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Satellites reveal localized algal bloom intensification in a culturally significant reservoir

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Algal blooms are a growing human and ecosystem health concern for many freshwater systems, particularly reservoirs. However, reservoirs are poorly monitored relative to large lakes and thus the dynamics of blooms are less understood. One such system is the Allegheny Reservoir (AR) where algal blooms have been documented as early as 1972 with annual bloom occurrence reported since 2012. The AR is located between New York and Pennsylvania and partially within the Seneca Nation of Indians' (SNI) Allegany Reservation where the persistence of blooms is an environmental justice concern. However, there is limited historical data to quantify where blooms occur and if frequency or severity are increasing. This study attempts to fill these gaps and focus on how chlorophyll-a (chl-a) concentrations and bloom dynamics are changing over time by generating high resolution chl-a maps back to 1984 using satellite remote sensing. Algal blooms have occurred over the full record predominantly near the transitional zone of the AR, largely within SNI territory. Notably, mean whole reservoir bloom coverage over the entire record is 32.93% while mean bloom coverage within SNI territory is 52.39%, highlighting environmental justice concerns. Whole reservoir, spatially integrated mean chl-a concentrations display no significant change over time, however the SNI portion of the AR is increasingly changing at the pixel-level. These results highlight the power of spatially-explicit, long-term analysis enabled by satellites to reveal localized patterns of chl-a variation otherwise obscured by point sampling or whole-reservoir averaging. Pinpointing where blooms occur and where their spatial footprint may be changing is critical for understanding their formation, management, and highlighting environmental justice concerns that are often highly localized.

KEYWORDS

algal bloom, chlorophyll-a, environmental justice, landsat, remote sensing, reservoir, water quality

1 Introduction

Reports of algal blooms, both cyanobacteria and green algae, in inland waterbodies have increased considerably throughout the world over the past several decades (Carmichael, 2008; Ho et al., 2019). Increased reporting has been attributed to increases in bloom frequency and severity (Legleiter et al., 2022). However, other recent studies attribute bloom increases to more awareness and monitoring efforts (Gobler, 2020; Hallegraef et al., 2021).

Algal blooms can negatively impact aquatic ecosystems, public health, and economies, with annual estimated economic loss in the United States to be in the several billions of dollars (Paerl et al., 2001; Dodds et al., 2009). Blooms can inhibit recreational use and increase drinking water treatment costs (Dearmont et al., 1998; Kudela et al., 2015). Moreover, toxins produced from cyanobacteria and green algae can harm human health, impacting skin, digestion, and liver functions (Moore et al., 2008; Kouakou and Poder, 2019). Blooms typically occur during the recreational season (May – November) and can decrease water quality and species richness while increasing eutrophication and pH (Amorim and Moura, 2021). While the occurrence of algal blooms has been well-documented over the past decade in economically important large lakes (Binding et al., 2013; Ho and Michalak, 2015; Stumpf et al., 2016; Ho et al., 2017; Castagna et al., 2020), historical records of bloom indicators, such as chlorophyll-a (chl-a), in smaller lakes and reservoirs are often lacking. These long-term chl-a records from inland water bodies are needed to understand how algal blooms are changing over time in critical inland waterbodies vital for drinking water and recreation (Hayes et al., 2017; Wilkinson et al., 2020; Steyaert and Condon, 2022; Steyaert et al., 2022).

Satellite remote sensing using Landsat data has been widely used to observe the spatiotemporal trends of various water quality parameters including suspended sediment (Gardner et al., 2023), dissolved organic matter (Slonecker et al., 2016), trophic state (Meyer et al., 2024), and chl-a (Kuhn et al., 2019; Topp et al., 2021) in inland waterbodies. In addition to these parameters, remote sensing can also be used to estimate algae proxies, such as chl-a at recurrent flyover frequencies, over long time periods, and with detailed spatial coverage (Yip et al., 2015; Binding et al., 2018; Rolim et al., 2023). Although quantifying algal blooms in inland waterbodies using remote sensing derived measurements of chl-a can accurately estimate bloom coverage, extent, frequency, and concentration (Brezonik et al., 2005; Matthews et al., 2012; Binding et al., 2013; Torbick et al., 2013), the majority of remote sensing for freshwater algal bloom monitoring studies have been conducted in large lakes, as these water bodies can be resolved using sensors with coarse spatial resolution (Binding et al., 2013; Soontiens et al., 2019). In contrast to large lakes, reconstructing long-time series of chl-a in smaller lakes and reservoirs requires sensors with higher spatial resolution, such as Landsat. For smaller reservoirs that lack a historical record, Landsat is the only satellite currently capable of generating observations of algal blooms over multiple decades. Importantly, high-resolution per-pixel analysis enabled by Landsat allows characterization of spatial heterogeneity in bloom occurrence within a single waterbody that can reveal localized hotspots and spatial trends otherwise obscured by whole-reservoir averaging or sparse *in-situ* point sampling.

The Allegheny Reservoir (AR) is a data-scarce reservoir that has experienced algal blooms (Coin, 2017; NYDEC, 2019; Schellhammer, 2019). Since 1972, the AR has experienced occasional blooms occurring every two to five years (USEPA, 1975). However, since 2012, bloom frequency has anecdotally increased and also seem to be of longer duration (WINs, 2014). Yet the causes and history of algal bloom in the AR do not conform to typical nutrient delivery conditions observed in many lakes where blooms occur. The entire

watershed of the AR is dominated by forest cover (80%) and there is little agricultural land use to yield extensive fertilizer inputs (9%) (Figure 1). Internal phosphorus loading from sediment resuspension and release under periodic anoxia may also serve as a nutrient source independent of watershed land use (Nowlin et al., 2005). In the case of the AR, bloom events are also a significant environmental justice concern, as the northern portion of the reservoir, where blooms are often visually observed, lies within the Seneca Nation of Indians' (SNI) Allegany Reservation (Figure 1).

Until the construction of the Kinzua Dam in 1965 that created the AR, the Allegheny River Valley was inhabited by over 600 Seneca natives who were relocated following the breaking of the 1794 Treaty of Canandaigua (Joseph, 1968; Bilharz, 1998). Seneca families were relocated as the US Army Corps of Engineers (USACE) invoked eminent domain that designated 32% of the Seneca Allegany reservation as necessary for flood control (Randell and Curley, 2023). Families lost their homes, but the Seneca community also lost sacred burial grounds and religious areas. Of particular concern to the Seneca Nation was the loss of access to the burial site of Chief Cornplanter, war chief during the U.S. Revolutionary War and negotiator of treaties between the Seneca and U.S. government (Campisi and Starna, 1995; Rosier, 1995). Given that the AR remains an area of immense cultural, spiritual, ecological, and economic importance to the people of the Seneca Nation, it is all the more important to understand how algal bloom occurrence is impacting the AR as a resource.

Characterizing the frequency, duration, and spatial extent of algal blooms provides critical insight into their underlying causes. Quantitative records of chlorophyll-a concentrations prior to 2012 are limited, with scarce data available before 2000. In their absence, visual observations of algal bloom occurrence were sporadically documented by the U.S. Army Corps of Engineers (USACE) from 1965 to 2011. Since 2012, the USACE has collected chl-a field samples throughout the bloom season. In addition to grab samples, in 2018 the USACE installed a buoy to measure chl-a continuously during the bloom season. Even with this additional data source, knowledge gaps remain about the AR algal blooms. What is the spatial extent each year? Is there interannual variability? Do blooms generally start in the same location annually? Where are bloom intensities the worst? How much Seneca land surrounding the AR is unusable because of the blooms?

To address these observational questions, this study focused on three key objectives: 1. How do chl-a concentrations vary interannually? 2. Where are the hotspots for algal blooms within the AR? 3. How are metrics of algal bloom severity and extent changing over time? Additionally, preliminary associations between bloom metrics and hydroclimate drivers including discharge and precipitation were explored. These questions are addressed by utilizing both paired pixel-level and whole-reservoir analyses, allowing us to distinguish spatial heterogeneity in bloom occurrence from whole-system trends.

To address these objectives, Landsat's long historical record to reconstruct chl-a concentrations in the AR from 1986 to present were used. Landsat 5, 7, 8, and 9 images from 1986–2023 were used to estimate chl-a at the pixel level (30 meters) across the AR. Using this approach, annual bloom severity that accounts for both bloom

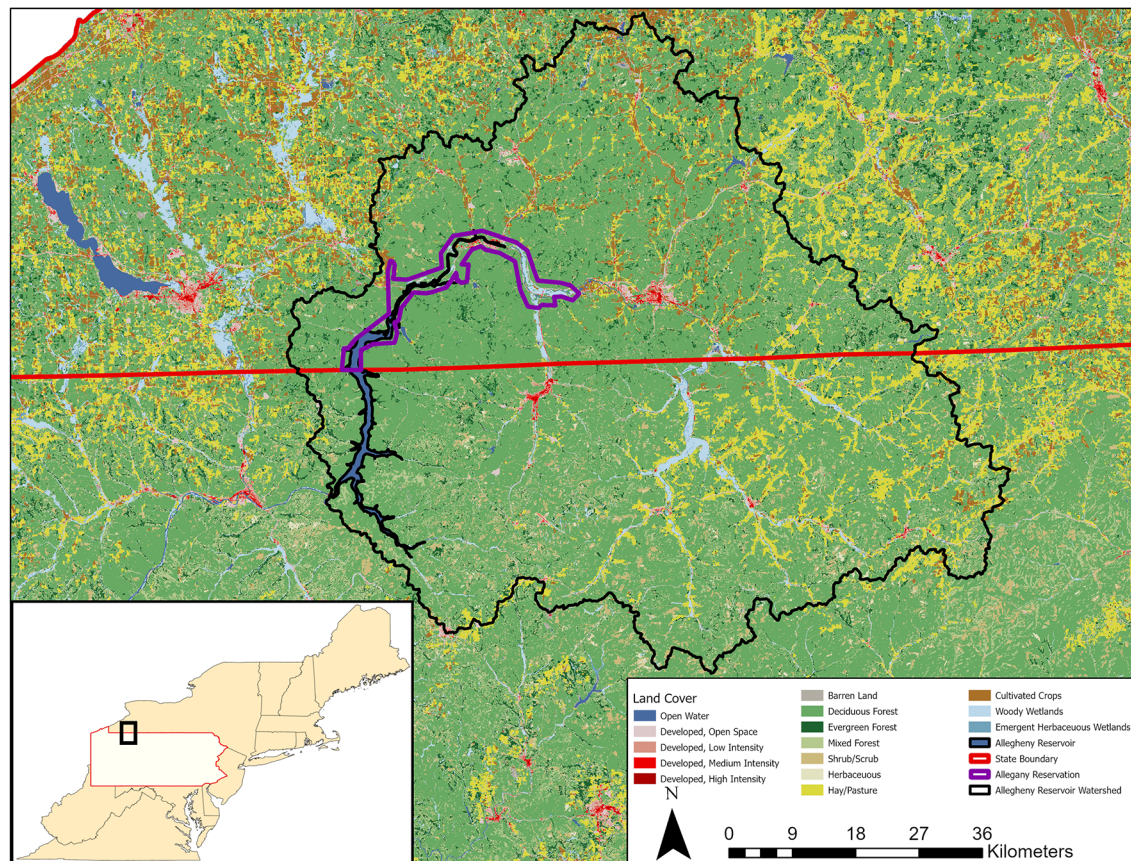


FIGURE 1

Land cover classifications of the Allegheny Reservoir watershed. Source National Land Cover Database (Dewitz and U.S. Geological Survey, 2021), public domain.

concentration and size was quantified (Stumpf et al., 2016; Binding et al., 2021). Using Landsat, only modeled bulk chl-a can be estimated and the presence of cyanobacteria or any specific algal taxa cannot be distinguished, therefore this study focuses on algal blooms generally and not specifically on harmful algal blooms.

2 Materials and methods

2.1 Study site

The AR is a 24-mile-long reservoir, with a total storage capacity of 1.6km³ that drains a 5650 km² watershed located between Pennsylvania and New York (41°46'22"N – 42°09'24"N, 78°52'55"W – 78°42'58"W) where the reservoir is within the Allegheny Reservation of the SNI (Figure 1). Primary uses for the reservoir are flood control and improving downriver water quality with secondary benefits that include recreation and fishing (USACE, 1977; Ensign, 2014). The reservoir is not used for drinking water. Mean water residence time is 77 days from the northern reach of the AR to the Kinzua Dam (USEPA, 1975). The entire reservoir watershed land use is dominated by forest cover, 80% including Allegheny State Park in New York and Allegheny National Forest in Pennsylvania with farmland accounting for 9% and development accounting for less than 1% of the watershed area above the reservoir. There are

over fifteen federal, state, county, and tribal agencies with jurisdiction for parts or all the reservoir with USACE and SNI being the two most active entities (WINs, 2014).

Since 2012, the USACE has conducted field sampling of varying frequencies throughout each bloom season, but only data from 2016–2025 has been made available for this study. Beginning in 2018, the USACE initiated high frequency monitoring using *in-situ* chl-a and phycocyanin sensors. This data documents two annually recurring bloom events; one typically in mid-May and a second in mid-September (Figure 2A). The first bloom predominantly consists of green algae while the second bloom is primarily composed of cyanobacteria, *Microcystis aeruginosa* and *Aphanizomenon flos-aquae* (Supplementary Figure 1). Both blooms create seasonal peaks in chl-a, whereas the later cyanobacterial bloom generates peaks in both phycocyanin and chl-a indicating that satellite retrieval of chl-a is a suitable proxy for detecting both bloom types in the AR (Figure 2).

2.2 Image processing and chlorophyll-a model

Given the interest in long-term trends, Landsat is the only long-running mission with imagery before 2000 and with high enough spatial resolution (30 m) for this study site. Images from Landsat Collection 2-Tier 1 Surface Reflectance product including Landsat 5, 7, 8, 9 (Earth Resources Observation and Science (EROS) Center, 1982, 1999, 2013, 2020) from 1986–2023 were processed in Google

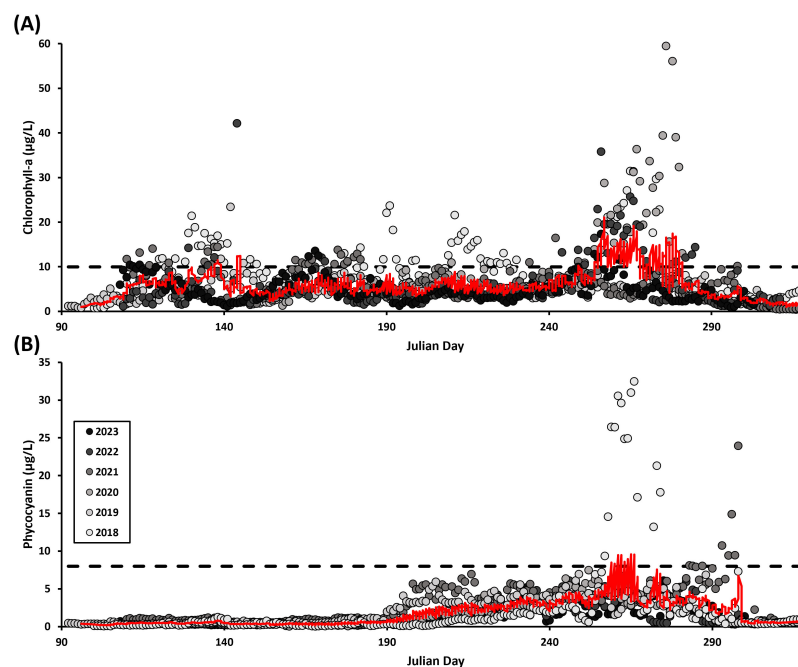


FIGURE 2

USACE *in-situ* sensor data from 2018–2023 for chl-a (A) and phycocyanin (B) measurements as points against day of year. The red lines represent a 5-point rolling average for chl-a (A), phycocyanin (B). The dashed line, located at 10 µg/L for panel (A) and 8 µg/L for phycocyanin in panel (B), represents the threshold used to determine algal bloom occurrence. Day 140 represents May 20th which is around the start of the first bloom. Day 265 is September 22nd and is the approximate start of the second bloom.

Earth Engine (Gorelick et al., 2017). Collection 2 is the best available product with improved radiometric and geometric corrections and atmospheric corrections, resulting in improvements such as more accurate surface temperature over water than land (Rengarajan et al., 2020; Wulder et al., 2022; Crawford et al., 2023). The Landsat surface reflectance product uses atmospheric corrections intended for land including the Landsat 5 and 7 Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm and Landsat 8 and 9 Landsat Surface Reflectance Code (LaSRC) (Ju et al., 2012; Crawford et al., 2023). However, there is no consensus on the best atmospheric correction method for inland waters (Ansper and Alikas, 2018; Pereira-Sandoval et al., 2019; Grendaitė and Stonevičius, 2022). Further, Landsat surface reflectance has comparable performance to water-based atmospheric correction algorithms when extracting water quality (Kuhn et al., 2019). Moreover, there is a large and growing literature that has successfully applied Landsat surface reflectance for time series analysis of a wide range of water quality variables from a single waterbody to global scale (Topp et al., 2021; Dethier et al., 2022; Yang et al., 2022; Cao et al., 2023; Yin et al., 2023; Prum et al., 2024; Mamun and Yang, 2025; Sillen et al., 2026).

Images during the bloom season from May through November and that had less than 40% cloud cover were analyzed. The selected threshold was used to balance the number of quality scenes while minimizing the risk of cloud and cloud-shadow contamination in chl-a estimates. This 40% cloud cover filter is the first of two filters applied in this study; a second filter excludes images in which more than 40% of the reservoir water extent is masked by clouds, cloud shadow, or low-confidence water classification. This is consistent

with the previous rationale of prioritizing scene quality over raw scene count. Images were processed with the goal of maximizing high quality, open-water pixels over the AR. Clouds, cloud-shadow, snow, and ice were removed using FMask (Zhu and Woodcock, 2012; Zhu et al., 2015) and water masks were created using the Dynamic Surface Water Extent (DSWE) algorithm (Jones, 2015, 2019). From DSWE, only pixels classified as “high confidence water” were included removing low confidence water and vegetated water. Bottom reflectance is unlikely to be a significant source of error in this study as these effects on chl-a retrieval are most pronounced in optically shallow, clear waters where light penetrates to the soil substrate (Yan et al., 2025b). The eutrophic conditions of the AR during bloom events increase light attenuation from chl-a and other particulates, reducing bottom visibility when chl-a concentrations are highest. Sillen et al. (2026) further identified that shallow, clear-water reaches is the primary risk for benthic algae interference in this same system, specifically the tailwater immediately downstream of Kinzua Dam, which falls outside the reservoir boundary analyzed within this study. To enable time series analysis across Landsat missions and USGS atmospheric correction approaches, widely used methods for empirical correction that harmonizes surface reflectance for each band across Landsat 5, 7, 8, and 9 using a second-order polynomial regression of quantiles during periods of mission overlap were applied (Roy et al., 2016; Claverie et al., 2018; Gardner et al., 2021; Sillen et al., 2026). In total, 279 images of the reservoir were exported spanning the period 1984–2023.

To retrieve chl-a concentrations from multispectral images, a recently developed data-driven model (Sillen et al., 2026) that was trained, validated, and tested in rivers and lakes across the Ohio

River Basin was applied. This model was chosen as it is the only chl-a retrieval model that has been trained and tested in the region containing the AR that is also applicable across Landsat 5–9. Further, the AR does not have adequate laboratory-extracted chl-a measurements to develop a local model or robustly test existing models. Only 15 matchups ± 2 days between field chl-a measurements and the Landsat 5–9 record were found from 2016–2025. A ± 1 day matchup window has been used in previous literature (Ross et al., 2019), however a ± 2 day matchup window was applied to increase the sample size for training and testing while reducing the impacts of temporal variability (Sillen et al., 2026). This methodology is used in remote sensing of large rivers and is consistent with established practices in Landsat-based water quality remote sensing (Dethier et al., 2020; Gardner et al., 2023). Chl-a is more temporally dynamic than other common water quality parameters, such as turbidity or dissolved organic carbon, particularly during bloom conditions where concentrations can shift over the course of days (Bosse et al., 2019). The Sillen et al. (2026) model is an extreme gradient boosting (XGBoost) machine learning model trained on 18,815 field and satellite matchups (Ross et al., 2019) that only uses laboratory-extracted (grab sample) chl-a. Fluorometric *in-situ* probe data were explicitly excluded from training due to known interoperability issues between fluorometric and extracted measurements. To maximize transferability within the domain and minimize overfitting, the model incorporates spatial-temporal cross validation, feature engineering, and hyperparameter tuning (Meyer et al., 2018; Topp et al., 2021; Gardner et al., 2023). The cross-validation procedure internally builds and validates thousands of models with different subsets of spatial and temporal blocks and selects the best performing model; this makes the model robust to unseen sites within the domain and is designed for spatially coherent chl-a estimates (Meyer et al., 2018). Further, water color, quantified as dominant wavelength, is an important predictor in the model providing information that helps the model learn spectral signals of chl-a under different conditions with high and low sediment, or yellow vs blue water (Balasubramanian et al., 2020; Yan et al., 2025a). Model performance was quantified with 4,543 hold-out test samples from rivers and lakes across the Ohio River Basin not used in model training-validation achieving a Mean Absolute Error (MAE) of 6.21 $\mu\text{g/L}$. The model's error metrics are within the range of recently published state-of-the-art machine learning and semi-empirical models for retrieving chl-a from Landsat within one to hundreds of waterbodies (Cao et al., 2020; Leggesse et al., 2023; Mamun and Yang, 2025). Sillen et al. (2026) directly compared their model against a compiled review of 34 published Landsat-based chl-a retrieval models, finding similar performance among models. Studies reporting lower error are typically focused on small, singular waterbodies that do not generalize across sites. Among large-scale, cross-validated regional models, the only directly comparable study, Mamun and Yang (2025), reports higher error (RMSE = 21.85 $\mu\text{g/L}$, MAE = 12.62 $\mu\text{g/L}$) than the model applied in this study. While data limitations do not allow for robust local model testing, a comparison of all available USACE laboratory-extracted chl-a measurements collected from 2016–2025 with estimates from the Sillen et al. (2026) model using Landsat result in a MAE of 8.1 $\mu\text{g/L}$. However, there

are only 15 field measurements that coincided ± 2 days with Landsat and thus should be considered as additional qualitative model evaluation using sparse available data from a poorly monitored reservoir rather than a local model test (Supplementary Figure 2).

A potential limitation of the chosen model is its predictable chl-a range of 0.1–200 $\mu\text{g/L}$. Although severe algal blooms can reach concentrations exceeding 200 $\mu\text{g/L}$, concentrations above 200 have not been reported for the AR (0–86 $\mu\text{g/L}$) based on sampling records from 2016–2025. Additionally, if concentrations did exceed 200 $\mu\text{g/L}$, it would not impact data interpretation as the research questions focus on the frequency and extent of concentrations above a 10 $\mu\text{g/L}$ threshold. A chl-a threshold of 10 $\mu\text{g/L}$ is used to indicate bloom presence as it has been documented in the past as a conservative indicator of algal blooms (Boucher et al., 2018; Soontiens et al., 2019; Binding et al., 2021; Chorus and Welker, 2021; Maciel et al., 2023).

2.3 Algal bloom analysis

To evaluate patterns in the spatial extent of blooms, the percentage of pixels that exceed the assigned bloom threshold of 10 $\mu\text{g/L}$ was calculated. Each pixel threshold percentage was individually calculated by dividing by the total number of threshold exceedances for individual pixels over a 40-year time range to reduce biases from different parts of the reservoirs masked by clouds in different images. All 279 chl-a images are utilized for this analysis to maximize the number of observations at the pixel level. The total number of valid observations at each pixel over the 1984–2023 study period were further mapped to characterize spatial variation in observation density (Supplementary Figure 3). Lastly, to assess the sensitivity of the selected bloom threshold, pixel-wise exceedance frequencies were computed at three alternative thresholds: 8 $\mu\text{g/L}$, 12 $\mu\text{g/L}$, and 24 $\mu\text{g/L}$. For each pixel the highest threshold tier was classified at which the pixel was bloom-prone in at least 50% of valid observations over the full study period (Supplementary Figure 4).

To determine if there were significant trends in chl-a ($p < 0.05$), a Mann-Kendall (MK) statistical test was performed on the entire time series (Mann, 1945; Kendall, 1975). To limit the analysis to pixels with representative observations, only pixels were used with at least four observations per year for at least 20 years. If the individual pixel had at least 4 observations for a specific year, all data for that pixel for that year was used in the MK test. As this was for trend analysis, all 279 remotely sensed chl-a images for this test were used to maximize data density. All analyses, except for image masking, was conducted in RStudio and the WQL package was used for MK tests (Schertz et al., 1991; Helsel and Hirsch, 2002). To account for the large number of per-pixel trend tests, the Benjamini-Hochberg False Discovery Rate (FDR) correction was applied to the per-pixel p-values (Benjamini and Hochberg, 1995). No individual pixel survived FDR correction at $q < 0.05$ or $q < 0.10$, likely due to high variability in chl-a relative to the long-term trend and the strictness of the FDR test. Therefore, pixel-level Sen's slope results are presented as descriptive spatial patterns of trend direction and magnitude rather than as claims of pixel-level significance. However, if there is spatial coherence of Sen's slope direction and magnitude across neighboring pixels prior to FDR correction, this suggests there are real trends and

therefore a focus on clusters of pixels, or hotspots, was used in this study's analysis and interpretation.

From the original 279 chl-a images, scenes that had greater than 40% of reservoir water extent masked (by clouds, cloud shadow, not high confidence open water, poor pixel quality) were removed leaving 194 images for reservoir-wide bloom analyses. This second filter was created to maximize the number of images with suitable chl-a data spanning across the entire reservoir ($\geq 60\%$ reservoir area) while also providing enough images for appropriate whole-reservoir time series analyses. Per-pixel analyses retained all 279 cloud-filtered images to maximize per-pixel observation density. The 194 images were used to quantify whole-reservoir mean bloom intensity ($\mu\text{g/L}$), spatial bloom size (km^2), and bloom severity ($\mu\text{g/L} \times \text{km}^2$). A severity index (Stumpf et al., 2016; Binding et al., 2021) was used to account for both concentration and spatial extent variability. For each study year, the mean number of images was 5.5 and the standard deviation was 2.1. Only years that had at least 3 observations were used for time series analysis (Figure 3); this excluded the years 1989, 1997, 2016, 2018, and 2020. Whole reservoir average chl-a concentrations were calculated for each year using these 194 images to explore the variations in bloom concentrations, bloom size, and bloom severity from 1986–2023. To explore historical bloom variations, mean bloom values were calculated for all pixels $\geq 10 \mu\text{g/L}$ indicating bloom conditions. For each year, the standard error of whole-reservoir bloom concentration, bloom area, bloom severity, and percent bloom coverage were calculated as the standard deviation of the per-image values divided by the square root of the number of images within that year. These standard errors are displayed as error bars in Figures 4 and 5 to convey within-year image-to-image variability around each annual mean.

To examine potential inter-annual hydrologic drivers that influence whole-reservoir bloom metrics, total annual precipitation (cm) and inflowing river discharge (m^3/s) were compared to annual bloom area and severity. Mean annual discharge data from 1984–2023 was retrieved from USGS gage site 03011020. Annual precipitation data from 1984–2023 was obtained from Allegany State Park station USC00300093. Both discharge and precipitation datasets were normally distributed and relationships with bloom size, severity, and intensity were evaluated using linear regressions ($p < 0.05$).

3 Results

3.1 Summary of chl-a concentrations

Estimated chl-a values for individual pixels in the study years ranged from 0.099 to 168.494 $\mu\text{g/L}$ where the minimum value occurred on 8/25/2013 and the maximum value occurred on 7/26/1999 (Supplementary Table 1). Over the entire time series (1986–2023), the mean pixel value aggregated from May – November was 14.45 $\mu\text{g/L}$ with a standard deviation of 12.6 $\mu\text{g/L}$ ($n = 42,243$). Additionally, whole reservoir spatial means of chl-a (Figure 6) reveal elevated chl-a concentrations in mid-May with another peak in mid-September. This observation is similar to the seasonal patterns documented by USACE using a buoy-based sensor (Figure 2A).

3.2 Pixel level spatial variability in chl-a concentrations

On a per-pixel basis, the most upriver extent of AR (northern portion of the reservoir), as well as four tributaries located east of the reservoir have the highest proportion of pixels that exceed the 10 $\mu\text{g/L}$ threshold value (Figure 7). The northern reach of the reservoir displays the highest values of chl-a with a maximum mean value of 50.168 $\mu\text{g/L}$ observed within this area (Supplementary Figure 5). Chl-a concentrations generally decrease further south with the lowest calculated values located near the Kinzua dam with the exception of four tributary inlets (Figure 7).

Threshold sensitivity analysis indicates that the spatial concentration of bloom-prone pixels in the northern reach is preserved across all tested thresholds (Supplementary Figure 4). At the reference threshold of 10 $\mu\text{g/L}$, 28.7% of reservoir pixels meet the bloom-prone criterion (exceedance $\geq 50\%$ of valid observations). This percentage shifts as the thresholds vary, but the spatial footprint of bloom-prone pixels remains centered on the same northern hotspot and tributary inlets identified at the 10 $\mu\text{g/L}$ threshold. A persistent core of 2.2% of the reservoir surface, located in the northernmost reach, is bloom-prone at all four tested thresholds, including 24 $\mu\text{g/L}$.

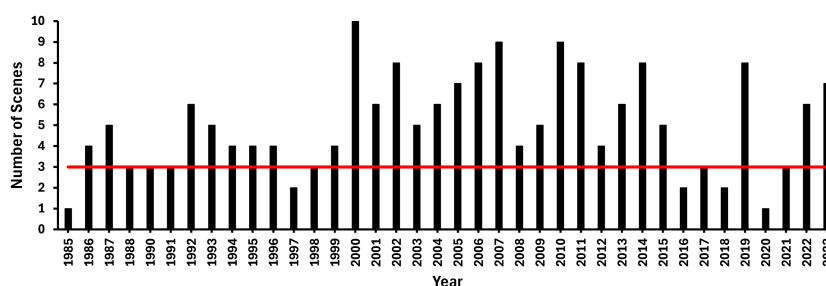


FIGURE 3

Number of Landsat observations per year of the AR. Every year that had ≥ 3 observations were used for time series analysis. The red line indicates the observation threshold.

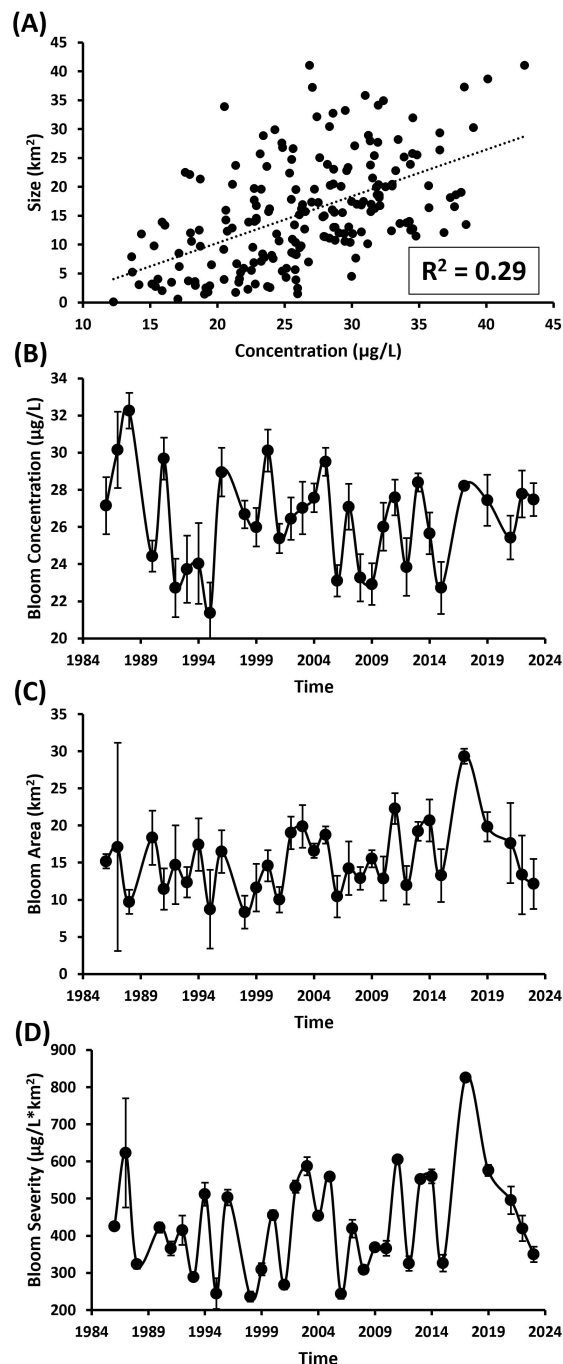


FIGURE 4

(A) Correlation plot of chl-a concentration on the x-axis and bloom size on the y-axis. $R^2 = 0.29$ and is statistically significant ($P < 0.05$). (B) Yearly averaged bloom concentration data from May – November 1986–2023. (C) Yearly averaged bloom spatial size from May – November 1986–2023. (D) Yearly averaged bloom severity data from May – November 1986–2023. Severity considers both concentration and size, allowing for a more holistic view of bloom conditions when compared to only observing concentration or size. Error bars in panels (B–D) represent ± 1 standard error of the within-year image-to-image variability for each metric.

3.3 Pixel-level chl-a trends over time

Discrete, spatially-coherent areas within the reservoir show positive Sen's slopes that in sum account for 26% of the reservoir area, suggesting there are hotspots of increasing chl-a concentration responding to similar mechanisms (Figure 8). Areas that were in the moderate decreasing rate of change of -0.013 to -0.048 cover 0.88 km^2 or 2.5% of the total reservoir. The slowest decreasing rates of change, -0.003 to -0.012 , accounted for 9.45 km^2 or 9.4%. Areas with little to no change, -0.002 to 0.003 , covered 15.46 km^2 or 44.4%, which accounts for the largest fraction of the reservoir compared to others. The slow increasing rates of change, 0.004 – 0.012 , represents 6.44 km^2 or 18.5% of the reservoir area. Lastly, the moderately increasing, rates of change 0.013 – 0.043 , account for 2.61 km^2 or 7.5% of the AR total area.

Pixel-level Sen's slope analysis revealed four descriptive spatial patterns (Figure 8). First, the northern portion of the AR displays the highest bloom-threshold exceedance frequencies (80–100%; Figure 7) with the steepest negative Sen's slopes in the dataset (-0.013 to -0.048 µg/L per 39-day unit time; Figure 8). Second, in the northern-to-central portion of the AR near the New York-Pennsylvania border, pixels display positive Sen's slopes (0.004 to 0.043 µg/L per 39-day unit time). The Willow Bay branch, located near the southern border of the Allegany reservations (circle A in Figure 7), displays a similar pattern (0.013 – 0.043 µg/L per 39-day unit time) in chl-a concentration. Third, the southern reach of the AR closest to Kinzua Dam displays weak negative Sen's slopes (-0.003 to -0.012 µg/L per 39-day unit time). Fourth, the spatial distribution of positive Sen's slopes lies south of, rather than within, the area of highest threshold exceedance. Unit time is calculated by dividing the total number of days of the bloom season (213) by the mean number of observations per year (5.47).

3.4 Algal bloom hotspots

The northern portion of the AR exceeded bloom thresholds 80% of the time from the months of May to November 1984–2023 (Figure 7). This area is the shallowest portion of the reservoir at an average depth of around 30 feet (Personal Communication, USACE). Areas that exceeded the threshold 0–20% accounted for 8.33 km^2 (17.78%) of the total area, 20–40% accounted for 19.75 km^2 (42.14%) of the total reservoir, 40–60% accounted for 9.97 km^2 (21.28%) of the reservoir, and 60–80% above threshold was 7.73 km^2 (16.50%). Lastly, areas between 80–100% above threshold accounted for 1.08 km^2 (2.30%) of the AR.

Further south in the reservoir, areas of substantially high exceedance (60–100%) decrease to moderate exceedance (40–60%) at the southern end of the SNI Allegany Reservation and the New York Pennsylvania border. Exceedance gradually decreases going downstream towards the dam corresponding with the deepest portion of the AR. Areas closest to the dam show exceedance values in the 0–40% range, a stark difference just 20 miles below the bloom formation area located within the northern portion of the reservoir

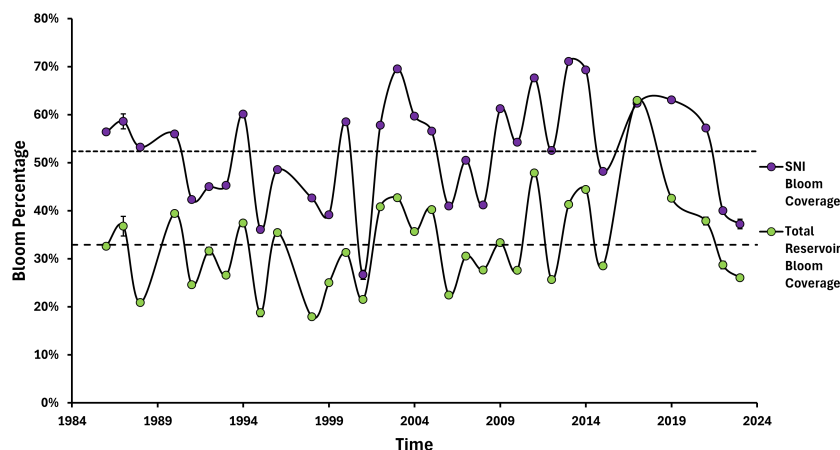


FIGURE 5

Yearly averaged bloom percent coverages for the total reservoir (green) and SNI portion of the reservoir (purple) from May – November 1986–2023. The average bloom percentage of the SNI portion throughout May – November 1986–2023 is 52.39%. The average bloom percentage of the total reservoir from May – November 1986–2023 is 32.93%. Error bars represent ± 1 standard error of the within-year image-to-image variability in bloom coverage.

(Figure 7), and is consistent with historical documentation of bloom occurrence in this region (Coin, 2017; NYDEC, 2019; Schellhammer, 2019). Interestingly, the most southern reach of the AR, indicated by circle D in Figure 7, displays elevated threshold exceedance values above 40%.

At least 60% of the total chl-a observations over the entire reservoir exhibit bloom like conditions with the highest exceedance percentages being observed in the northern portion with the southern portion exhibiting the lowest values typically within the 0–40% range. Bloom coverage was found to be repeatedly over one-third of the total reservoir area with a mean bloom coverage of 32.93% over the entire range (Figure 5). Total reservoir bloom coverage was highest in 2017 at a mean value of 62.97% and was lowest during 1998 with a mean value of 17.94%. When only focusing on the portion of the AR that is within SNI territory, the mean algal bloom coverage is 52.39% over the entire range with the highest mean percentage occurring in 2013 at 71.10% and the lowest coverage was in 1995 at 36.10%.

3.5 Whole reservoir algal bloom extent and severity over time

Spatially aggregating all chl-a data across the reservoir by year, mean bloom concentrations ranged from 21.36 $\mu\text{g/L}$ in 2020 to 32.26 $\mu\text{g/L}$ in 1988. There is no long-term trend in mean bloom concentration (MK test, p -value = 0.31). Total bloom area varied throughout the time range with a minimum average area in 1998 at 8.35 km^2 with the highest average value of 29.32 km^2 found within 2017. From 1986–2023, there was no discernable trend of bloom size increasing with time (MK test, p -value = 0.144). Algal bloom size and concentration were correlated (R^2 of 0.29, p -value < 0.001) (Figure 4A) indicating a statistically significant, positive relationship between chl-a concentration and bloom size. Although there is no significant increase in bloom size, concentration, or severity in the time series, the largest bloom occurred in 2017 at 29.32 km^2 which coincided with the largest severity value at 825.91 $\mu\text{g/L} \times \text{km}^2$.

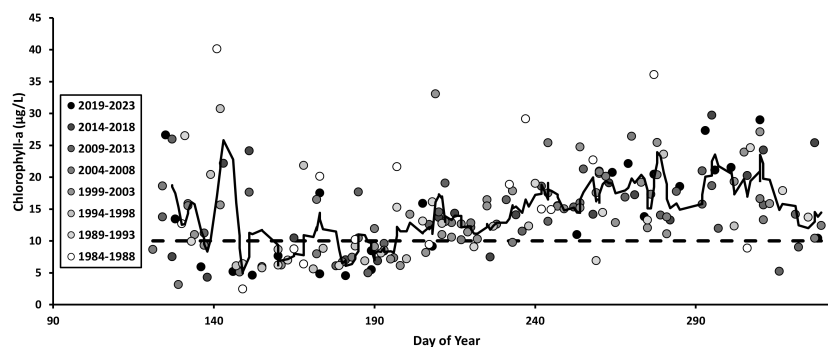


FIGURE 6

Whole reservoir spatial mean chl-a values from May – November 1986–2023 demonstrating that remotely sensed chl-a is capturing similar seasonal patterns of chl-a concentrations compared to buoy-based sensor data from USACE. Day 140 indicates May 20th and day 290 represents October 17th. The black line represents a 5-point rolling average for remotely sensed chl-a. The dashed line, located at 10 $\mu\text{g/L}$ represents the threshold used to determine algal bloom occurrence.

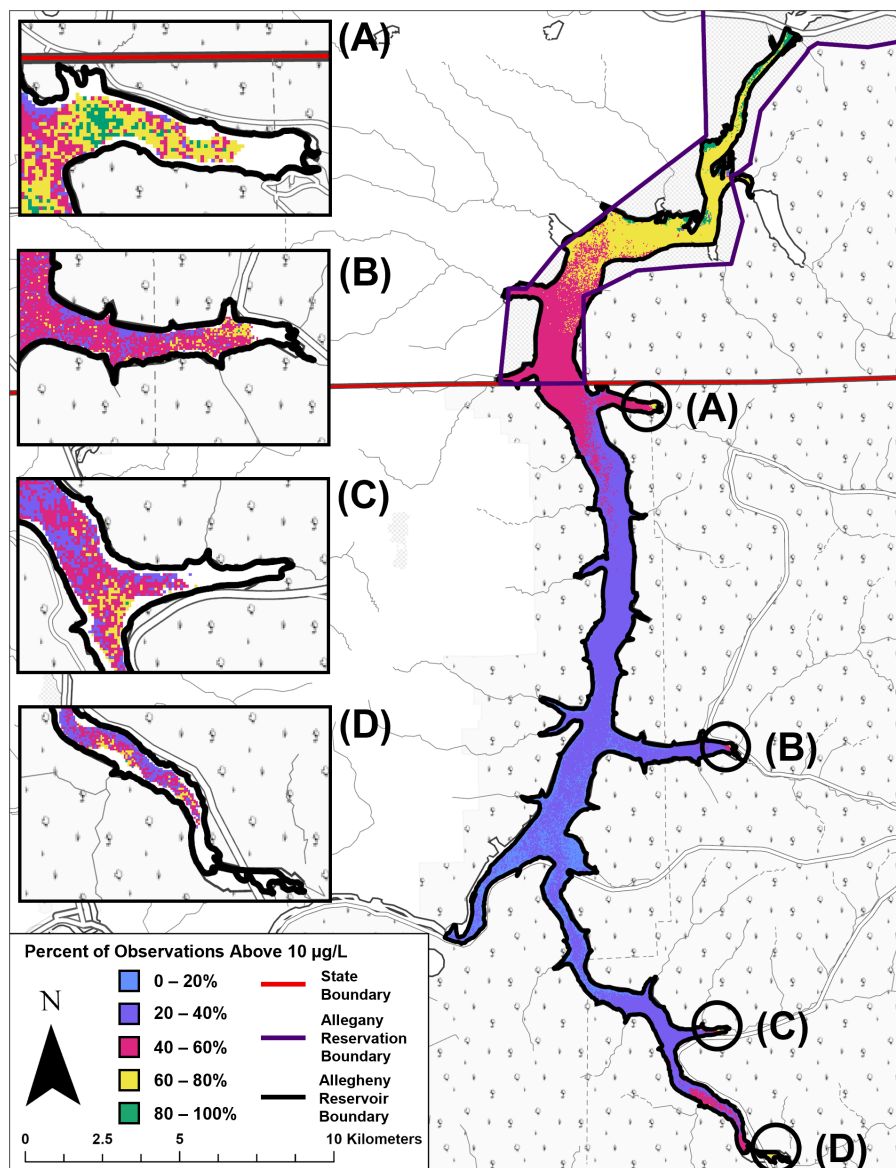


FIGURE 7

Percent of observations above the 10 $\mu\text{g/L}$ algal bloom threshold. Each pixel represents the normalized percentage of observations over 10 $\mu\text{g/L}$ over May – November 1986–2023. (A) Willow Bay and the Willow Creek inlet. (B) Sugar Run inlet. (C) Chappel Fork inlet. (D) the Kinzua Creek and Root Run inlets.

3.6 Potential hydrologic drivers

Linear correlations between discharge, precipitation, bloom extent, and bloom severity were statistically significant (p -values < 0.001) suggesting they explain a modest portion of variance interannually with R^2 values ranging from 0.23–0.37 (Figure 9). Precipitation versus bloom area had the strongest relationship with an R^2 of 0.37 and a slope of $2.28 \text{ km}^2/\text{cm}$. Discharge versus bloom area showed the second highest R^2 at 0.35 with a slope of $0.18 \text{ km}^2/\text{cms}$. Lastly, discharge versus bloom severity had the lowest R^2 of 0.23 but had the steepest slope at $5.23 (\mu\text{g/L} \cdot \text{km}^2)/\text{cms}$. It should be noted that 2017 had both the largest observed bloom extent (29.32 km^2) and the highest annual precipitation (12.15 cm) in the study period. Due to this anomalous year, regression results should be interpreted with awareness that 2017 may disproportionately influence these relationships.

4 Discussion

4.1 Spatial and hydrologic drivers of bloom dynamics

These results demonstrate that Landsat reconstruction of chl-*a* provides important insights into algal bloom spatial dynamics, temporal trends, and bloom characteristics, in data-poor reservoirs. A central finding of the analysis is that bloom-related changes in the AR appear at fine spatial scales (pixel-level) rather than at the scale of the entire reservoir. In the following discussion, “increasing” and “decreasing” describe directional trends in satellite estimated chl-*a* concentration. However, a declining trend does not suggest that bloom occurrence is no longer ecologically relevant.

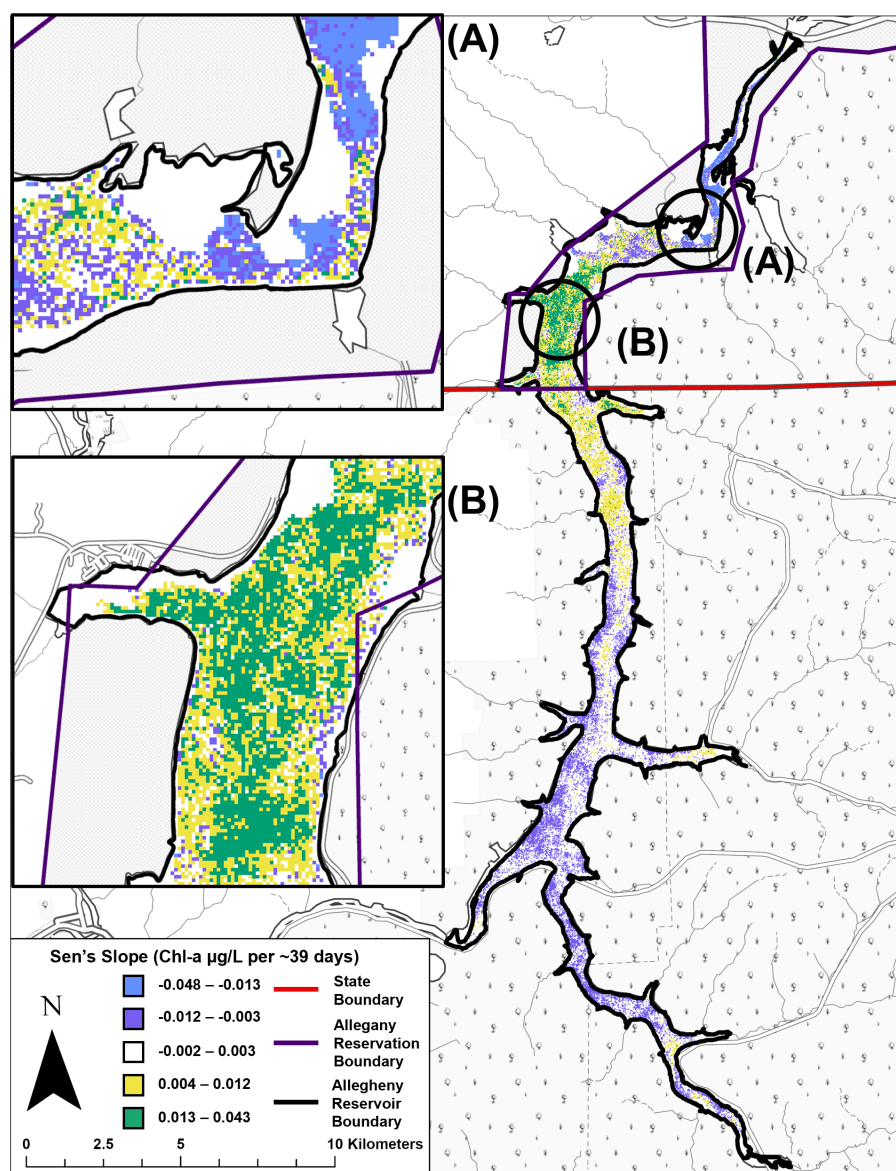


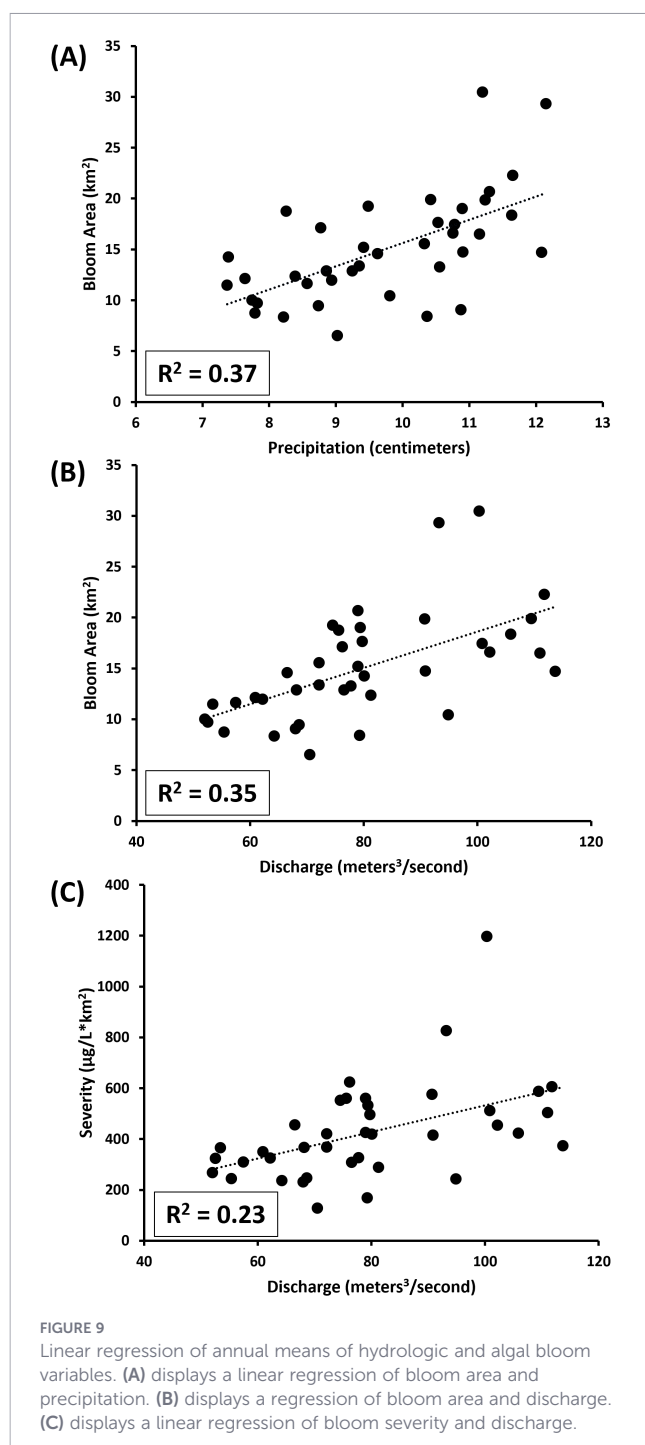
FIGURE 8

Per-pixel Sen's slope product from the Mann-Kendall statistical analysis of modelled chl-a across the Allegheny Reservoir (1984–2023). Yellow to green pixels indicate positive Sen's slopes (modelled chl-a increasing with time). Purple to blue pixels indicate negative Sen's slopes (modelled chl-a decreasing over time). White pixels indicate little to no change. (A) Zoomed in view of United States Army Corps of Engineer's KIN 1009 buoy. (B) Zoomed in area displaying the largest increases in chl-a with time.

Temporal trends of mean values at the whole-reservoir level indicate that blooms are not increasing in intensity (chl-a concentration), spatial extent (total bloom area), or severity (Figure 4), although mean algal bloom chl-a concentrations were higher in earlier years (1986–1988) compared to more recent years (Figure 4B). Moreover, algal blooms were observed annually from 1986–2023 suggesting blooms are not a new, post-2012 phenomenon as previously suggested in reports.

Pixel-level analysis indicates that the spatial distribution of increasing concentrations lies south of, rather than within, the historical bloom hotspot in the northernmost reach (Figure 7; Figure 8). Areas with increasing chl-a concentrations over time are concentrated in the northern-to-central portion of the reservoir, immediately downstream of the zone with the highest persistent

bloom-threshold exceedance. This suggests blooms are either extending or shifting further south over time, but further work is needed to confirm this hypothesis. Bloom formation in the northern portion of the AR agrees with historical reports and may be a bloom hotspot due to its historical eutrophic conditions, shallower depths compared to the southern portion of the reservoir and the related function as a transition zone characterized by higher chl-a concentrations (USEPA, 1975; Thornton et al., 1990). The combination of consistently high bloom-threshold exceedance with declining chl-a concentrations in the northernmost reach is consistent with sustained bloom occurrence within a eutrophic zone whose peak intensity may be gradually decreasing, even as the spatial footprint of bloom-like conditions appears to extend southward.



With bloom formation occurring in the shallower northern portion of the AR, the linear relationships between annual precipitation and river discharge with bloom area and severity (Figure 9) suggest that riverine inputs of nutrients could be an important driver of blooms (Bargu et al., 2011), in addition to the physical conditions where the river transitions to reservoir water at the northern end. We hypothesize that as nutrient-rich river discharges from the Allegheny River and flows into the reservoir, suspended particulates can be rapidly deposited as water velocities slow, creating ideal algal growth conditions that include more light, slower and nutrient rich water, and warmer temperatures. Moving downstream, water depth increases and water temperature

decreases, and nutrient sources can be depleted making bloom formation less likely in the southern portion closest to the dam, although internal loading of phosphorus from anoxic sediments could provide an additional, spatially localized nutrient source not captured within this study (Scott et al., 2009; Albright and Wilkinson, 2022). Reservoirs typically receive higher quantities of nitrogen, phosphorus, and organic carbon than a majority of small lakes due to their large watershed to surface ratio (Thornton et al., 1990). Algal bloom hotspots within the transition zone between river and reservoir fits classic conceptual models of reservoir zonation and agrees with recent empirical studies (McClain et al., 2003; Bernhardt et al., 2017; Marcé et al., 2021; Woelmer et al., 2023). If this suggested mechanism is supported by future targeted measurements of nutrient and hydrologic inputs, bloom mitigation may benefit from a focus on nutrient and sediment inputs from major river tributaries as well as managing water depth in the northern portion of the reservoir.

Bloom formation in four tributary inlets were also observed and are an emerging area of concern. While there are no reported blooms in these tributary inlets, personal communication with multiple agencies that attended the April 2024 Allegheny Shared Aquatics Management Strategy meeting suggested the southeastern portion of the AR has eutrophic characteristics. Further emphasis should be placed on these areas to monitor potential bloom formation and expansion further into the AR.

The year 2017 displays the largest bloom extent, severity, and total reservoir bloom percentage which coincides with the hurricane season being especially damaging for other areas within the United States (Lee, 2021). The annual precipitation of 2017 was also found to be highest during the study period at 12.15cm. Annual precipitation and discharge co-vary with bloom area and severity (Figure 9), and explain some inter-annual variance ($R^2 = 0.23$ – 0.37) and are sensitive to 2017, which was both the highest precipitation and largest bloom year in the record. The shift to more dramatic weather patterns, such as an increase in longer dry spells and prolonged extreme precipitation and heatwave events, attributed to anthropogenic climate change may lead to significant growth in the extent of and severity of algal blooms (O’Gorman, 2015; Schoof, 2015; Carpenter et al., 2022; Wilkinson et al., 2022; Jong et al., 2023; Soranno et al., 2025; Szydlowski et al., 2025). At the annual scale, these findings indicate that a 1 cm increase in annual precipitation is associated with an additional 2.28 km² of bloom area ($SE = 0.49 \text{ km}^2/\text{cm}$), and a 1 m³/s increase in mean annual discharge is associated with an additional 0.18 km² of bloom area ($SE = 0.04 \text{ km}^2/\text{cms}$). There is hope that these results motivate further investigations to address how and where bloom formation occurs by analyzing pixel-level information in the AR before climatic trends intensify.

Identifying trends in chl-a and the specific areas where blooms are occurring was only possible by examining pixel-level data instead of calculating whole reservoir averages. It is common for remote sensing of chl-a to focus on whole lake/reservoir averages or the centroid of the waterbody (Stumpf et al., 2016; Ho et al., 2017; Binding et al., 2018; Topp et al., 2021; Soranno et al., 2025). However, for reservoirs which typically have distinct zones, spatial gradients, and local communities that are disproportionately

impacted by localized deterioration of water quality, this analysis highlights the importance of both pixel-level analysis and whole reservoir averages to more accurately estimate trends in chl-a and bloom severity and extent.

4.2 Environmental justice and management implications

Placing these findings in an environmental justice context, satellite estimated bloom occurrence and localized increases in chl-a spatially overlap with culturally significant territory of the Seneca Nation of Indians, raising environmental justice concerns about the distribution of bloom-related impacts within the AR. It should be noted that this analysis quantifies spatial overlap with SNI territory rather than direct measures of social burden, exposure, or health risk. Attributing these results with potential environmental justice concerns would require integrating the data presented here with cultural-use, recreational-access, and health-outcome information. However, the persistent localization of bloom-prone conditions within SNI territory warrants continued attention from management agencies and supports the SNI's stewardship of these waters.

4.3 Limitations

This methodology reconstructs historical chl-a dynamics of the AR (Figures 4, 6). However, there are several limitations to this approach. The 8–16 day Landsat revisit, combined with cloud cover and low-confidence water pixel exclusion, creates uneven temporal sampling across years (Figure 3). Aggregating to annual means partially mitigates this but does not fully resolve it. Short-lived bloom events between overpasses or under cloud cover are not captured, and annual estimates of bloom area and severity should be interpreted as conservative characterizations, particularly in years with few valid scenes.

Four interpretive limitations apply to this study's analyses. First, the four tributary inlets identified as zones of elevated bloom threshold exceedance are shallow nearshore environments where sediment-derived spectral signals may interfere with chl-a retrieval; the tributary-inlet hotspots should therefore be treated cautiously until validated with targeted field monitoring. Second, the linear relationships between annual precipitation, discharge, and bloom metrics (Figure 9) describe co-variation at the annual scale, but without nutrient flux measurements it cannot be determined whether wet years deliver more nutrients or dilute reservoir nutrient concentrations. Third, satellite analyses are best interpreted as relative spatial patterns and temporal trends in chl-a concentration rather than absolute concentration at any single location. Accordingly, this analysis focuses on relative spatial-temporal changes rather than absolute accuracy at a single location to best match interpretations and conclusions match with this approach. Fourth, per-pixel MK significance does not survive the strict FDR correction across the analyzed pixels. However, the Sen's slope estimates remain robust descriptors of slope direction and magnitude, and the spatial coherence of slope direction across the reservoir is interpreted as the primary line of evidence for real trends in chl-a. Future work could apply spatially-aware inference to formally test for regionally clustered trend signals.

4.4 Future steps

This analysis documents that while whole reservoir mean bloom concentrations and severity have not increased since 1984, there are localized hotspots primarily within SNI territory that are increasing in bloom concentration and severity and are persistent locations of high chl-a conditions, suggesting algal blooms are common. Given these important findings, there are several recommend approaches that would strengthen future bloom monitoring efforts. First, leveraging the Harmonized Landsat Sentinel-2 dataset (Claverie et al., 2018) would improve the temporal resolution of bloom monitoring from approximately 16 days to as few as 2–3 days, enabling better characterization of bloom dynamics that are difficult to resolve using Landsat alone. Second, the inability to spectrally distinguish cyanobacteria from green algae blooms is a significant limitation with Landsat. Future work should explore sensors with additional spectral bands to parse out a phycocyanin signature and to inform whether blooms occurring in SNI territory could pose health risks to its community. Third, targeted field monitoring is needed in the four tributary inlets identified as areas of elevated bloom threshold exceedance, both to validate these as bloom hotspots and to disentangle algal from sediment-derived spectral signals.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: CUAHSI Hydroshare: <https://www.hydroshare.org/resource/2ca885d5f5d6464299d1d82e79a78408>.

Author contributions

EH: Visualization, Formal analysis, Writing – original draft, Data curation, Investigation, Conceptualization, Software. EE: Writing – review & editing, Conceptualization. SS: Writing – review & editing, Software, Data curation, Methodology. GZ: Writing – review & editing, Software, Methodology. JG: Conceptualization, Methodology, Writing – review & editing, Software.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fevo.2026.1850819/full#supplementary-material>

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