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Article

Tracking Phytoplankton Biomass Amid Wildfire Interference Using Landsat 8 OLI

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Abstract: The increasing frequency and severity of phytoplankton blooms worldwide highlight the need for advancements in monitoring technologies. Optical remote sensors, such as Landsat, have proven to be a cost-effective method for large-scale, near-real-time assessments of phytoplankton biomass in lakes. However, its effectiveness is often compromised by atmospheric interferences like clouds, dust, and wildfire smoke, which can obscure the clear-sky conditions essential for accurate remote sensing. While partial atmospheric correction (removing only the Rayleigh effect) is commonly applied to address these interferences, it remains inadequate for mitigating the impact of wildfire smoke. This study investigates the potential of Landsat's coastal/aerosol band (B1) for assessing wildfire smoke interference effects on Chlorophyll-*a* (Chl-*a*) retrieval models, which serve as proxies for phytoplankton biomass. We employed cluster analysis of B1 values to create a screening system based on aerosol reflectance, categorizing smoke interference into low, moderate, and high levels. Subsequently, we applied both partial (Rayleigh-corrected reflectance) and full (Landsat 8 Level 2 surface reflectance) atmospheric corrections before developing the Chl-*a* retrieval models. Excluding high wildfire smoke interference ($B1 > 0.07$) from the Chl-*a* calibration dataset significantly enhanced model performance, increasing the *r*-squared value from approximately 0.55 to 0.80. Moderate smoke interference ($0.05 < B1 < 0.07$) yielded results comparable to low-interference conditions. Notably, Rayleigh-corrected reflectance, even without additional aerosol band filtering, achieved higher *r*-squared values for the Chl-*a* retrieval model than full atmospheric correction. B1 thus proves to be a valuable tool for identifying low smoke-impacted observations, offering an effective method to monitor phytoplankton biomass amid increasing wildfire activity and improving the capacity to monitor aquatic environments in a changing global landscape.

Keywords: chlorophyll-*a*; freshwater; phytoplankton; remote sensing; wildfire

1. Introduction

Since the late 20th century, freshwater environments have experienced a troubling rise in phytoplankton blooms, marked by increasing frequency, intensity, and shifts in community composition [1]. Although phytoplankton populations typically exhibit seasonal patterns, anthropogenic stressors such as nutrient loading and climate change can disrupt these natural cycles, leading to harmful algal blooms [2,3]. These blooms degrade water quality, causing issues like toxin production, disruption of food webs, and anoxia, which in turn create substantial social, economic, and ecological challenges [4,5]. Given their responsiveness to environmental changes, phytoplankton are crucial indicators of water quality and are routinely monitored to assess the health of water bodies globally [6,7]. Developing tools to monitor phytoplankton dynamics within freshwater lakes is essential for enabling lake managers and practitioners to make informed decisions [8].

Chlorophyll-*a* (Chl-*a*) concentration, commonly used as a proxy for phytoplankton biomass [9], is measured through both field-based and remote sensing methods. Traditional field sampling

provides high-resolution data at specific locations but lacks comprehensive spatial coverage and is resource-intensive [10,11]. The time-intensive nature of these methods can delay water management responses, which are critical for addressing phytoplankton-related threats [12]. In contrast, remote sensing offers a time-sensitive and cost-efficient technique for monitoring phytoplankton biomass across large areas [7,13–19]. This approach enables near-real-time, quantitative, and qualitative analyses of phytoplankton communities by capturing optical data on water bodies [17,20]. However, optical remote sensing is dependent on cloud-free and minimal atmospheric interference, as clouds, smoke, and haze can significantly degrade image quality [6,21].

One emerging concern is the increasing prevalence of wildfires, which produce smoke that obstructs remote sensing capabilities. Recent years have seen a global rise in wildfire frequency and intensity, exacerbated by climate change and historical fire suppression practices [22,23] (Figure 1a). For example, Canada experienced its worst wildfire season on record in 2023, with atmospheric carbon emissions four times higher than in previous years (Figure 1b). Wildfires not only impair water quality through ash deposition and light inhibition [23–27], but also degrade the quality of remote sensing images. Elevated aerosol levels can be partially mitigated through atmospheric correction in remote sensing products like Landsat Level 2 or Sentinel-2C [28,29]. However, for aquatic applications that often use partial atmospheric correction, wildfire smoke remains a challenge. Developing methodologies to classify and mitigate smoke effects in satellite imagery is crucial as wildfire activity increases globally. Such methodologies should enable the exclusion of smoke-impacted observations from analysis, thereby enhancing the reliability of water quality models in wildfire-affected areas.

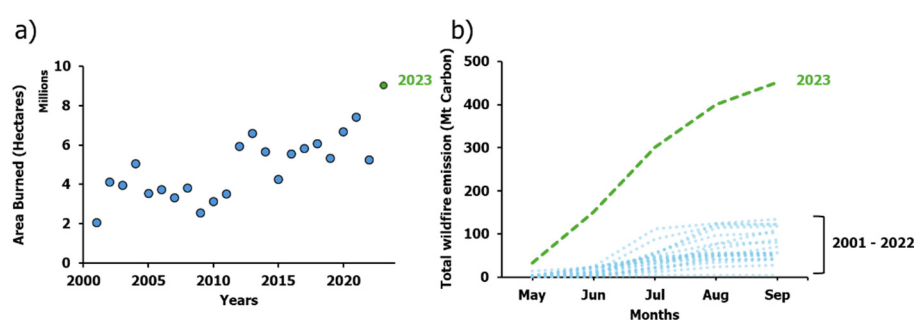


Figure 1. a) Annual global tree cover loss caused by fires (data source: Global Forest Watch), b) Cumulative annual carbon emissions released during wildfires in Canada during wildfire season (data source: Copernicus Climate Change Service).

This study utilizes the Landsat 8 coastal/aerosol band (B1) to categorize and quantify the level of wildfire smoke interference in remote sensing images. We assessed the impact of excluding varying degrees of smoke interference on the performance of Chl-*a* retrieval models. To validate our approach, we compared partially corrected reflectance data filtered by the aerosol band with fully corrected Landsat 8 Level 2 products. The results show that this methodology offers a reliable tool for mapping lake surface Chl-*a*, even in regions impacted by wildfires. This approach provides lake managers with a valuable tool for monitoring aquatic environments, establishing thresholds for wildfire interference, and ensuring the accuracy of remote sensing in an era of increasing wildfire activity.

2. Materials and Methods

2.1. Ground-Based Dataset

Chl-*a* samples were collected from 106 lakes within the Prairie Pothole Region of Canada, spanning Alberta, Saskatchewan, and Manitoba (Figure 2). Water samples were obtained using a 1-meter integrated sampler at the center or deepest point of each lake, as determined by bathymetric data. Phytoplankton samples were taken during the peak growing season, from mid-July to end of

August [30,31]. To concentrate phytoplankton for Chl-*a* analysis, lake water was filtered through Whatman GF/F filters. The volume of water filtered ranged from 30 to 500 milliliters, depending on the algae concentration. The filters were then frozen at -20°C to preserve the pigments. Chl-*a* was extracted using 90% (v/v) acetone under dim light, and the filters were mechanically disrupted with a bead beater (3 × 10-second cycles) containing 0.1 mm zirconia/silica beads [32]. The mixture was stored at -20°C for 4 hours, followed by centrifugation (6,000 g for 5 minutes) for an initial clarification. The supernatant was further clarified by filtering through a 0.22 µm filter and then measured at 664 nm using a spectrophotometer (1 cm cuvette) following the Jeffrey and Humphrey method [33]. Chl-*a* concentrations were reported in µg L⁻¹.

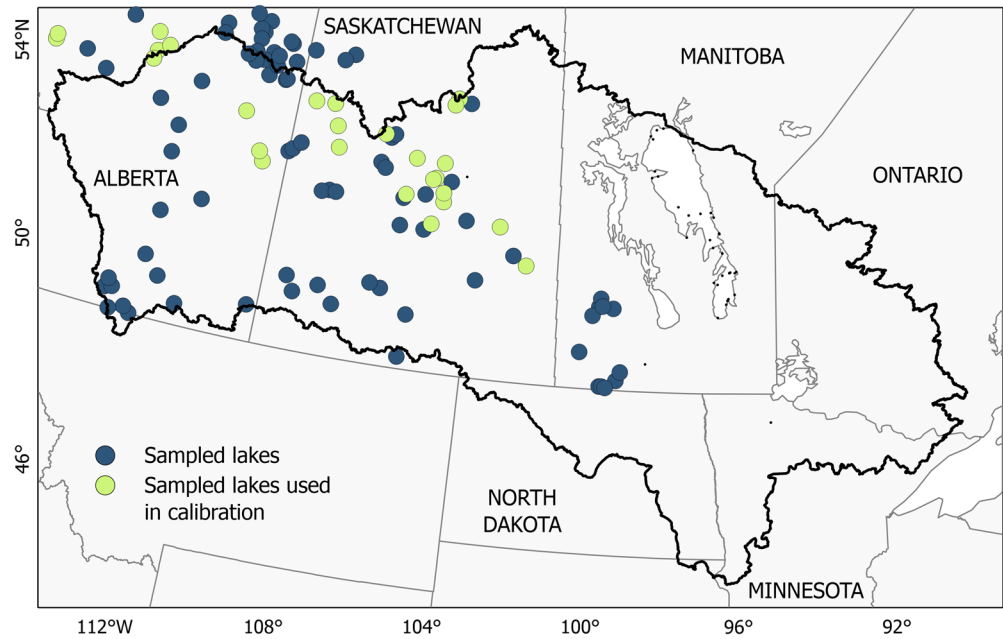


Figure 2. Locations of ground-based Chl-*a* samples. Green and blue circles represent all the sampling lakes, while blue circles represent the lakes used for the Chl-*a* retrieval model development (matchups between in situ sampling and satellite overpass occurred within +/-3 days).

2.2. Landsat Image Acquisition, Processing, and Analysis

Data were acquired using the Landsat 8 Operational Land Imager (OLI), with the first six spectral bands extracted for each study lake (Table 1). Radiometric and atmospheric corrections were carried out using Google Earth Engine (GEE), a cloud-based platform that facilitates the processing of large geospatial datasets, including remote sensing data [34,35]. GEE has become a widely utilized tool for monitoring water quality in both inland and marine environments [36–40].

Table 1. Summary of Landsat OLI bands and bandwidths used in this research.

Sensor	Bands	Wavelengths (nm)	Resolution (m)
Landsat 8 OLI	Band 1: Coastal/Aerosol	0.43-0.45	30
	Band 2: Blue	0.45-0.51	30
	Band 3: Green	0.53-0.59	30
	Band 4: Red	0.64-0.67	30
	Band 5: Near Infrared (NIR)	0.85-0.88	30
	Band 6: Shortwave Infrared (SWIR)	1.57-1.65	30

2.2.1. In Situ and Satellite Match Up Considerations

Ground-based Chl-*a* measurements were matched to corresponding satellite observations at the point of sampling within a temporal window of ± 1, 3, 7 days of satellite image capture. The selected

temporal window was selected based on considerations of the sample size and the correlation between satellite band formula and in situ $\ln(\text{Chl-}a)$.

2.2.2. Atmospheric Correction

Atmospheric correction is essential for accurately mapping water optical properties, as it mitigates atmospheric interferences such as aerosol and Rayleigh scattering effects in satellite imagery [41,42]. Despite its importance, inland water research still lacks a standardized atmospheric correction algorithm [43,44]. Many studies (e.g., [17,44–50]) advocate for partial atmospheric correction—specifically removing Rayleigh scattering effects—because accurately estimating aerosol correction for water bodies is challenging and often results in overestimation of atmospheric radiance contributions.

In this study, partial atmospheric correction was performed as follows:

1. **Conversion to at-sensor spectral radiance:** Landsat 8 OLI Level 1 data, comprising raw digital numbers (DN) ranging from 0 to 65,000, were used. Converting DN values to a common radiometric scale by calculating radiance is the first step in analyzing images from different sensors and platforms [51,52]. The DN values were converted to Top-of-Atmosphere (TOA) radiance using Equation (1) (Table 2; [51]).
2. **Calculation of Rayleigh scattering effects on at-sensor spectral radiance:** To remove Rayleigh scattering from the TOA radiance, Equation (2) was applied (Table 2; [53]). The Rayleigh pressure (P_r) was calculated using Equation (3) (Table 2; [54,55]), Rayleigh optical thickness (τ_r) was determined using Equation (4) (Table 2; [53]), and ozone transmittance (τ_{oz}) was computed using Equation (5) (Table 2; [56,57]). Finally, Rayleigh-corrected TOA radiance (L_r) was obtained by subtracting it from L_λ using Equation (6) (Table 2).
3. **Conversion of Rayleigh-corrected radiances to partially-corrected BOA reflectance:** The Rayleigh-corrected TOA radiance was then converted to Rayleigh-corrected Bottom-of-Atmosphere (BOA) reflectance (R_{rc}) using Equation (7) (Table 2), which was used to develop Chl-*a* retrieval models. This step offers multiple advantages: it eliminates the impact of varying solar zenith angles due to different image acquisition times, accounts for differences in Earth-Sun distances, and compensates for varying exoatmospheric solar irradiances [52].

2.3. Wildfire Correction

Wildfires are a frequent occurrence in Canada, but the 2023 wildfire season was unprecedented, marking the worst on record (Figure 1b). The resulting smoke significantly degraded the quality of satellite images. To quantify the extent of smoke interference, we used the Landsat coastal/aerosol band ($B1 = 0.43\text{--}0.45 \mu\text{m}$), which is particularly effective for monitoring atmospheric aerosol properties [58]. A k-means clustering approach ($k = 3$) was applied to the B1 data, allowing us to classify the lakes based on the severity of smoke interference into three categories: low (cluster 1), moderate (cluster 2), and high (cluster 3).

2.4. Chl-*a* Retrieval Model Development

For Chl-*a* retrieval model development, we used matchup results within a ± 3 -day window. The blue ($B2$) and red ($B4$) bands were selected for their alignment with the maximum absorption of Chl-*a*, while the green band ($B3$) was chosen for its alignment with the maximum reflectance (i.e., minimal absorption) of Chl-*a*. These bands were incorporated into the development of band formulae to create a physically-based approach for Chl-*a* retrieval from remote sensing images. The performance of three band formulas—Blue/Green, Blue/Red, and (Blue-Red)/Green—was evaluated using 3-fold cross-validation. The Blue/Green [14,45] and Blue/Red [14,45,59,60] ratios are single-band formulas commonly used for mapping Chl-*a* in Landsat products. The third formula, (Blue-Red)/Green, has been widely adopted in Chl-*a* mapping on Landsat products (e.g., [17,19,59,61–66]).

2.5. Chl-*a* Retrieval Model Evaluation

To determine the optimal relationship between the band formulae and Chl-*a*, we employed 3-fold cross-validation. The 3-fold cross-validation process involves dividing the data into three sets for training and testing, enhancing the generalizability and predictive accuracy of the models. The performance of each model was assessed using multiple metrics, including the coefficient of determination (R^2) (Equation (8); Table 2), Root Mean Square Error (RMSE) (Equation (9); Table 2), Normalized Root Mean Square Error (NRMSE) (Equation (10); Table 2), Mean Absolute Error (MAE) (Equation (11); Table 2), and Bias (Equation (12); Table 2).

Table 2. Table of formulae used to calculate Rayleigh-corrected bottom-of-atmosphere (BOA) reflectance (R_{rc}) (Equations (1)–(7)) and to calculate model performance metrics (Equations (8)–(12)).

$$L_{\lambda} = (DN_{\lambda} \times gain_{\lambda}) + bias_{\lambda} \quad (1)$$

where,

L_{λ} is the TOA radiance for band λ ,

DN_{λ} is the raw digital number (DN) for band λ ,

$gain_{\lambda}$ is the multiplicative rescaling factor for band λ , and

$bias_{\lambda}$ is the additive rescaling factor for band λ .

$$L_{r(\lambda)} = \left(\frac{ESUN_{\lambda} \times \cos \theta_s \times P_r}{4\pi \times (\cos \theta_s + \cos \theta_v)} \right) \times \left((1 - \exp -\tau_{r(\lambda)}) \times \left(\left(\frac{1}{\cos \theta_s} \right) + \left(\frac{1}{\cos \theta_v} \right) \right) \right) \times \tau_{oz(\lambda)} \quad (2)$$

where,

L_r is the Rayleigh path radiance,

$ESUN_{\lambda}$ is the exo-atmospheric solar irradiance constant for band λ ,

θ_s is the solar zenith angle in degrees,

θ_v is the satellite view angle in degrees,

P_r is the Rayleigh phase function (Equation (3)),

$\tau_{r(\lambda)}$ is the Rayleigh optical thickness for band λ (Equation (4)), and

$\tau_{oz(\lambda)}$ is the ozone transmittance for band λ (Equation (5)).

$$P_r = \frac{3}{4} \times \frac{1 - \gamma}{1 + 2\gamma} \times (1 + \cos^2 \Phi) + \frac{3\gamma}{1 + 2\gamma} \quad (3)$$

where,

γ is obtained from $\gamma = \frac{\rho_n}{2 - \rho_n}$ in which is ρ_n the depolarization factor, and

Φ is the scattering angle in degrees ($180 - \theta_s$).

$$\tau_{r(\lambda)} = 0.008569\lambda^{-4} \times (1 + 0.0113\lambda^{-2} + 0.00013\lambda^{-4}) \quad (4)$$

$$\tau_{oz}(\lambda) = \exp(-\tau_{oz}) \times \exp\left(\frac{-\tau_{oz}}{\cos \theta_s}\right) \quad (5)$$

where,

$\tau_{oz(\lambda)}$ is the ozone optical thickness for band λ .

$$\hat{L}_{\lambda} = L_{\lambda} - L_r \quad (6)$$

where,

$\hat{L}_{\lambda}$ is the Rayleigh-corrected radiance for band λ .

$$R_{rc} = \left(\frac{\pi \hat{L}_\lambda \times d^2}{ESUN_\lambda \times \cos \theta_s} \right) \quad (7)$$

where,

R_{rc} is the partially corrected BOA reflectance for band λ , and

d is the Earth–Sun distance in astronomical units.

$$R^2 = 1 - \frac{RSS}{TSS} \quad (8)$$

where,

R^2 is the coefficient of determination,

RSS is the residual sum of square, and

TSS is the total sum of square.

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}} \quad (9)$$

where,

$RMSE$ is Root Mean Square Error,

$\hat{y}_i$ is the predicted value,

y_i is the observed value, and

n is the number of samples.

$$NRMSE = \frac{RMSE}{\sigma} \quad (10)$$

where,

$NRMSE$ is Normalized Root Mean Square Error,

σ is the standard deviation of the observed values.

$$MAE = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n} \quad (11)$$

where,

MAE is Mean Absolute Error.

$$Bias = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n} \quad (12)$$

3. Results

3.1. Landsat Image Acquisition, Processing, and Analysis

The selected temporal window for matchups between ground-based Chl-*a* measurements and corresponding satellite observations at the point of sampling was ± 3 days of satellite image capture (Figure 3). This temporal window achieved a balance between sample size and the correlation between satellite band formula and in situ $\ln(\text{Chl-}a)$. The ± 1 day had the smallest number of samples but the highest correlation with in situ $\ln(\text{Chl-}a)$, while the ± 7 days had the largest number of samples but a marginally smaller correlation with in situ $\ln(\text{Chl-}a)$ compared to ± 3 days.

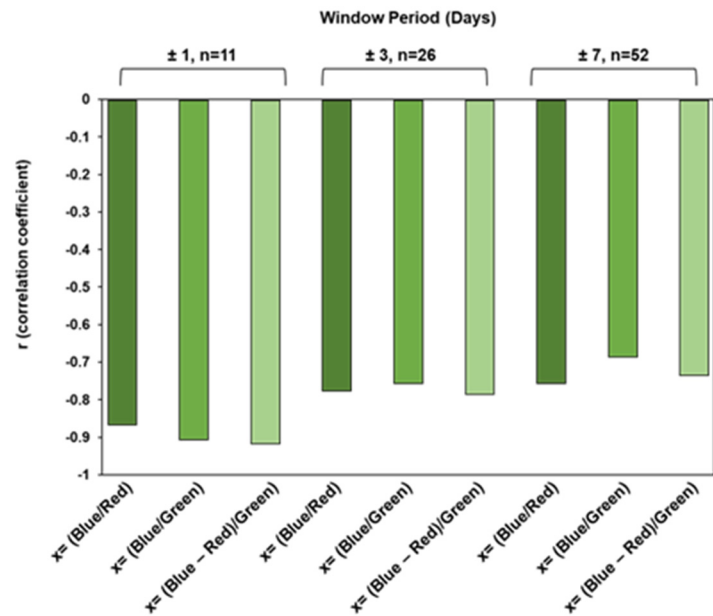


Figure 3. The correlation between the band formulae and ln(Chl-a) for different temporal windows of in situ-satellite match-ups.

3.2. Clustering the Impact of Wildfires on Remote Sensing Imagery

To assess wildfire effects on remote sensing imagery, B1 values at the in-situ sampling locations were extracted and subjected to k-means clustering analysis ($k = 3$) (Figure 4). The first cluster comprised samples with low aerosol band values ($B1 < 0.05$, Rrc), indicating minimal interference. The second cluster represented lakes with moderate aerosol levels ($0.05 \leq B1 \leq 0.07$, Rrc), while the third cluster consisted of observations with high aerosol levels ($B1 > 0.07$, Rrc). The significance of differences between these clusters was evaluated using the Kruskal-Wallis test, a nonparametric method that compares the mean ranks across clusters. The results indicated that the clusters were statistically distinct ($p < 0.001$).

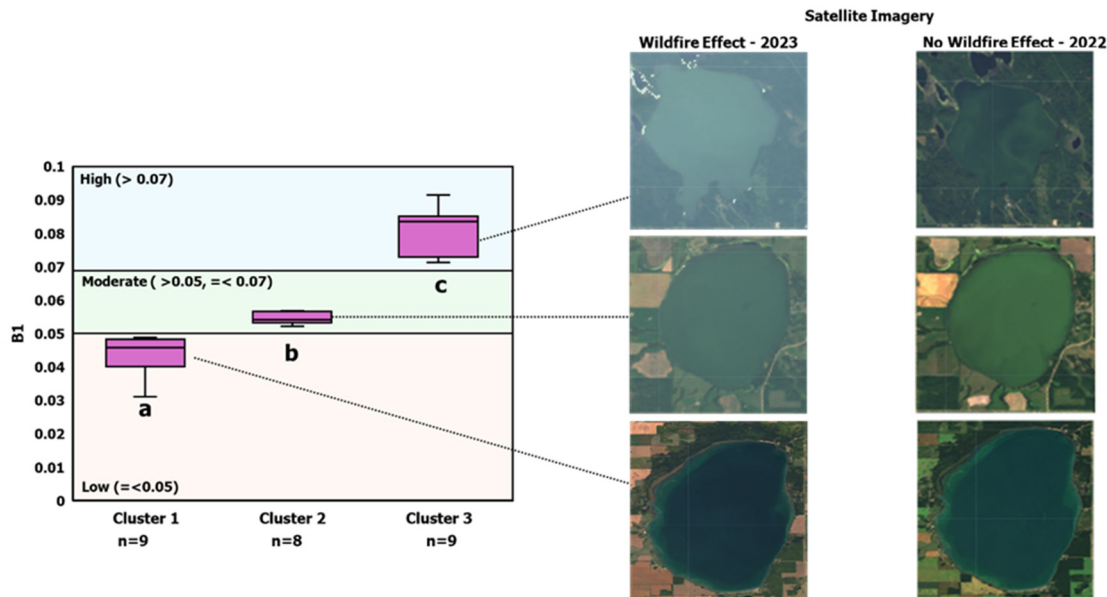


Figure 4. Cluster analysis of B1 values with example images showing wildfire interference. “Wildfire Effect - 2023” showcases examples of lakes that were differentially affected by wildfire smoke, whereas “No Wildfire Effect - 2022” represents the same lakes in 2022, a year without wildfire interference.

3.3. Performance of Chl-a Retrieval Models with Partial Atmospheric Correction

To investigate the impact of incorporating samples with varying aerosol band values into the Chl-a retrieval model, three calibration datasets were established:

- 1. **Calibration set 1:** Includes cluster 1 (low wildfire interference).
- 2. **Calibration set 2:** Includes clusters 1 and 2 (low and moderate wildfire interference).
- 3. **Calibration set 3:** Includes all clusters (low, moderate, and high wildfire interference).

A 3-fold cross-validation method was applied, and Table 3, section A presents the performance metrics of the best fold based on the test fold. It outlines the performance of models developed using three predictors across different calibration sets. Calibration set 1 consistently outperformed the other sets in terms of all predictors' performance metrics. Specifically, models based on (Blue-Red)/Green exhibited superior R² and NRMSE compared to the other predictors across all calibration sets. Calibration set 2 showed slightly lower performance than set 1 across all predictors, while Calibration set 3 exhibited the weakest performance among all calibration sets.

Table 3. The linear regression models developed for the three predictors using a +/- 3 days window based on a) partial atmospheric correction using Rayleigh-corrected reflectance and b) full atmospheric correction using the Landsat 8 level 2 process ready reflectance.

A. Partial atmospheric correction (Rayleigh-corrected reflectance)													
Calibration set (Sample Size)	Predictor	Correlation (r)	Chl- <i>a</i> Models	Train					Test				
				R ²	RMSE	NRMSE	Bias	MAE	R ²	RMSE	NRMSE	Bias	MAE
1 (n = 9)	x = (B/R)	-0.90	ln(Chl- <i>a</i>) = - 2.796*x+7.685	0.80	0.48	0.41	0	0.41	0.79	0.53	0.37	0.07	0.45
	x = (B/G)	-0.93	ln(Chl- <i>a</i>) = - 6.36*x+9.923	0.84	0.51	0.37	0	0.48	0.87	0.18	0.3	- 0.03	0.17
	x = (B- R)/G	-0.95	ln(Chl- <i>a</i>) = - 5.988*x+5.61	0.83	0.43	0.37	0	0.38	0.99	0.10	0.08	0.05	0.08
2 (n = 17)	x = (B/R)	-0.89	ln(Chl- <i>a</i>) = - 2.646*x+7.342	0.78	0.52	0.45	0	0.40	0.74	0.64	0.46	- 0.09	0.58
	x = (B/G)	-0.90	ln(Chl- <i>a</i>) = - 4.631*x+8.017	0.80	0.45	0.42	0	0.38	0.77	0.68	0.43	- 0.01	0.55
	x = (B- R)/G	-0.90	ln(Chl- <i>a</i>) = - 4.58*x+4.879	0.80	0.55	0.43	0	0.45	0.87	0.42	0.32	0.04	0.34
3 (n = 26)	x = (B/R)	-0.77	ln(Chl- <i>a</i>) = - 3.315*x+8.383	0.58	0.88	0.63	0	0.73	0.61	0.62	0.59	0.05	0.46
	x = (B/G)	-0.75	ln(Chl- <i>a</i>) = - 4.749*x+8.377	0.52	0.90	0.67	0	0.64	0.61	0.70	0.59	0.02	0.64
	x = (B- R)/G	-0.78	ln(Chl- <i>a</i>) = - 4.685*x+5.016	0.58	0.85	0.63	0	0.60	0.68	0.63	0.53	0.06	0.58
B. Full atmospheric correction (Landsat 8 Level 2 reflectance)													
Calibration set (Sample Size)	Predictor	Correlation (r)	Chl- <i>a</i> Models	Train					Test				
				R ²	RMSE	NRMSE	Bias	MAE	R ²	RMSE	NRMSE	Bias	MAE
1 (n = 9)	x = (B/R)	-0.84	ln(Chl- <i>a</i>) = - 2.033*x+4.637	0.71	0.65	0.49	0	0.61	0.71	0.54	0.44	0.01	0.51
	x = (B/G)	-0.86	ln(Chl- <i>a</i>) = - 3.75*x+4.695	0.72	0.64	0.48	0	0.54	0.79	0.45	0.37	- 0.05	0.39
	x = (B- R)/G	-0.88	ln(Chl- <i>a</i>) = - 4.331*x+2.501	0.8	0.47	0.41	0	0.41	0.74	0.65	0.41	0.00	0.60
2 (n = 17)	x = (B/R)	-0.67	ln(Chl- <i>a</i>) = - 2.157*x+5.121	0.37	0.95	0.76	0	0.76	0.64	0.74	0.53	0.00	0.56
	x = (B/G)	-0.66	ln(Chl- <i>a</i>) = - 2.981*x+4.787	0.38	0.87	0.75	0	0.74	0.46	1.03	0.66	- 0.10	0.85
	x = (B- R)/G	-0.69	ln(Chl- <i>a</i>) = - 3.515*x+2.932	0.42	0.93	0.73	0	0.75	0.63	0.69	0.54	- 0.06	0.56
3 (n = 26)	x = (B/R)	-0.63	ln(Chl- <i>a</i>) = - 1.923*x+5.064	0.32	1.08	0.8	0	0.80	0.53	0.78	0.65	0.09	0.68

$x = (B/G)$	-0.63	$\ln(\text{Chl-}a) = -4.003 \cdot x + 5.325$	0.37	1.13	0.77	0	0.90	0.53	0.57	0.65	-0.06	0.50
$x = (B-R)/G$	-0.63	$\ln(\text{Chl-}a) = -3.867 \cdot x + 3.018$	0.35	1.06	0.78	0	0.81	0.52	0.79	0.66	0.09	0.59

3.4. Performance of Chl-*a* Retrieval Models with Full Atmospheric Correction

To assess whether Chl-*a* retrieval models developed with partial atmospheric correction are comparable to those with full atmospheric correction, Landsat 8 level 2 (process-ready) products were utilized. A calibration dataset incorporating both in-situ and satellite overpass data, with a match-up window size limited to +/- 3 days, was employed. Table 3, section B presents the performance metrics of Chl-*a* retrieval modeling using Landsat level 2 products for different calibration sets. Calibration set 1 demonstrated superior performance across all predictors compared to other calibration sets. Models based on (Blue-Red)/Green showed the highest R² and NRMSE values for Calibration sets 1 and 2. Calibration set 3 consistently exhibited the weakest performance among all calibration sets.

3.5. Comparison of Chl-*a* Retrieval Modeling

Figure 5a illustrates the performance of different band formulas on the Rayleigh-corrected reflectance dataset. Calibration set 1 achieved the highest R² values among all calibration sets. Calibration set 2 showed a slight decline in performance across all models, although a two-way ANOVA test indicated no statistically significant difference in R² values between calibration sets 1 and 2 ($p > 0.1$). Calibration set 3 consistently demonstrated lower performance compared to sets 1 and 2, with ANOVA results confirming significant differences in mean R² values ($p < 0.01$).

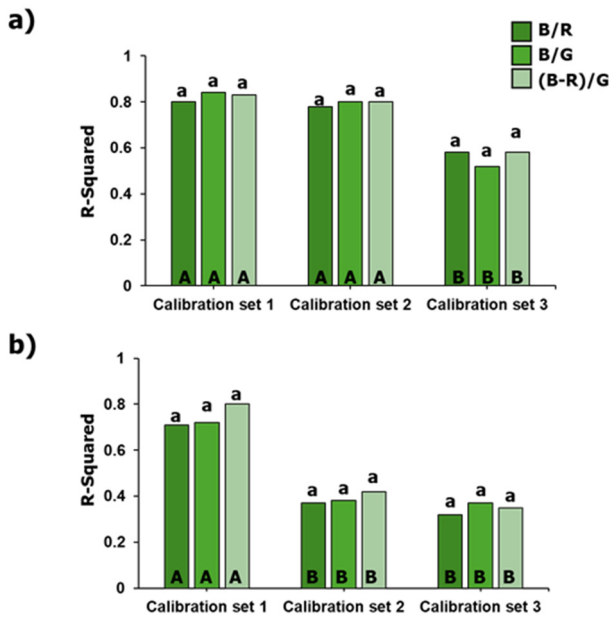


Figure 5. The correlation between the band formulae and ln(Chl-*a*) for different temporal windows of in situ-satellite match-ups.

Figure 5b depicts the performance of different band formulas on the surface reflectance product. Similarly, ANOVA tests revealed that Calibration set 1 significantly outperformed both calibration sets 2 and 3 ($p < 0.001$), while the performance difference between Calibration sets 2 and 3 was not statistically significant ($p = 0.2$). Within each calibration set, there were no significant differences in the performance of each band formula ($p > 0.1$).

Observations in Calibration set 1 for both Rayleigh-corrected reflectance (Figure 5a) and Landsat level 2 products (Figure 4b) indicated minimal aerosol disturbance. Comparing these two calibration sets highlighted the impact of aerosol effects on Chl-*a* retrieval modeling in surface waters.

Specifically, the full atmospheric correction used in the Landsat level 2 product (Figure 5b - Calibration set 1) underperformed compared to partial atmospheric correction (Figure 5a - Calibration set 1), with R^2 values decreasing by approximately 0.1.

The two-way ANOVA showed that the (a) Rayleigh-corrected reflectance and (b) Landsat level 2 calibration sets between both products were statistically different across all three calibration sets ($p < 0.001$).

3.6. Effect of Aerosol Band Filtering on Lake Chl-*a* Concentrations Across the Lake Winnipeg Watershed

To assess the impact of using aerosol band filtering for removing pixels with elevated aerosol levels in the process of mapping lake Chl-*a* concentrations, we employed a model based on the (Blue-Red)/Green band formula. This model was used to map phytoplankton biomass (i.e., Chl-*a* concentration) across lakes in the Lake Winnipeg Watershed from 2013 to 2023. The formula was derived from Calibration set 2, which utilized Rayleigh-corrected reflectance. While Calibration set 2 did not achieve the highest performance among all sets ($R^2 = 0.83$), its performance was only slightly lower than that of Calibration set 1 ($R^2 = 0.80$), with no statistically significant difference between the two. Notably, Calibration set 2 included nearly twice as many samples as Calibration set 1 (17 versus 9), thus providing a more extensive dataset for model development. Figure 6a maps the differences in average Chl-*a* concentration for each lake between 2013 and 2023, with and without aerosol band filtering. Figures 6b and c show the frequency distributions of lake Chl-*a* concentrations, comparing the scenarios without and with aerosol filtering for the average Chl-*a* concentration between 2013 to 2023.

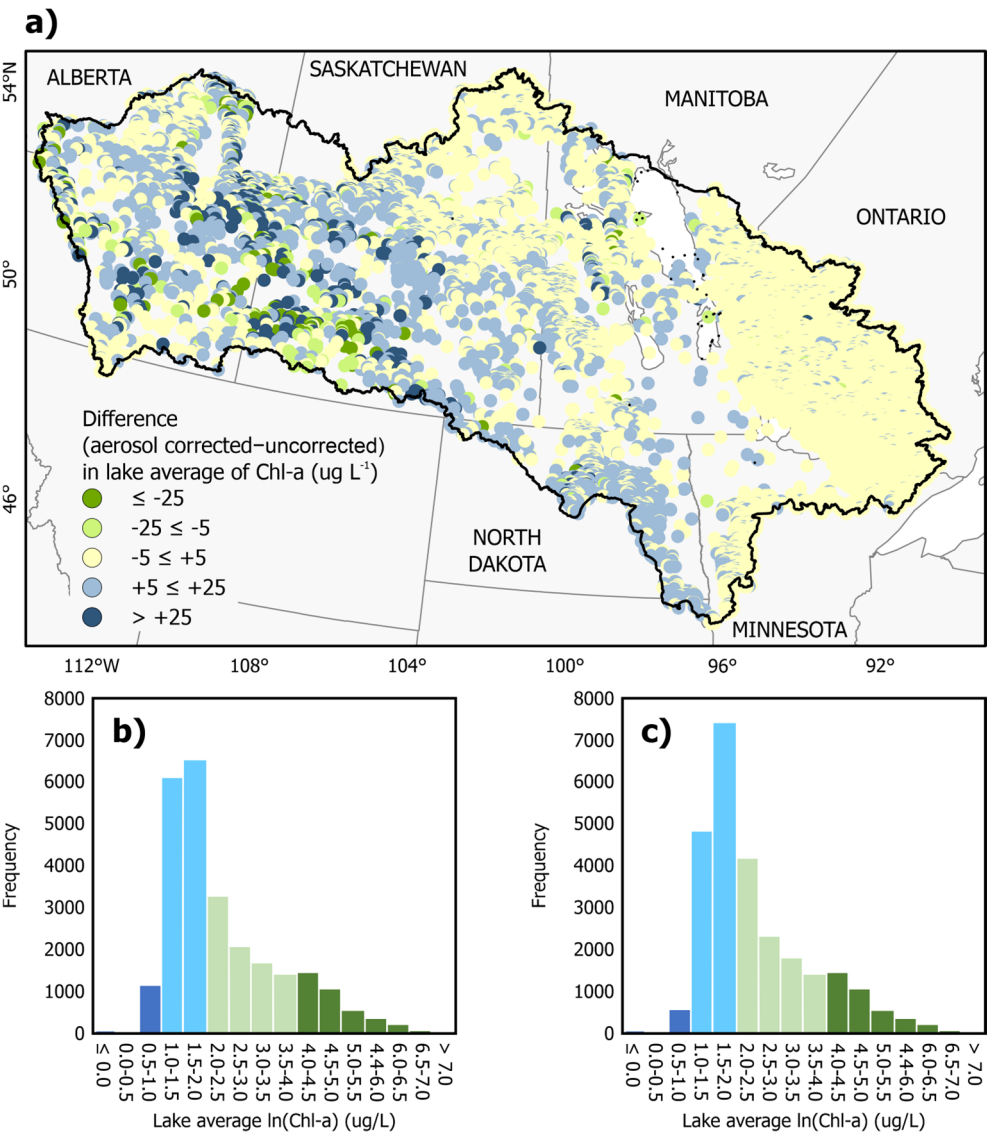


Figure 6. a) Map of the differences in lake average Chl-*a* with and without B1 aerosol screening (with aerosol screening minus without) for the period from start of availability of Landsat OLI with B1 in 2013 to 2023. Frequency distributions of b) lake average Chl-*a* without aerosol screening, and c) with aerosol screening.

4. Discussion

The increasing frequency and intensity of wildfires highlight the need for advanced monitoring techniques to address the challenges posed by heightened haze and smoke levels on remote sensing methods [67]. Elevated haze and smoke from wildfires reduce visibility and degrade satellite imagery quality [68,69], making it difficult to extract reliable information about surface properties, such as water quality characteristics [21,70,71]. Lake managers and practitioners need guidance on whether image quality is sufficient for accurately characterizing algal dynamics.

4.1. Removing Effects of Severe Smoke

In this study, we applied a three-tiered image categorization system based on aerosol band values to assess smoke severity. We found that including samples with higher aerosol band values (i.e., higher smoke levels) in the calibration dataset led to a continuous decline in model performance, as indicated by decreasing R^2 values for all band formulae. When aerosol band values exceeded a threshold of 0.07 (R_{rc} , unitless), the accuracy of the Chl-*a* model was significantly affected, and such observations should be excluded to avoid inaccuracies. Nevertheless, even with highly smoke-affected observations (cluster 3), the models achieved R^2 values around 0.55 (Table 3, section A, Calibration set 3), which is still considered acceptable in previous studies using Landsat 8 OLI (e.g., [63,72,73]).

Our long-term and large-scale analysis of the effects of aerosol band filtering on pixel selection for Chl-*a* mapping (Figure 6a) showed that, for most monitored lakes in the Lake Winnipeg Watershed between 2013 and 2023, the observed differences between including and excluding this filter were relatively small (between -5 to 5 $\mu\text{g/L}$), indicating similar results. However, for some lakes, the observed differences exceeded 5 $\mu\text{g/L}$. Additionally, Figure 6b shows that for phytoplankton-rich lakes with Chl-*a* concentrations over 53 $\mu\text{g/L}$ (or $\ln(\text{Chl-}a) > 4$), both methods produced similar frequency distributions of lakes. In contrast, for lakes with Chl-*a* concentrations below 53 $\mu\text{g/L}$, the differences between the two methods were more pronounced. Specifically, for $\ln(\text{Chl-}a)$ values below 2.5 (equal to 12 $\mu\text{g/L}$), implementing aerosol band filtering mapped more lakes than without the filter, while in the range of $\ln(\text{Chl-}a)$ between 2.5 and 4, excluding aerosol filtering resulted in mapping more lakes.

A growing number of researchers are relying on Rayleigh-corrected reflectance, which remains vulnerable to smoke interference from wildfires [74]. This underscores the need for continued research into correction algorithms that can accurately account for elevated aerosol levels from wildfires across diverse surface types. Filtering Rayleigh-corrected reflectance with the coastal/aerosol band can be useful for detecting and excluding observations with high levels of smoke in the remote sensing of water bodies. Moreover, we found that full atmospheric correction, commonly used in previous studies, is often ineffective at removing wildfire effects and can impair model performance. This underperformance may be due to the overestimation of aerosol contributions, as documented in the literature [46,75].

4.2. Evaluating Chl-*a* retrieval Model Performance after Removal of Smoke Effects

The study area, covering the prairie and boreal plain ecozones, spans a wide range of lake productivity, from oligotrophic to eutrophic conditions [28]. In the southern prairie ecozone, lakes are often eutrophic due to the region's phosphorus-rich geology together with intensive human activity. In contrast, the northern boreal plain ecozone, lakes are often oligotrophic due to minimal human activity [31]. Our study lakes exhibited a varied range of phytoplankton biomass, from 3.7 to 216 $\mu\text{g/L}$ of Chl-*a* (Table S1).

All three band combinations used for Chl-*a* retrieval showed high performance ($R^2 > 0.78$) when using Calibration sets 1 and 2. Regardless of the band combination, Calibration set 3 performed poorly ($R^2 < 0.58$), illustrating the negative impact of high wildfire smoke on model performance. The (Blue-Red)/Green ratio exhibited the best performance in modeling Chl-*a* across all three calibration sets. This band formula has been widely used for mapping Chl-*a* in various water bodies (e.g., [19,59,62,63]) and is known for its broad applicability, effectively tracking Chl-*a* across different trophic states [17,62].

A key consideration when applying the (Blue-Red)/Green ratio is its susceptibility to high chromophoric dissolved organic matter (CDOM). High CDOM can limit the effectiveness of this method, as CDOM interferes with phytoplankton detection in the blue spectrum [64]. However, our study lakes had relatively low color (<65 mg/L PtCo), supporting the suitability of this method in our analysis (Table S1).

4. Conclusion

As wildfires become more frequent and intense worldwide, the resulting smoke plumes can travel hundreds to thousands of kilometers, posing significant challenges to the accuracy of satellite sensor data, which is crucial for monitoring freshwater lakes. To maintain precision in water quality assessments under these wildfire-affected conditions, it is essential to implement tailored strategies, such as refined atmospheric corrections and well-defined cutoff thresholds. In this study, we identified a specific threshold at which wildfire smoke significantly impairs the prediction of algal productivity. By integrating this threshold with Rayleigh-corrected reflectance, we effectively assessed lakes impacted by wildfire smoke. This highlights the need for remote sensing practitioners to recognize when predictive accuracy is compromised, ensuring more reliable monitoring and assessment of wildfire-affected regions.

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Data Availability Statement: This research has used Landsat OLI images, openly available in the Google Earth Engine (<https://earthengine.google.com/>) platform. The raw chlorophyll-*a* data supporting the conclusions of this article will be made available by the authors on request.

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