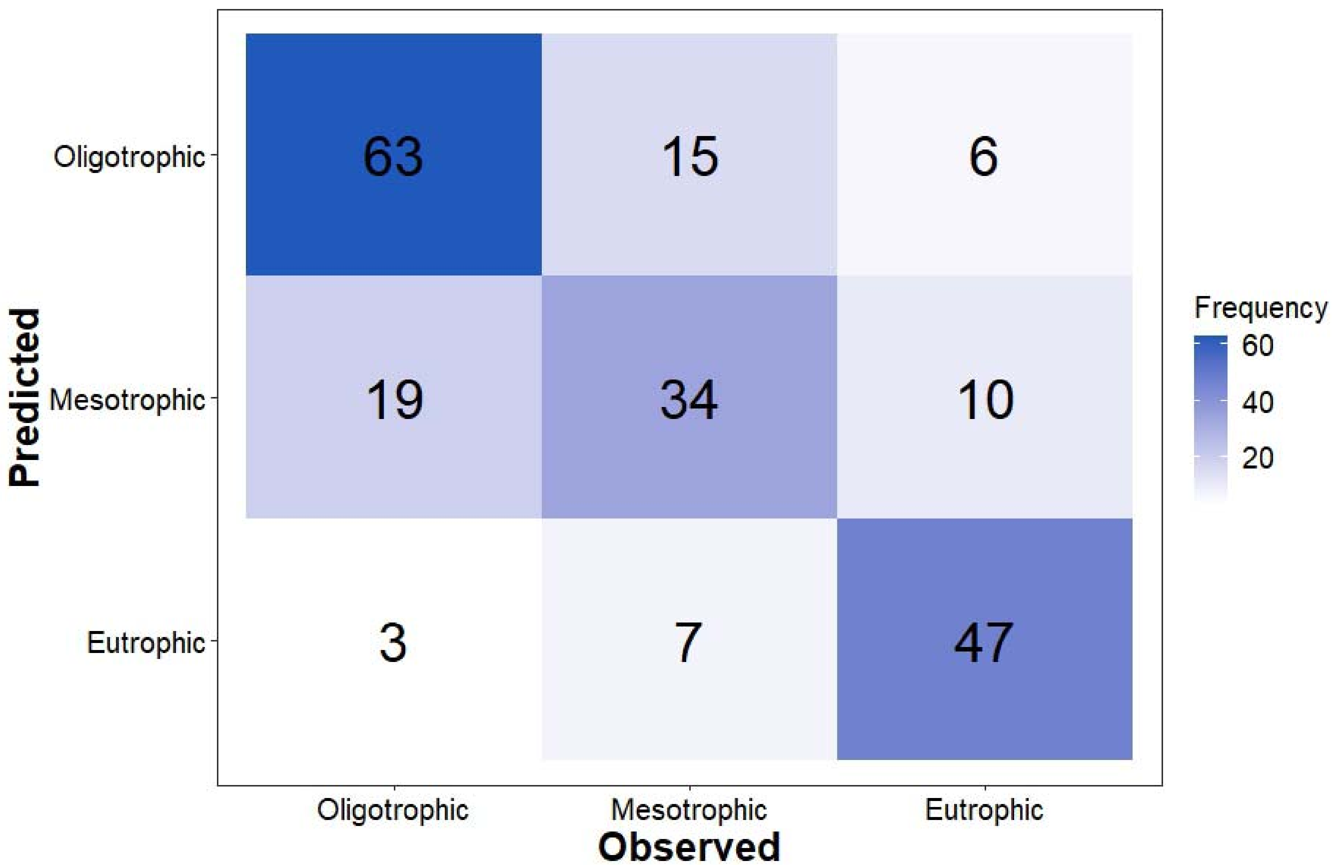

Figure 2. Confusion matrix illustrating the frequency and accuracy of predictions across all three trophic states. The most common misclassification was among mesotrophic predictions that had observed classes of oligotrophic (middle panel, far left). Overall, our model had a global accuracy of 70% with a 95 % confidence interval of 63% - 76%.

The integration of fine-scale, daily temperature and climate features significantly improved our ability to predict across these trophic states. In terms of feature importance measured by model gain, mean 14 – day surface water temperature and meridional wind speed were the second and fourth most important predictor variables, behind the band ratio of blue to green and dominant wavelength (Figure 3). In addition, model scenarios without climate variables reported global accuracies of around 63%, with a 95% confidence interval of between 57 – 69%.

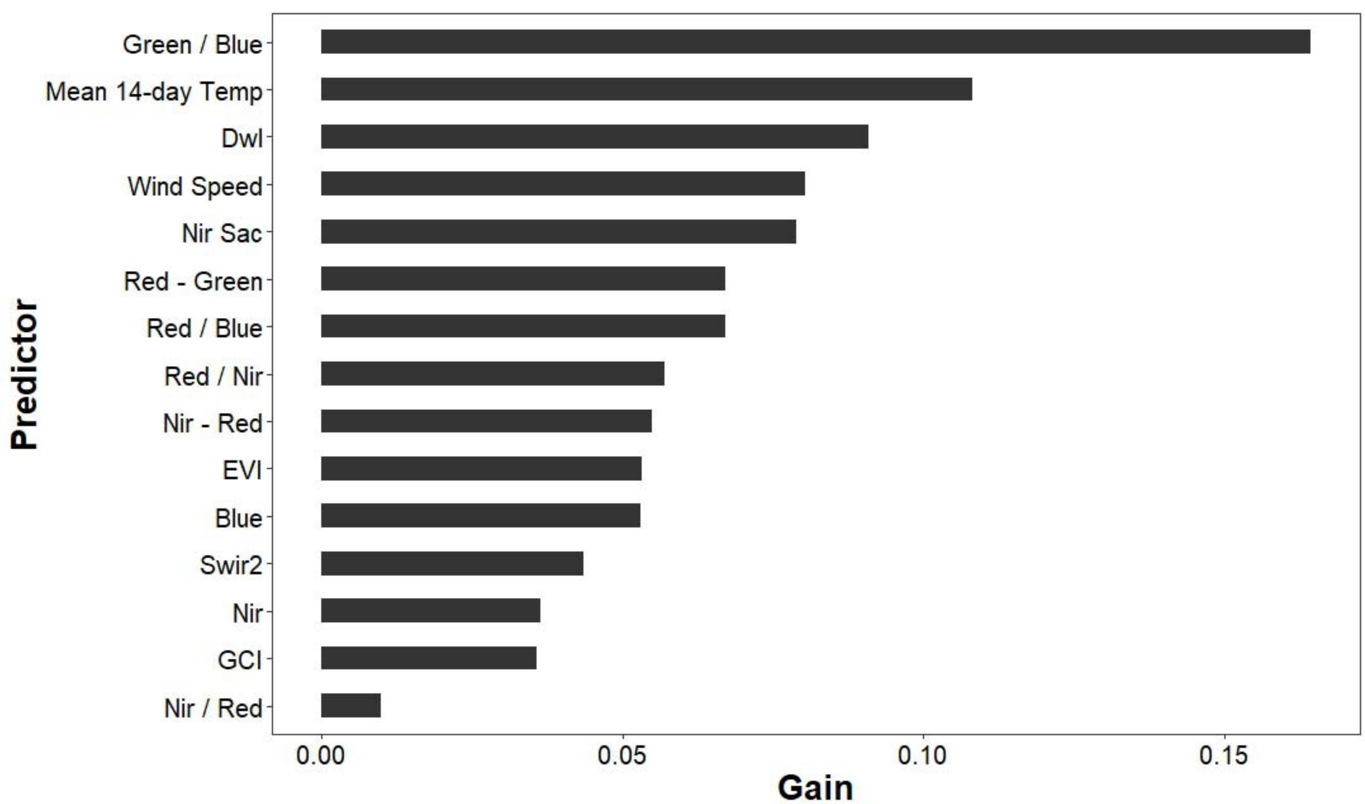

Figure 3. Feature importance, measured as model gain, for the predictor variables included in model development.

3.2 Productivity Trends

Most lakes included in this study did not show trends in chlorophyll-a (Figure 4). Overall, a total of 651 lakes (55%) did not meet our 10% thresholds for shifts across all three categories More than half of the lakes that weren't changing from 1985-2019 were oligotrophic lakes with most observations classified as oligotrophic. In contrast, 24% of lakes within this category were eutrophic lakes. The remaining lakes (16%) in this trend category likely represent a more complex, mesotrophic lake status.

The second most common trend we observed were lakes that had substantial shifts in trophic status by becoming more oligotrophic. We found that 17% of lakes switched from predominantly being classified as eutrophic to being classified primarily as oligotrophic. Most of these lakes tended to be dominated by eutrophic observations, suggesting that they are eutrophic lakes that are improving in water quality. Few lakes showed evidence of extreme (>30%) shifts in oligotrophic observations. In other words, shifts in oligotrophic observations within this lake trend was relatively moderate (10 - 30%, Figure S1).

Lastly, a minority (3%) of all lakes were shifting towards becoming more eutrophic. Interestingly, these trends were equally distributed across lakes with high levels of eutrophic observations and those with high levels of oligotrophic observations. In other words, lakes that were predominately oligotrophic and were becoming more eutrophic were equally as common as lakes that were eutrophic and were intensifying in this way. The magnitude of change was similar to that of lakes that trended oligotrophic, with little evidence of extreme shifts in eutrophic observations (Figure S1).

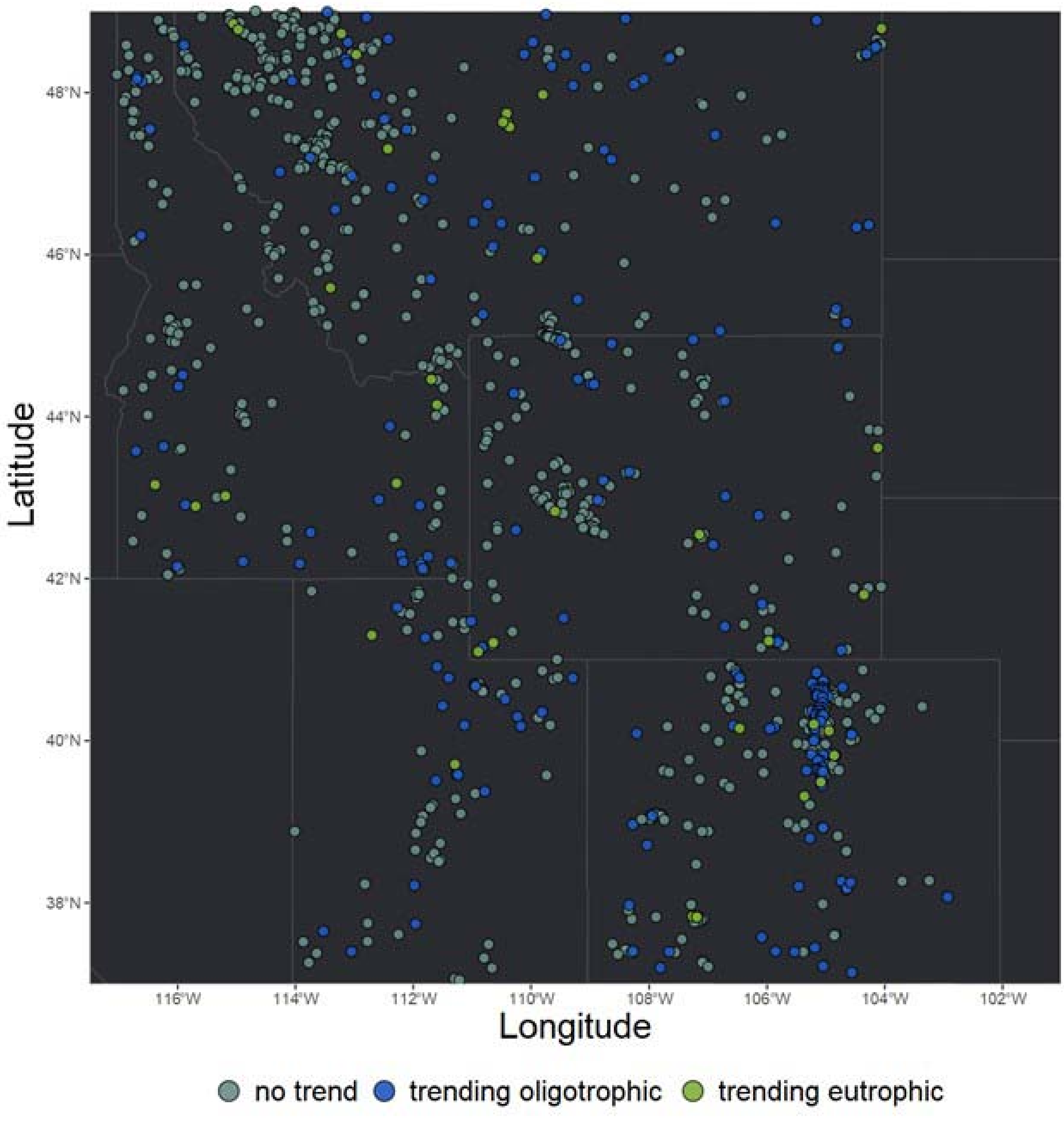

Figure 4. Spatial distribution of trophic state trends across the five states included in this analysis.

The remaining lakes that were included in this analysis and did not fit into these rigid categories reflect various levels of trophic state change. For example, 7% of lakes could be described as becoming more oligotrophic and less mesotrophic by the same thresholds outlined in Figure 1. In contrast, few lakes (1%) were found to be becoming more mesotrophic during this time. The 12% of lakes that did not fit into these categories displayed slight trends in certain categories (such as becoming more oligotrophic), but did not satisfy thresholds for trends in other categories such that we would be confident of defining clear trends in productivity.

3.3 Drivers of Trends

Our random forest model was able to identify partially important variables for explaining trends in productivity. Lake catchment data such as 30 year normal mean temperature, base flow index, and mean runoff were more important in explaining overall lake trends (Figure 5). Specifically, lakes becoming more oligotrophic tended to have longer residence times and were located in catchments that were generally less forested and more developed (Figure 6). Whereas, lakes that were becoming more eutrophic also tended to be less forested but were located in smaller catchments and were shallower on average (4.13 m) compared with lakes that were not trending (9.12 m). Lastly, a number of climate and landscape metrics displayed a high level of variation across trophic state trends, however some of these metrics had significant cross correlation with other variables (Figure S2).

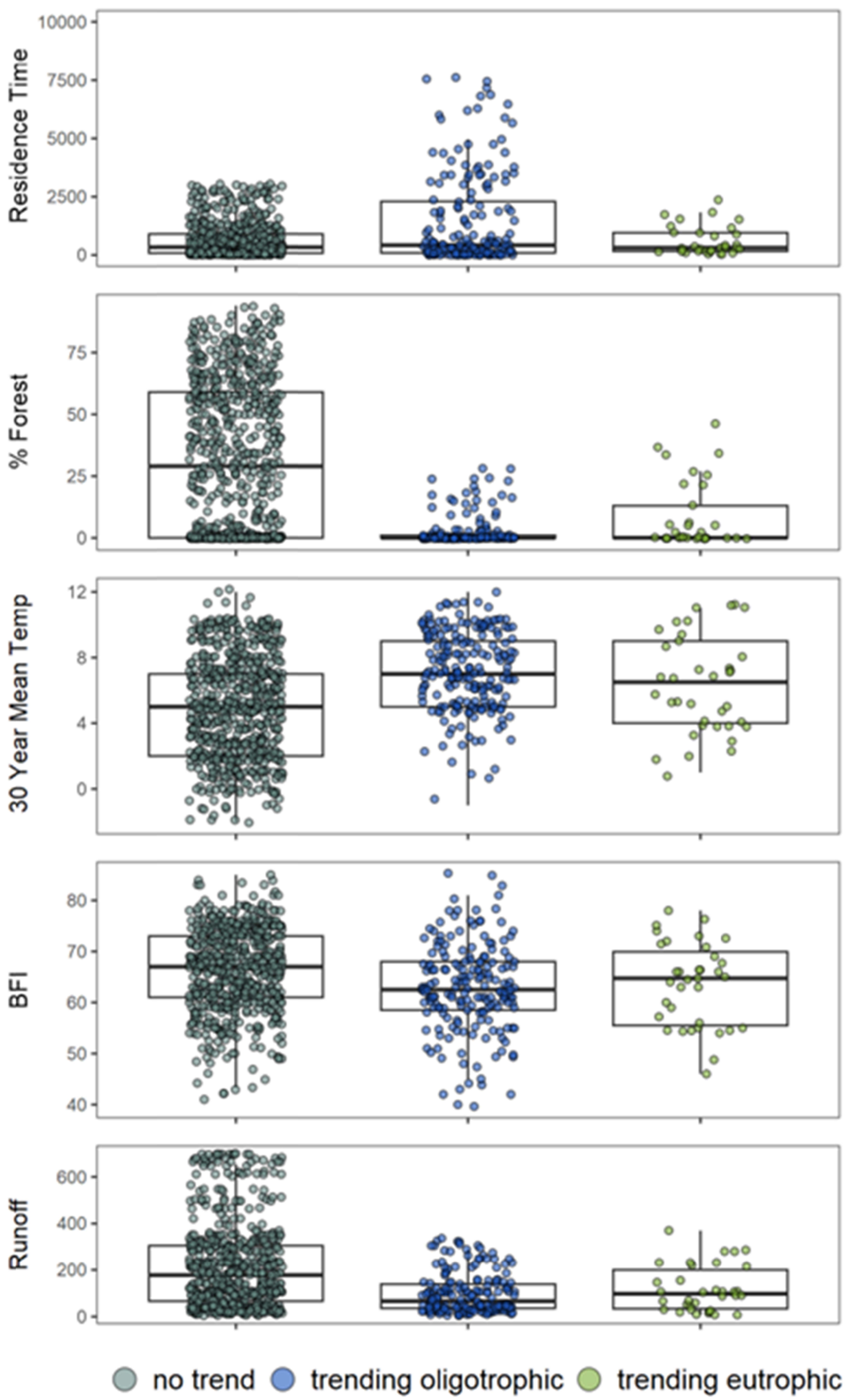

Figure 5. Boxplots across trend categories of the top five most important variables based on the decrease in accuracy from the overall (global) random forest model.

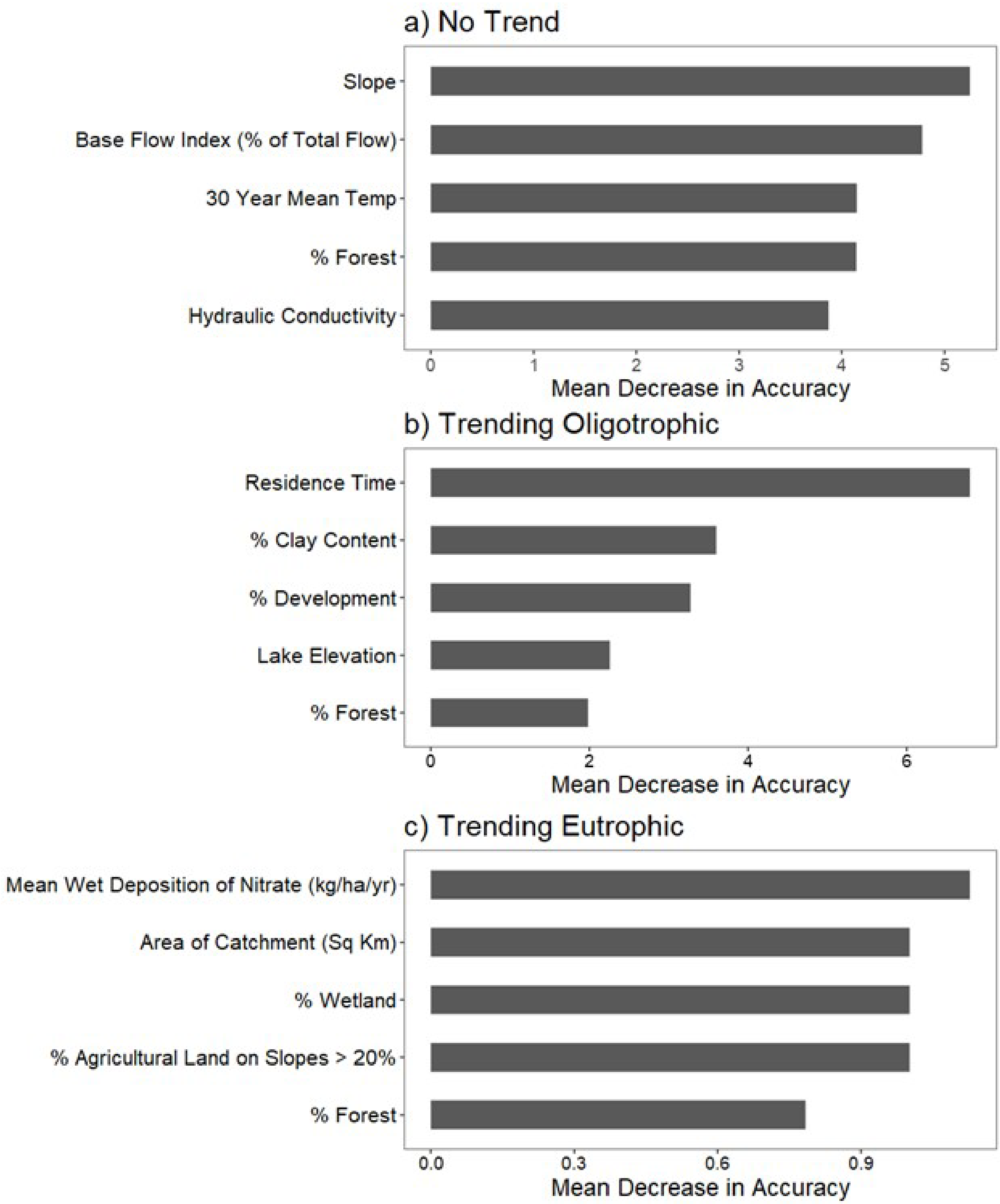

Figure 6. Mean decrease in accuracy of the top five variables used to explain each trend category in the random forest model. The mean decrease in accuracy describes variable importance by quantifying how much accuracy is lost by excluding that particular variable.

4 Discussion

Eutrophication and the development of algal blooms are global phenomena that threaten aquatic systems. Given the effects of global change and the expected increasing intensity of these disturbances, there has been a substantial level of interest in investigating recent productivity trends in lakes and reservoirs. Our analysis found that most lakes in the Intermountain West region have remained relatively static in terms of their productivity over the last 35 years. In addition, we found that a greater percentage of lakes were improving with regards to productivity, as opposed to becoming more eutrophic.

4.1 Productivity Trends

The majority of lakes included in this analysis showed no evidence of substantial changes in trophic state and supplement other regional-scale analyses of in-situ chlorophyll-a data. This is consistent with previous analyses demonstrating that magnitude, severity, and duration of algal blooms are not intensifying in US lakes (Wilkinson et al. 2022). Similarly, long-term trends of Florida lakes have indicated that a majority (73%) have not shown evidence of changes in chlorophyll-a and trophic state (Canfield et al., 2018). While there is a growing concern of eutrophication and HABs becoming pervasive in the Intermountain West, our results build on recent studies that suggest no indication of widespread intensification in algal blooms. Rather, the large percentage of lakes not trending combined with the presence of algal blooms across the region suggest a historical baseline of eutrophication and that blooms could have predated the 1980s.

Our analysis revealed that, in fact, the smallest percentage (3%) of lakes were trending eutrophic. Global analyses of long-term phytoplankton blooms have shown a substantial (68 %) number of lakes to be increasing in bloom intensity (Ho et al., 2019). However, only 5% of U.S.

lakes have been shown to be increasing in the same metric over the past 40 years (Wilkinson et al., 2022). In addition, a minority of lakes (13%) in the Rocky Mountain region have shown to be shifting from blue to greener wavelengths during this time (Oleksy et al., 2022). With our analysis, we show that concerns regarding the widespread intensification of algal blooms are not captured in our analysis of chlorophyll-a and trophic state.

Our analysis of lakes that were trending eutrophic revealed several important hydrologic and climate factors associated with eutrophication. Specifically, 30-year normal mean temperatures tended to be higher among lakes trending eutrophic and an important variable for explaining overall trends. In addition, hydrologic variables such as lake depth and lake area revealed that lakes trending eutrophic tended to be smaller and shallower than other lakes. Small, shallow lakes are often more productive than deeper lakes because of the effects that lake morphology can have on ecosystem structure (Richardson et al., 2022; Henderson et al., 2021). Shallow lakes have also been shown to be more sensitive to climate conditions (Mooij et al., 2007) and could explain the interaction between climate and depth driving these trends.

In contrast, 19 % of study lakes were found to be improving by simultaneously becoming less eutrophic and more oligotrophic. Lake-specific characteristics reveal that lakes improving in water quality were in more developed and less forested catchments, as well as at lower elevations. These results are consistent with studies on water clarity (Topp et al., 2021), lake color (Oleksy et al., 2022), and chlorophyll-a (Wilkinson et al., 2022), that highlight improvements in water quality metrics over the same time period. These trends have been hypothesized to be the result of management actions or restoration projects (Wilkinson et al., 2022), although we lacked the information to make conclusions about the mechanisms of these trends. However, concentrations of nutrients across urban watersheds have significantly decreased over the past 20 years and have been directly attributed to the Clean Water Act (Stets et al., 2020). Given the greater variable importance of developed land use across lakes becoming more oligotrophic (3.9 compared to 1.6 among no trend lakes), it is possible that water quality implementation projects have had a positive effect on mitigating eutrophication in the region.

Despite the 35-year study period and wide range of lakes involved, the remote sensing data used in this study may not capture various spatial and temporal characteristics of eutrophication or algal blooms. Algal blooms tend to have high temporal and spatial variance in the short term, as wind dynamics drive the spatial distribution of phytoplankton blooms (Bosse et al., 2019). Therefore, the 16-day return period for Landsat observations may not capture short-term peaks in chlorophyll-a. Furthermore, some images can be unusable due to extensive cloud cover and may extend the period between observations up to months at a time. However, given that our analysis includes 35 years of data across 1,169 lakes, we would expect to capture widespread eutrophication and the spatial clustering of eutrophication trends if it were present.

Additionally, Landsat's long-term record restricted us to coarse analyses of chlorophyll-a and trophic state. Our analysis does not capture cyanobacteria dynamics or those of cyanotoxins directly. Satellites with spectral resolution to capture cyanobacteria abundance, such as MERIS and Sentinel-3, have lacked the data availability for long-term, retrospective analyses (Coffer et al., 2020). However, future studies that are able to capture trends in cyanobacteria blooms specifically will help provide further context regarding the concerns of bloom intensification.

4.2 Modeling Approach

Our research focused on leveraging long-term remote sensing and environmental datasets that would supplement the ongoing debate regarding recent trends in phytoplankton blooms.

While the application of remote sensing for inland water quality monitoring has grown over the past decade (Topp et al., 2020), the retrieval of certain optical properties such as chlorophyll-a has remained a challenge (Matthews, 2011). However, by incorporating daily surface temperature and meridional wind speed from datasets leveraging modern deep learning techniques we were able to show substantial improvements in model accuracy. The incorporation of fine-scale lake climate data over the 35-year time span of this study was instrumental to our ability to document trophic state changes and add evidence to the ongoing debate regarding the recent trends in increasing eutrophication and HABs.

Most notably, surface water temperature was the second most important predictor variable of our trophic state model and could be important for a wide range of remote sensing based water quality models. Water temperature has proven to be an important predictor of chlorophyll-a across inland lakes (Liu et al. 2019; Karcher et al. 2020) as well as oceans (Dunstan et al. 2018). However, applied remote sensing models that predict chlorophyll-a are often limited to strictly optical predictors such as band-ratio (blue-green) models. These models work well in waterbodies where other parameters such as colored dissolved organic matter co-vary with chlorophyll-a (O'Reilly et al., 1998). However, in optically complex waterbodies with higher levels of turbidity and dissolved organic matter band-ratio models struggle to accurately retrieve chlorophyll-a concentrations (Tzortziou et al., 2007; Zheng and DiGiacomo, 2007; Witter et al., 2009). Thus, relying on surface reflectance for predictive models has resulted in a lack of generalizability across a wide range of waterbodies. However, the incorporation of surface water temperature seems to have supplemented existing band-ratio features to better predict across a wide range of lake types.

Wind speed was another climate predictor variable that was substantially important in predicting trophic state. Correlations between wind speed and chlorophyll have been shown using remote sensing at global scales (Kahru et al., 2010). In addition, wind speed has been documented as an important driver of cyanobacterial bloom development with blooms favoring warm, calm weather (Kanoshina et al. 2003). Overall, the integration of daily, fine-scale weather data greatly improved our ability to predict trophic state and is likely to have a positive impact on similar approaches that leverage remote sensing data.

5 Conclusions

With increases in global lake temperatures (Maberly et al., 2020), lakes globally are expected to become more eutrophic as a response to climate change (Yang et al., 2020). Yet, there have been conflicting results thus far regarding intensifying eutrophication and algal blooms in U.S. and global lakes (Ho et al., 2019, Wilkinson et al., 2022, Topp et al., 2021). While increasing eutrophication is a major threat to freshwaters, our analysis found that lakes in the Intermountain West region have not undergone widespread change. Rather, we found that most lakes were not changing, and a substantial number of lakes were becoming less eutrophic and more oligotrophic over this time period. In addition, the number of eutrophic lakes that have not undergone substantial change over this time period suggests algal blooms have been present in the region since at least the early 1980s. These results highlight the complex nature of observing changes in freshwater lakes across large scales. However, our results suggest that despite the processes that drive eutrophication (warmer temperatures, nutrient accumulation, etc.) which have increased over the past several decades, we haven't yet observed a concurrent increase in eutrophication from a large, unbiased sample of 1,169 lakes in the Intermountain

West. This suggested suggesting controls on eutrophication in this region are complex and need further additional study.

Acknowledgments

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Open Research

The data used for this paper (Hydrolakes, LakeCat, AquaSat, LimnoSat, and LAGOS) are all freely available to download in online repositories (Messager et al., 2016; Hill et al., 2018; Ross et al., 2019; Topp et al., 2021; Cheruvelil et al., 2021). Links to the where this data can be downloaded can be found in the code for this analysis. The code used for this analysis can be found at https://github.com/SamSillen/ProductivityTrends.

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