

## **Drone-Based Water Quality Monitoring of a Small Urban Lake: Case of Swan Lake in the Greater Toronto Area, Canada**

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## **Drone-Based Water Quality Monitoring of a Small Urban Lake: Case of Swan Lake in the Greater Toronto Area, Canada**

### **Abstract**

Urban lakes face increasing pressure from land-use change, urban growth, and climate change, resulting in immediate and long-term social and environmental impacts. Advances in drone technology and payloads have revolutionized environmental monitoring, particularly water quality assessment, by enabling high-resolution, on-demand, and rapid sensing. Recent studies highlight the advantages and complementary role of drone-based monitoring. Swan Lake in the city of Markham in the Greater Toronto Area ( Ontario, Canada), has been monitored for water quality issues caused by high levels of phosphorus, nitrogen, and chloride, which promote algal blooms and ecological decline. A drone with a multispectral camera was used to collect data from May to November 2025. This data was analyzed to calculate water quality indices like NDCI, NDTI, and NDWI, along with relevant statistics. The results reveal detailed spatiotemporal patterns of these indices, supporting more targeted and timely water-quality improvement interventions. This study included a direct comparison of drone-based observations and satellite data to evaluate their relative spatial detail and ability to capture patterns, distributions, and changes over time and space.

**Keywords:** Water Quality Monitoring, Drone, NDCI, NDWI, NDTI, Swan Lake, Turbidity, Algal

## **1. Introduction**

Urban lakes are increasingly under pressure from land use changes, urbanization, and climate change (Krishnan et al., 2024). These pressures can lead to human and environmental impacts, including habitat degradation, the loss of crucial ecosystem services, the extinction of “keystone” species (Xie et al., 2024), and implications for human health. As urbanization accelerates, domestic and industrial runoff containing heavy metals, microplastics, salts, and untreated sewage increasingly flows into urban and suburban lakes and water bodies (Nawaz, 2023). These pressures result in eutrophication, oxygen depletion, and the decline of aquatic ecosystems, underscoring the need for advanced monitoring strategies (Dawn et al., 2025).

Practical water quality assessment and monitoring play a fundamental role in safeguarding both public health and aquatic ecosystems. Contemporary monitoring strategies integrate chemical analyses with remote sensing techniques to provide comprehensive assessments of water quality. Chemical approaches focus on quantifying water constituents and evaluating biological and biochemical processes. In contrast, remote sensing methods target both optically active parameters, such as turbidity and chlorophyll-a, and optically inactive parameters, including biochemical oxygen demand (BOD) and total dissolved solids (TDS), through indirect modeling approaches (Dawn et al., 2025).

Recent advances in uncrewed aerial vehicles (UAVs) and sensor payloads have significantly enhanced remote sensing capabilities for water quality monitoring, particularly in small and urban water bodies. Drone-based approaches offer a compelling alternative to traditional field-based methods, which are often labour-intensive, costly, and spatially constrained (Jansen et al., 2016), as well as to satellite-based remote sensing, which is limited by coarse spatial resolution and revisit frequency. By enabling high-resolution, high-frequency, and targeted observations, UAV-based

monitoring systems are increasingly being adopted as effective standalone proactive tools or as complementary solutions within integrated water quality monitoring frameworks.

A former gravel quarry, Swan Lake is an artificial urban lake and stormwater management pond located in Markham, Ontario, Canada. In addition to its stormwater control function, it is considered to be a “constructed wetland” and as such offers important ecological and recreational benefits to residents of Markham and York Region. Unlike natural lakes, Swan Lake has no natural inflows or outflows; it collects runoff from six stormwater sources and releases water through a single outflow that manages water levels. Despite ongoing management and monitoring, Swan Lake continues to suffer from persistent water quality challenges (City of Markham, 2023). Swan Lake’s water quality challenges are primarily driven by a high abundance of phytoplankton, which obstructs the development of in-water habitat and prevents the re-establishment of macrophytes. The lake’s health is further compromised by elevated internal nutrient loading, specifically phosphorus, and by high chloride concentrations (Burnside & Associates, 2025), reflecting the influence of urban runoff and winter road salt application.

To enhance Swan Lake's water quality initiatives and guide its long-term rehabilitation, the Swan Lake Citizen Science Lab has initiated UAV-based monitoring using multispectral and thermal sensors. The key goals of this project are: 1) High-resolution water quality mapping by employing multispectral data to detect, measure, and spatially map chlorophyll-a and algal blooms (cyanobacteria), enabling accurate assessment of chemical treatment results; and 2) Ecosystem restoration monitoring by using multispectral indices like NDVI to oversee the development, growth, and health of the newly planted Wild Celery (SAV) within the restoration zones.

This paper presents the findings of this study conducted between May 2025 and November 2025. The rest of this paper is organized as follows. Section two provides background and a literature

review of drone-based water-quality assessment in urban and small lakes. Section three describes the research methodology and data. Section 4 presents the main findings and discussions. Finally, section five concludes the paper.

## **2. Background and Literature Review: Drone-based Small Urban Lake Water Quality Assessment**

Recent studies on water-quality assessment using drones (UAVs) equipped with various sensors show an apparent increase in both methods and use cases. As effective environmental assessment and management require more frequent localized data, drones are becoming an essential tool for detailed, continuous spatial monitoring.

Traditional remote-sensing methods, though effective for large-scale observations, have historically relied on labour-intensive, spatially constrained, and temporally irregular satellite platforms (Wasehun et al. 2024; Pillay et al. 2024). Drone-based remote sensing provides higher spatial and temporal coverage with reduced field effort. Consequently, in recent years, there has been a significant shift toward drone-based approaches, driven by their high spatial and temporal resolution, operational flexibility, and cost-effectiveness, particularly for small and heterogeneous water bodies. Emerging studies highlight how drone-based monitoring fills critical gaps between broad-scale satellite observations and localized field sampling, enabling fine-scale and continuous water-quality monitoring that supports environmental monitoring and management (Jaywant et al. 2024). Among these approaches, multispectral drone-based imagery has received particular attention (Wu et al. 2025; Alemneh et al. 2025).

Drones equipped with multispectral sensors are used for optically active water quality parameters such as chemical oxygen demand (COD) (Zhang et al. 2023), chlorophyll-a (Castro et al. 2020;

Zhao et al. 2022), total suspended solids (TSS) and turbidity (Agrawal and Narulkar 2025), surface temperature (Giles et al. 2024), colored dissolved organic matter (CDOM) (Guo et al. 2024), and total nitrogen (TN) (Peng et al. 2025; Zhang and Wu 2025; Berka et al. 2025; He et al. 2025).

Empirical studies consistently report that multispectral bands in the red, red-edge, and NIR regions exhibit strong correlations with key water quality parameters. At the same time, band-ratio-based indices are often identified as effective predictors in both regression and machine learning models. These bands demonstrate strong physical and statistical relationships with TSS and Chlorophyll-a because they capture the unique scattering and absorption properties of these matters. For example, Agrawal and Narulkar (2025) found that red, red-edge, and NIR bands are the most sensitive for estimating TSS and turbidity with 93.65% accuracy.

Rich drone-based data with high quality and frequency has enabled a shift from basic mathematical relationships and empirical index-based retrievals to more advanced data-driven systems, inversion models, and machine-learning methods (Yan et al. 2023a; Long et al. 2025a). These methods leverage multispectral data to improve parameter estimation accuracy in complex inland water systems (Liu et al. 2025a). Several methodological and application-oriented pathways have been introduced (Yan et al. 2023b). A principal strand involves comparative analyses of inversion methods, including traditional regression (Zhao et al. 2022), neural networks (Liu et al. 2025b), random forest (Agrawal and Narulkar 2025), and gradient-boosting models (Wang et al. 2022) to determine which algorithms best translate observed spectral responses into water quality parameter estimates under varying environmental conditions.

Beyond algorithm development, researchers also focus on sensor and platform optimization, comparing different multispectral systems and exploring integration with other data sources, including satellite imagery, to enhance retrieval robustness. Studies have applied these approaches

to a range of contexts, from inland lakes and urban river systems to coastal waters and aquaculture ponds, demonstrating the feasibility and limitations of drone-based monitoring in diverse settings. For example, Shatnawi et al (2025) used multispectral drone imagery and machine-learning models to assess water quality in an artificial lake, correlating spectral indices with measured water quality parameters and demonstrating the feasibility of high-resolution drone-based monitoring in such environments.

Drone-based multispectral monitoring can detect fine-scale spatial variability and provides a robust approach for monitoring water quality in small, turbid reservoirs, addressing several of the inherent limitations of satellite-based remote sensing (Long et al. 2025b). For example, Xiao et al. (2022) used a combination of multispectral drone-based remote sensing, combined with machine learning, to monitor multiple water quality parameters (chlorophyll-a, total nitrogen, total phosphorus, COD) in a complex urban riverine context. Cheng et al. (2024) applied a “stacked” machine learning model to drone data to identify pollution “hotspots” in urban water systems that traditional sampling missed. This work demonstrated how drones address the “mixed pixel” problem, in which riverbanks and water typically blend in satellite images.

Drones are also used for environmental monitoring of small ponds such as aquaculture ponds. For example, Liu et al. (2024) combined drone multispectral imagery with machine learning models (including stacking) to estimate chlorophyll-a and turbidity and map their spatial distribution for water quality assessment. Similarly, in another study, Chen et al. (2024) showed that drones could accurately map Dissolved Organic Matter (DOM) and Dissolved Oxygen (DO) in fish and crab ponds.

The use of drones in water quality assessment has its own challenges (Yang et al. 2022). Some of these challenges are inherent to drone platforms. Drone sensors record raw digital numbers (DN)

that vary with light conditions and sensor consistency; calibration is required to convert these into scientific reflectance values (Iqbal et al. 2018). Water surface acts like a mirror, reflecting direct sunlight (glint) and sky light into the sensor, which can completely obscure the signal from inside the water (Lee et al. 2025). Therefore, calibrations and robust in-situ validation protocols are needed to ensure quantitative reliability (Koparan et al. 2018).

Although research and applications of drones in water quality monitoring are increasing, their wider use in this field remains in the early stages. Additional studies and practical applications are needed to understand better how drone-derived data can aid water quality assessment across diverse water bodies and environmental contexts. This study offers another example from North America, Canada in particular, of drone-based multispectral monitoring of a small urban lake over an extended period.

### **3. Methodology**

#### **3.1. Study Area: Swan Lake**

With an area of about 5.5 hectares and located at 43°53'49.1"N and 79°15'08.6"W, Swan Lake is a small artificial urban lake and stormwater management facility located in Swan Lake Park in Markham, Ontario, Canada (Fig. 1). In addition to its stormwater control functions, it provides important ecological and recreational benefits to residents of Markham and York Region. Unlike natural lakes, this artificial lake has no natural inflows or outflows. It collects runoff from six stormwater sources and releases it through a single outflow, managing water levels. Despite regular monitoring and interventions over the past few years, the lake continues to experience significant water quality issues. Swan Lake's water quality challenges are primarily driven by a high abundance of phytoplankton, which obstructs the development of in-water habitat and prevents the re-establishment of macrophytes. The lake's health is further compromised by

elevated internal nutrient loading, particularly phosphorus, and by high chloride concentrations (Burnside & Associates, 2025).

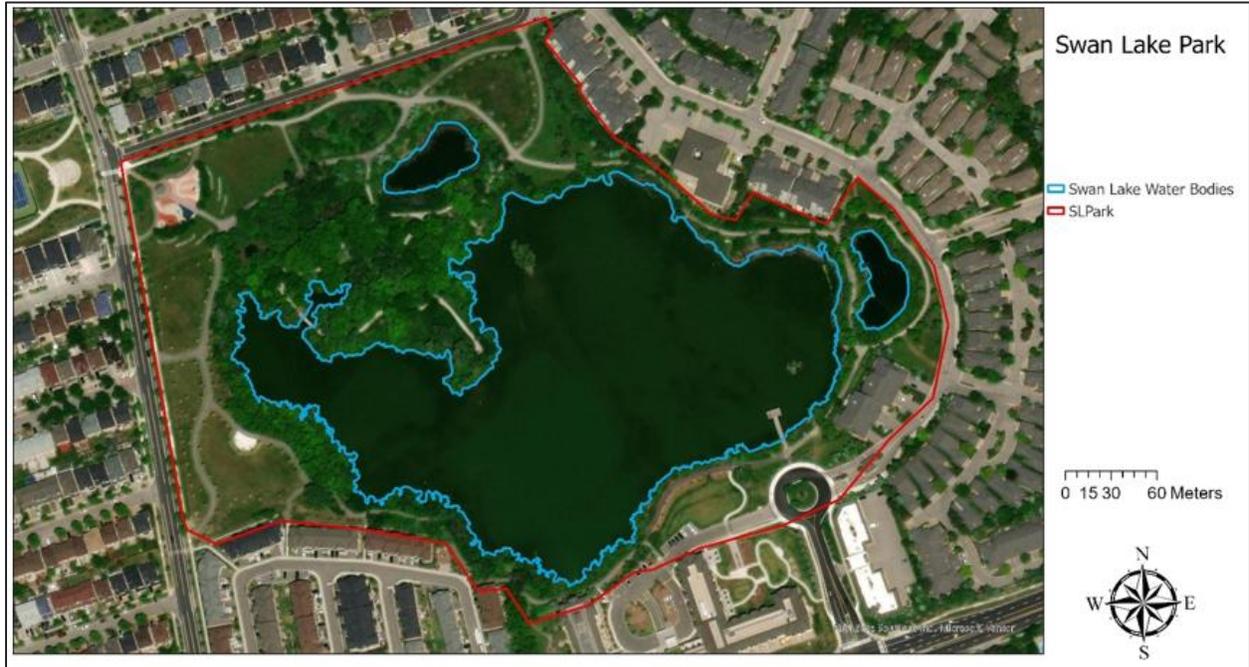


Fig. 1 Swan Lake Park in Markham, Ontario

Swan Lake is classified as a highly eutrophic lake, meaning it is nutrient-rich and regularly experiences harmful algal blooms, including cyanobacteria. The main water quality problems arise from high levels of phosphorus and nitrogen, which result from both internal sediment release and external sources, such as Canada goose populations. These nutrients promote rapid algal proliferation, including cyanobacteria (blue-green algae), leading to frequent blooms and surface scums. These can release toxins that pose risks to public health (Burnside and Associates, 2025).

Moreover, chloride contamination and low dissolved oxygen (DO) remain significant environmental concerns for Swan Lake. Chloride contamination is primarily due to de-icing road salt used during winter. Currently, six stormwater inlets introduce about 3 tonnes of chloride into the lake annually (Friends of Swan Lake Park, 2025).

### 3.2. Data Collection

Data was collected using a DJI Mavic 3 Multispectral (Mavic 3M) UAV, a compact and portable platform designed for high-precision surveying and environmental monitoring. The multispectral camera is equipped with 4 sensors, 5 MP each, capturing imagery in four spectral bands: Green (G:  $560 \text{ nm} \pm 16 \text{ nm}$ ), Red (R:  $650 \text{ nm} \pm 16 \text{ nm}$ ), Red Edge (RE:  $730 \text{ nm} \pm 16 \text{ nm}$ ), and Near-Infrared (NIR:  $860 \text{ nm} \pm 26 \text{ nm}$ ). Data were collected at least once per month between May and November 2025. We started in May, when the growing season starts, and ended in November, when the temperature falls near zero celcius. Days were mainly selected based on the weather conditions and availability of the drone and drone pilots. Weather conditions are critical for acquiring high-quality spectral data, as thermal and illumination gradients are most pronounced at specific times of day and under specific environmental conditions. Comprehensive weather monitoring (including temperature, precipitation, and wind) was conducted in the days leading up to the operation. Flights were avoided in high-wind conditions to ensure the drone's safety and the stability and quality of the collected data. Altogether, 14 flight datasets were collected, among which 13 flight datasets were used in the analysis. Flight 14 data was not analysed due to full snow coverage of the lake. All flights were conducted at a consistent altitude of 65 m following a predefined flight path (Fig. 2), resulting in a Ground Sample Distance (GSD) of 3.00 cm/pixel. The flight path and altitude were optimized to achieve a high degree of image front-to-side overlap, ensuring accurate 2D and 3D reconstruction of the area into a seamless orthomosaic. The mapping area covered about 14 hectares, and each full flight path was 5.59 km, collecting 498 images and taking between 38 and 68 minutes to complete.

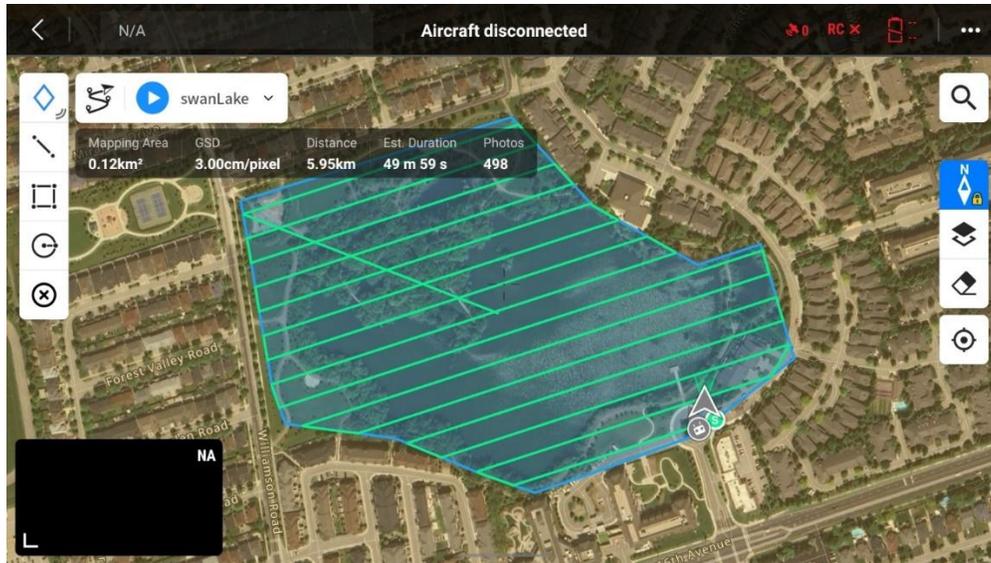


Fig 2. A screenshot of DJI Mavic 3M control station displaying the flight path and attributes

The majority of the flights were conducted under sunny conditions and generally mild temperatures, ranging from a cool 8 degrees in October to a warm 21 degrees in August (Table 1). Wind speeds were generally light to moderate, though a few flights, like Flight 13, experienced stronger winds up to 29 kmph. Most flights were conducted in the morning, just after sunrise.

Table 1. Drone flight details

Flight No.	Survey Date	Flight Duration (min)	Time (EST)	Weather & Conditions
1	05/12/2025	38	15:07 – 15:45	Sunny, 17°C, Wind 7 kmph SSW
2	05/20/2025	62	12:53 – 13:55	Sunny, 10°C, Wind 12 kmph S
3	06/02/2025	62	06:09 – 07:06	Sunny, 10°C, Wind 12 kmph SSW
4	06/07/2025	54	14:21 – 15:15	Sunny, 20°C, Wind 9 kmph SSW
5	06/15/2025	63	07:04 – 08:07	Cloudy, 17°C, Wind 17 kmph E
6	06/29/2025	55	05:41 – 06:36	Sunny, 14°C, Wind 6 kmph NW
7	07/31/2025	54	07:15 – 08:09	Sunny, 20°C, Wind 20 kmph NE
8	08/23/2025	54	08:43 – 09:36	Sunny, 20°C, Wind 20 kmph NE
9	08/31/2025	57	17:11 – 18:04	Sunny, 21°C, Wind 11 kmph S
10	09/17/2025	53	07:22 – 08:15	Sunny, 16°C, Wind 8 kmph N
11	10/08/2025	63	10:10 – 11:13	Sunny, 15°C, Wind 23 kmph NW
12	10/29/2025	63	09:20 – 10:16	Sunny, 8°C, Wind 20 kmph NNE
13	11/12/2025	63	10:20 – 11:13	Overcast, 4°C, Wind 29 kmph WSW
14	12/11/2025	65	10:22 – 11:14	Sunny -7°C, Wind 19 kmph W

For our comparative analysis, we used the Level-2A Surface Reflectance product (COPERNICUS/S2\_SR\_HARMONIZED) from the European Space Agency's Sentinel-2 satellite images. This product provides bottom-of-atmosphere reflectance data, which are essential for precise water-quality assessment (Abbas and Alameddine, 2023; Espinoza et al., 2025). The Sentinel-2 MSI sensor includes essential bands for water quality monitoring: Band 3 (Green, ~560 nm), Band 4 (Red, ~665 nm), Band 8 (Near-Infrared, ~842 nm), and Band 5 (Red Edge, ~705 nm). While Band 5 has a 20 m resolution, the other bands offer 10 m resolution. We filtered the satellite data to select the ones closest to our drone flights. To maintain data quality, images with over 80% cloud cover were excluded, and a pixel-level cloud mask was applied using the QA60 bitmask band. All satellite images were then clipped to the lake boundary, with a 5-meter inward buffer, to avoid mixed-pixel issues along the shoreline.

### **3.3. Data Processing**

Collected data was processed to calculate and compare water quality indices over time and space. To do so, we first created orthomosaic maps of single drone images for each date. While there are many tools for generating orthomosaic maps, we used WebODM for this part of the analysis. WebODM is an open-source photogrammetry software. WebODM uses Structure-from-Motion (SfM) algorithms to analyze thousands of overlapping images along with their accurate GPS/RTK coordinates (Vacca, 2020). The final output is a unified Multi-Band Raster file, such as a GeoTIFF (.tif). Subsequently, we added these layers to ArcGIS Pro and used the Raster Calculator function to calculate water quality indices for the entire park area. Since our focus was on the study area, we extracted the lake portion of the calculated raster files using the Extract by Mask tool. The lake boundary used as a masking layer was a shapefile generated from a drone-based orthomosaic map of the area. We captured the water surface and removed any edge vegetation from the shapefile. We also removed the two tiny, vegetated islands from the lake. The final index results were

mapped in ArcGIS Pro and also used in Google Earth Engine for further spatio-temporal analysis.

Fig. 3 shows the data analysis process of the study.

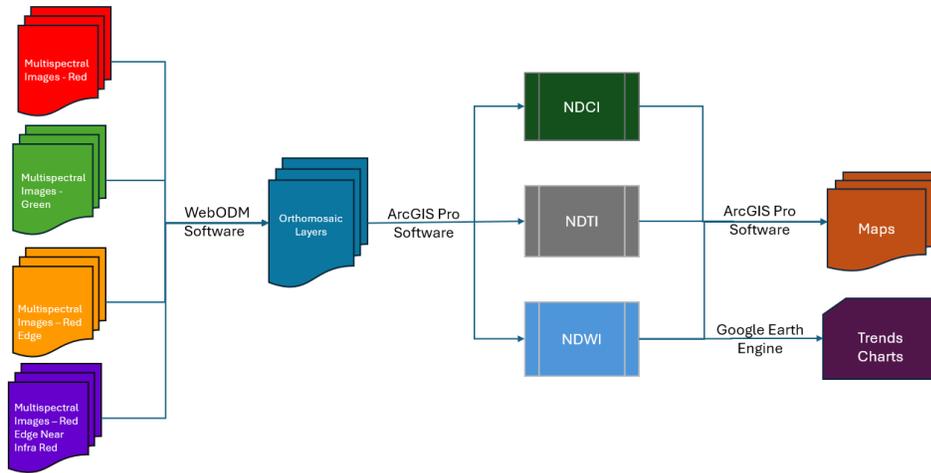


Figure 3. Data analysis process and tools used in the study

#### 4. Results and Discussion

Before presenting the results of the water quality assessment indices using multispectral bands, composite RGB orthomosaic maps of the Swan Lake during the study period are shown. The Mavic 3 M sensor captures wide-angle RGB imagery that can be used to produce true-colour orthomosaic maps of the lake. Figure 4 shows composite orthomosaic maps of the Swan Lake Park at different dates. These maps enable visual inspection of the watercolor and quality. By viewing the composite maps, it is possible to gain insights into water quality, including turbidity and chlorophyll-a. Dark blue/black colors typically indicate clear, deep water. Green/Cyan colors indicate varying levels of Chlorophyll-a (algae). Brown/Beige are usually representative of turbidity and dissolved organic matter (DOM) (Morel & Prieur, 1977; Wernand, & Van der Woerd, 2010). Spectral analysis of the Forel-Ule Ocean colour comparator scale. *Journal of the European Optical Society-Rapid Publications*, 5, 10014s.). Green color, while changing, is evident across the images, likely reflecting seasonal variations in algal biomass. On May 20, June 2, June 7, and June 15, the main lake's water appears dense, opaque, and deep olive-green. This visually confirms

the presence of surface algal mats or scum. The October 29 image shows that the watercolor shifts from the dense green of summer toward a brownish-green or gray-brown. The final image shows the lake's maximum visual clarity over the entire period. Data from November 12 shows that the water is noticeably darker, with a gray-blue/slate color, indicating a shift towards more clarity.

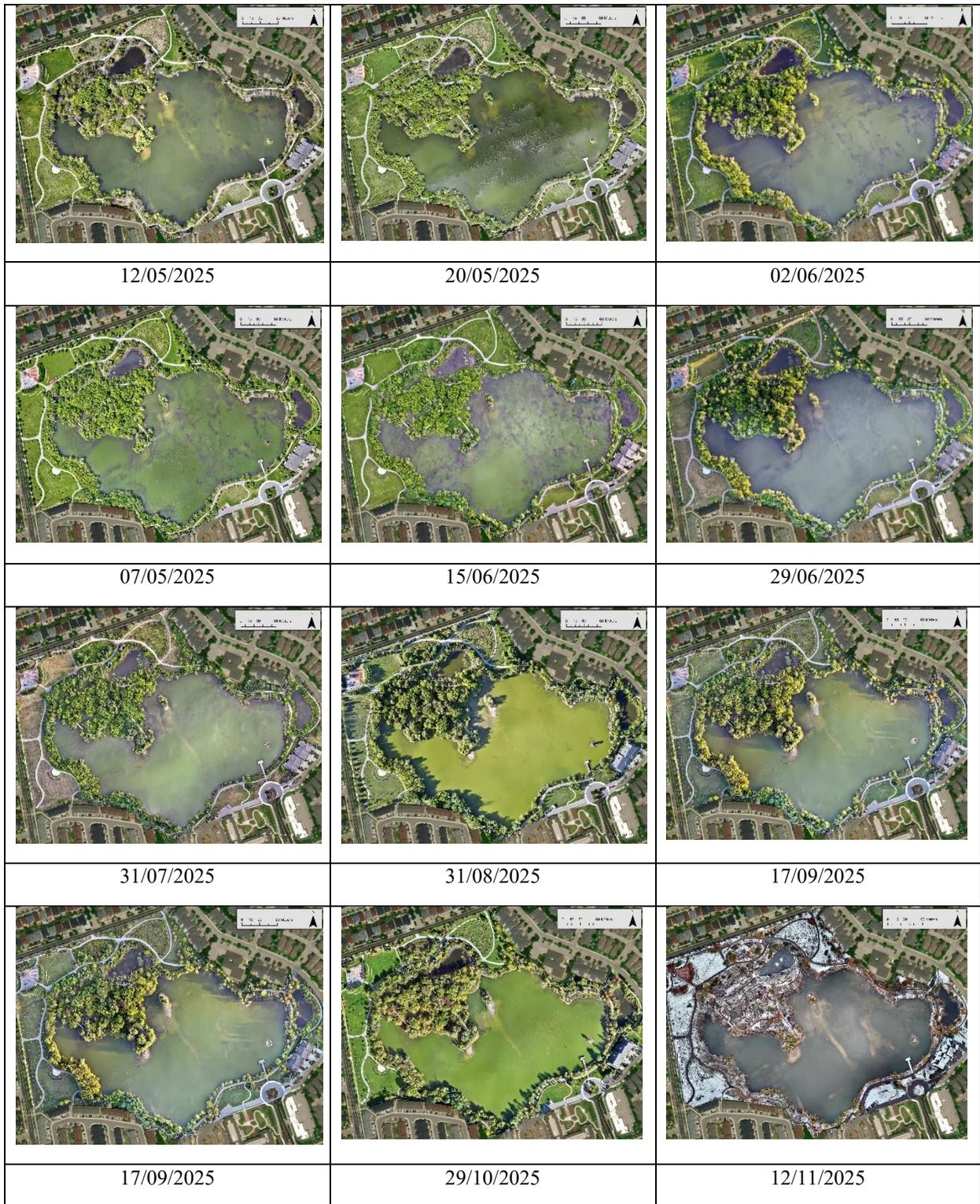


Fig. 4 True color maps of Swan Lake Park during different dates in 2025

#### **4.1. Normalized Difference Chlorophyll Index (NDCI)**

The NDCI tracks the levels of Chlorophyll-a (Chl-a), the main pigment involved in photosynthesis in algae and phytoplankton (Dabire et al. 2024). It provides a quick, quantitative estimate of algal biomass and helps evaluate the trophic state. It is calculated as:  $NDCI = (RedEdge - Red) / (RedEdge + Red)$ . Fig 5 shows the NDCI maps for the study period. The NDCI values range from -1 to 1. Values less than 0 indicate clear water with minimal algal presence; values between 0.0 and 0.1 represent minimal algal presence; 0.1 to 0.2 indicate moderate algal presence and growth; 0.2 to 0.4 indicate high algal biomass and growth; and values greater than 0.4 indicate very high algal biomass and bloom conditions.

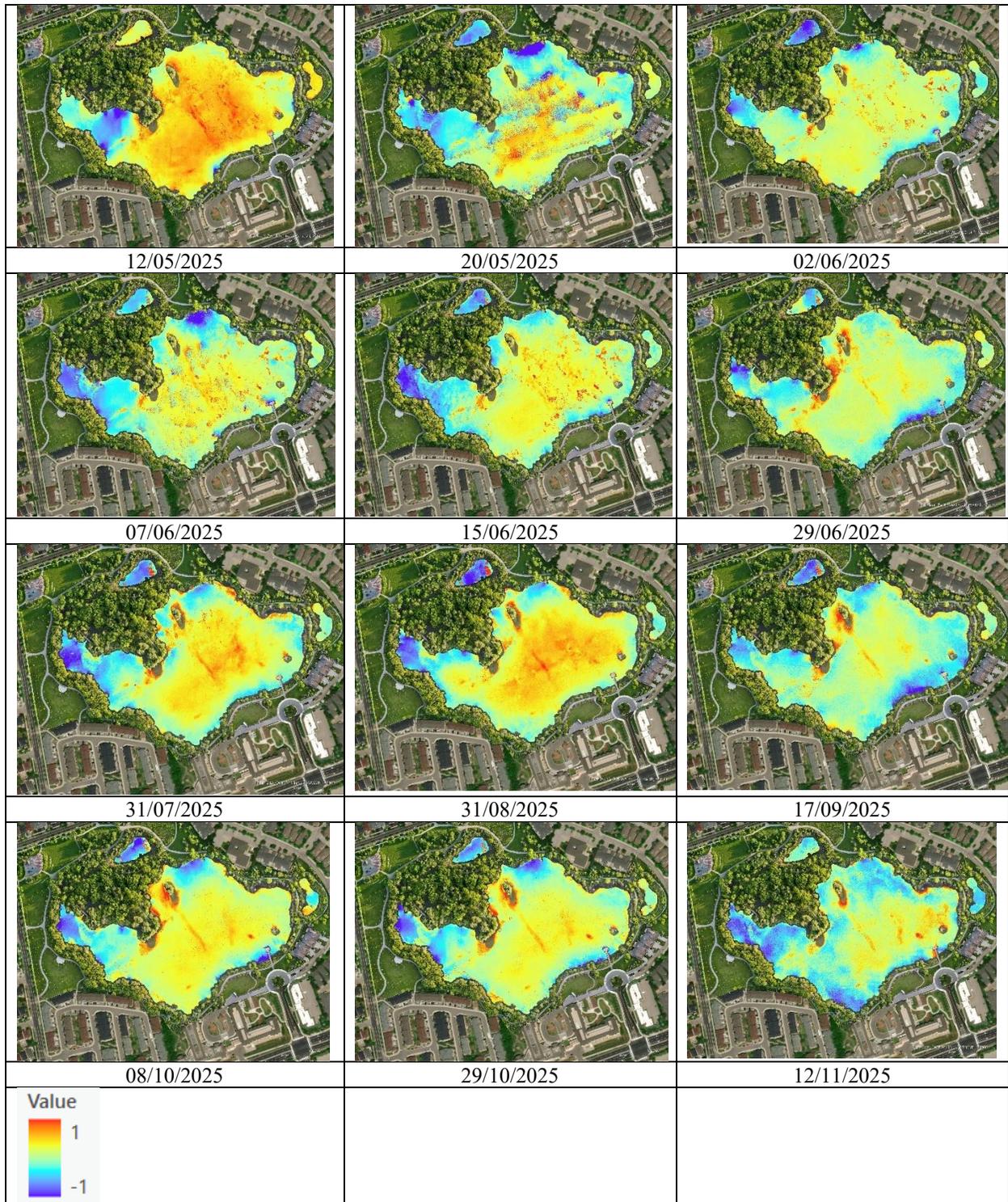


Fig. 5 Swan Lake NDCI maps for different dates

Figure 6 provides detailed insights into NDCI values by displaying the Maximum, Mean, Trend, and Variability (hotspots). Higher max values reveal areas with the highest algae concentrations.

Elevated mean values indicate regions with consistent algae presence. Increasing trend values suggest worsening algae conditions over the season, while lower trend values indicate improvement. Greater variability points to zones where bloom occurrences fluctuate frequently.

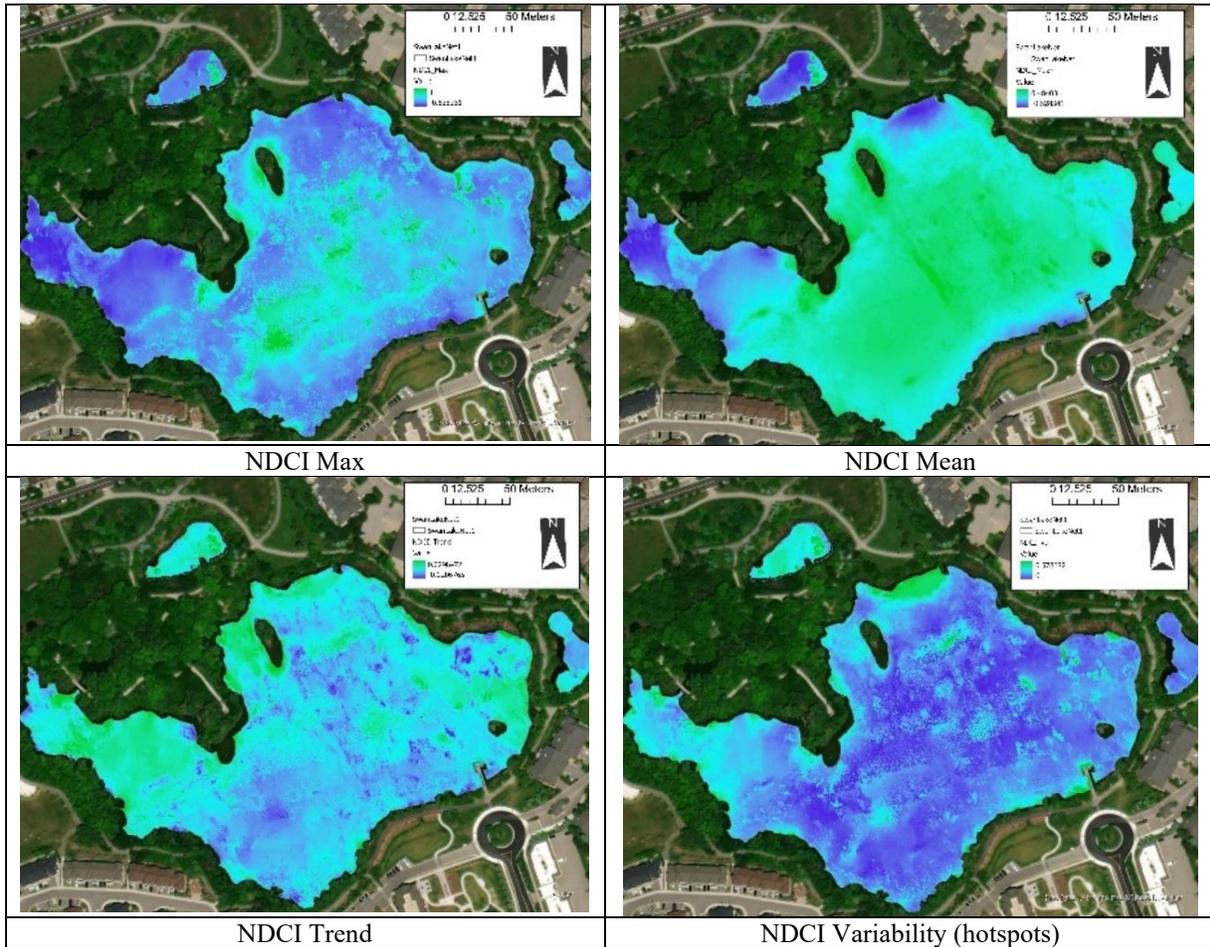


Figure 6. NDCI Max, Mean, Trend and Variability maps for Swan Lake during the study period

#### 4.2. The Normalized Difference Turbidity Index (NDTI)

The NDTI is a remote sensing metric used to gauge water turbidity by assessing total suspended solids (TSS) levels in water bodies. It is essential for water quality monitoring because it correlates with turbidity and suspended solids, aiding in tracking sedimentation, assessing pollutant movement, monitoring aquatic ecosystem health, assessing construction and dredging effects, and monitoring changes over time and space (Ardayan, 2025). Turbidity is a critical parameter for

drinking water sources. High turbidity makes water treatment more challenging and costly (Niu et al., 2025). NDTI is well-suited for monitoring water quality in small urban lakes. These lakes frequently receive runoff from impervious surfaces, which carries sediments, chemicals, pollutants, and organic matter, all increasing turbidity. NDTI can effectively track these effects (Deng et al., 2024).

Turbidity, which indicates water clarity, shows how particles like sediment, algae, or organic material scatter or absorb light. High turbidity can harm aquatic life, diminish water quality for humans, and limit light penetration for submerged plants. NDTI is calculated from the reflectance of the Red and Green spectral bands, which tend to rise with increased suspended particles. The NDTI is calculated as:  $NDTI = (Red - Green) / (Red + Green)$ . Elevated turbidity increases reflectance in both bands, and their relationship helps detect suspended particles (Bhardwaj et al., 2025).

Figure 7 shows the NDTI maps for Swan Lake for the study dates. Values lower than 0, shown in lighter colors, indicate clear water with low turbidity; values between 0 and 0.2, shown in the yellow color range, indicate low to moderate turbidity; values between 0.2 and 0.4 with light brown, indicate moderate to high turbidity; and values greater than 0.4, closer to brown, indicate very high turbidity. The results show temporal and spatial variations in turbidity.



Fig. 7 NDTI maps for Swan Lake for the study period

Fig 8 presents the maximum, mean, trend, and variability of NDTI values over the study period. Maximum values highlight the peak turbidity levels observed. Only in a few parts of the lake are the Max values high. Mean values identify regions with consistent turbidity levels. Elevated trend values indicate increasing turbidity, whereas lower trend values suggest decreasing turbidity during the period. Variability values show hot spot regions.

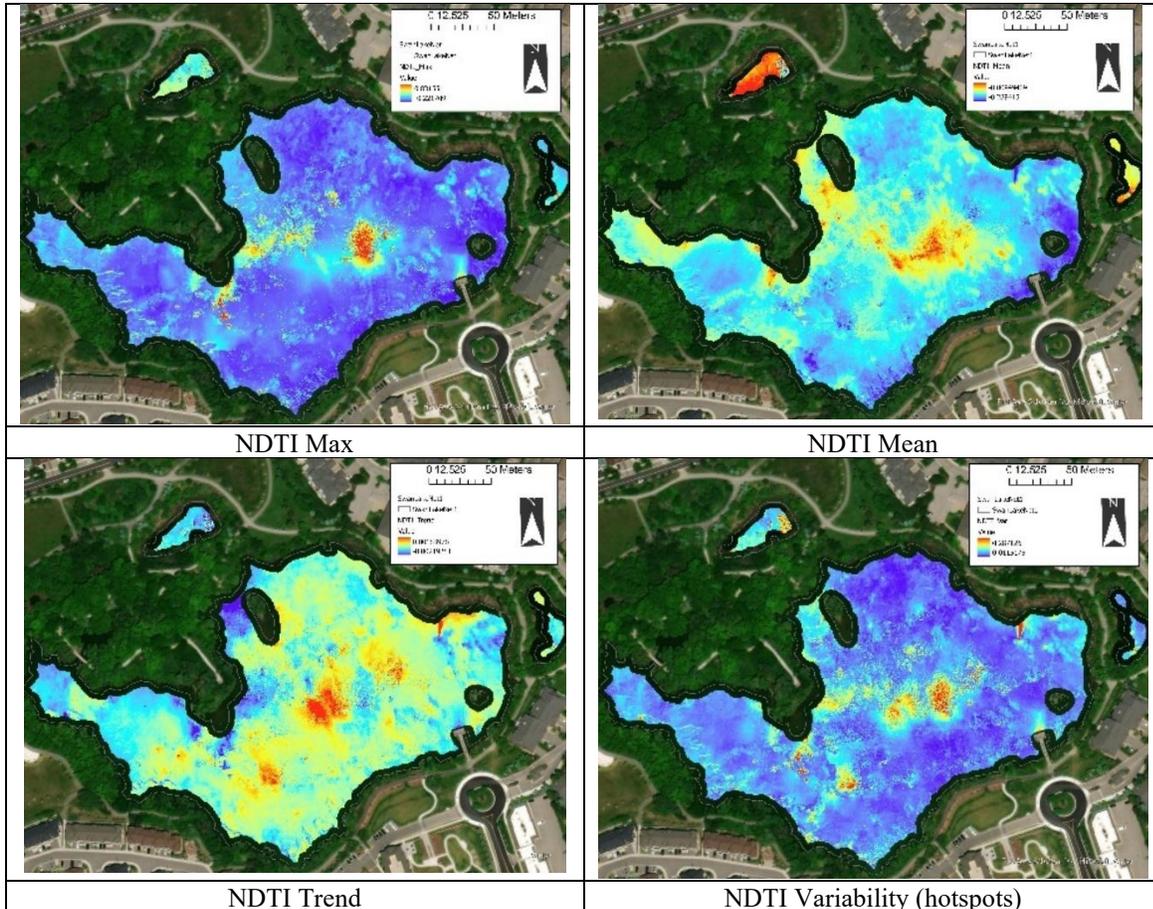


Fig. 8. NDTI Max, Mean, Trend and Variability maps for Swan Lake during the study period

### 4.3. The Normalized Difference Water Index (NDWI)

The NDWI is a remote sensing method primarily used to differentiate open water from other land covers. It can also reveal information about water depth, clarity, and mixing within water bodies. NDWI leverages water's unique spectral properties, characterized by strong absorption in the near-infrared (NIR) and reflection in the visible green spectrum. Created by McFeeters in 1996 for

water analysis, the original formula uses reflectance from the Green and NIR bands:  $NDWI = \frac{Green - NIR}{Green + NIR}$ . Fig 9 presents the NDWI results. Values above 0.4 indicate clear water (darker blue), 0.2 to 0.4 suggest moderate clarity (lighter blue), 0.0 to 0.2 imply mixed materials (yellow), -0.10 to 0.0 (brown) correspond to shorelines and reed/grass areas, and below -0.1 denote non-water surfaces. Again, the NDWI map shows temporal and spatial variations.

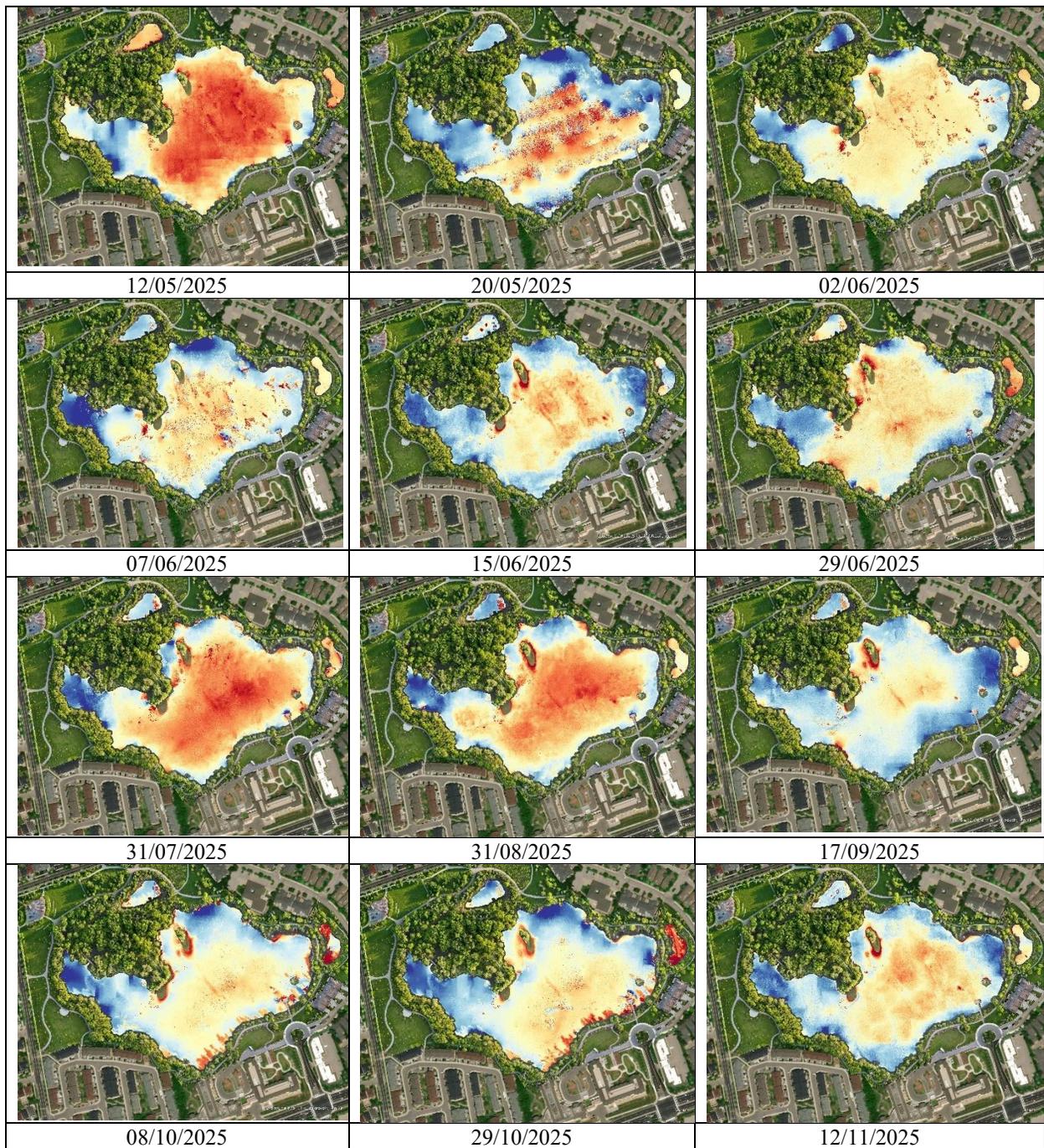


Fig. 9 NDWI maps for Swan Lake for the study period.

Fig 10 displays NDWI Max, Mean, Trend, and Variability over the study period. Max values indicate the clearest water in specific locations. Mean values highlight typical open-water areas

that are not mixed with other materials. Higher trend areas show improvements in water signals, while Variability indicates fluctuations between water and other materials, such as vegetation.

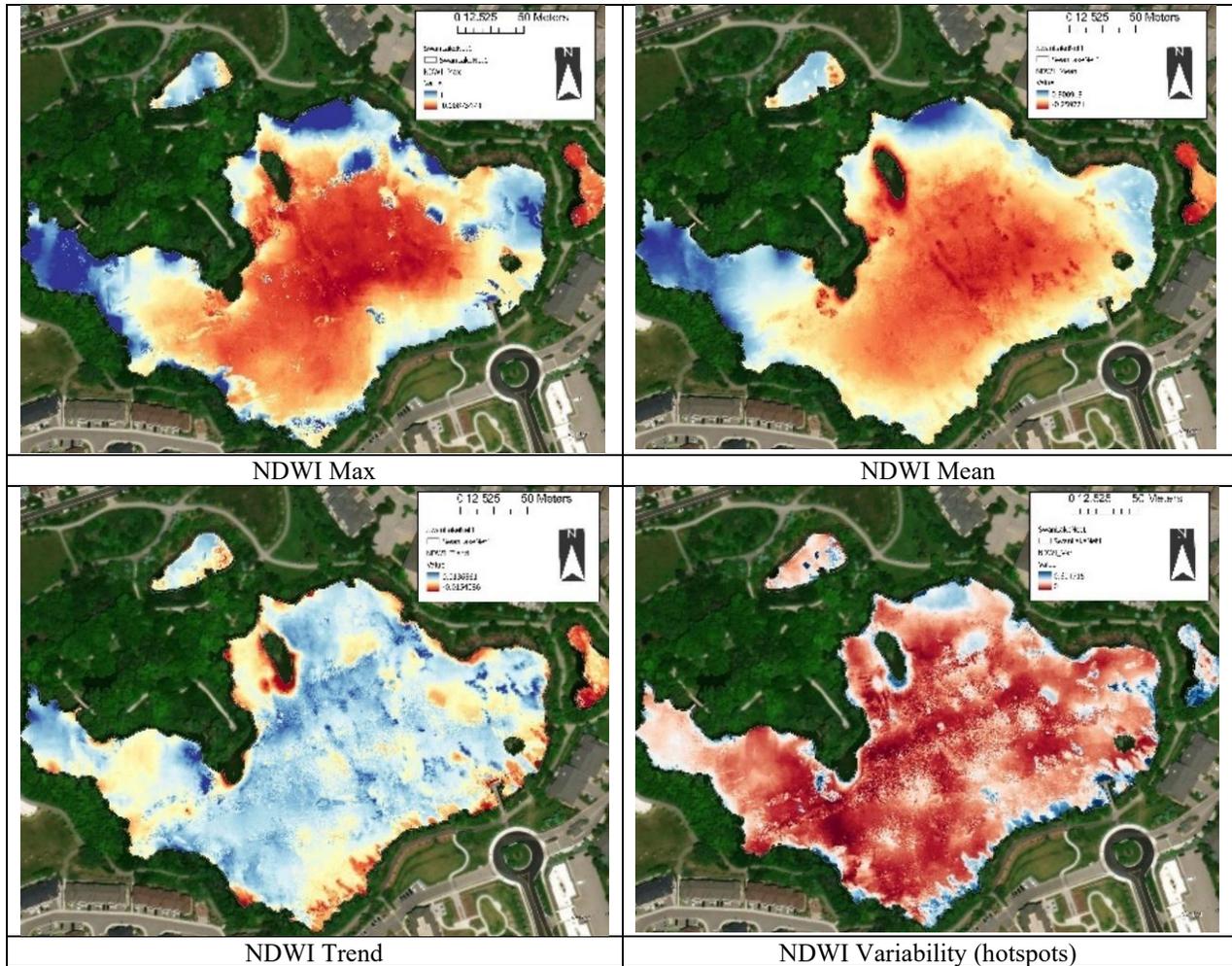


Fig 10 NDWI Max, Mean, Trend and Variability maps for Swan Lake during the study period

#### 4.4. Overall Trends and Distributions of NDCI Indicators

In this section, we present the overall trends for the NDCI, NDTI, and NDWI values and discuss the distributions of the Mean, Max, Variability, and Trend indicators for the NDCI. Figure 11 shows the overall trends for the average values of NDCI, NDTI, and NDWI for the entire lake water bodies for different dates. These average trend values show fluctuations and seasonal dynamics in the indices over time, while remaining within a specific range.

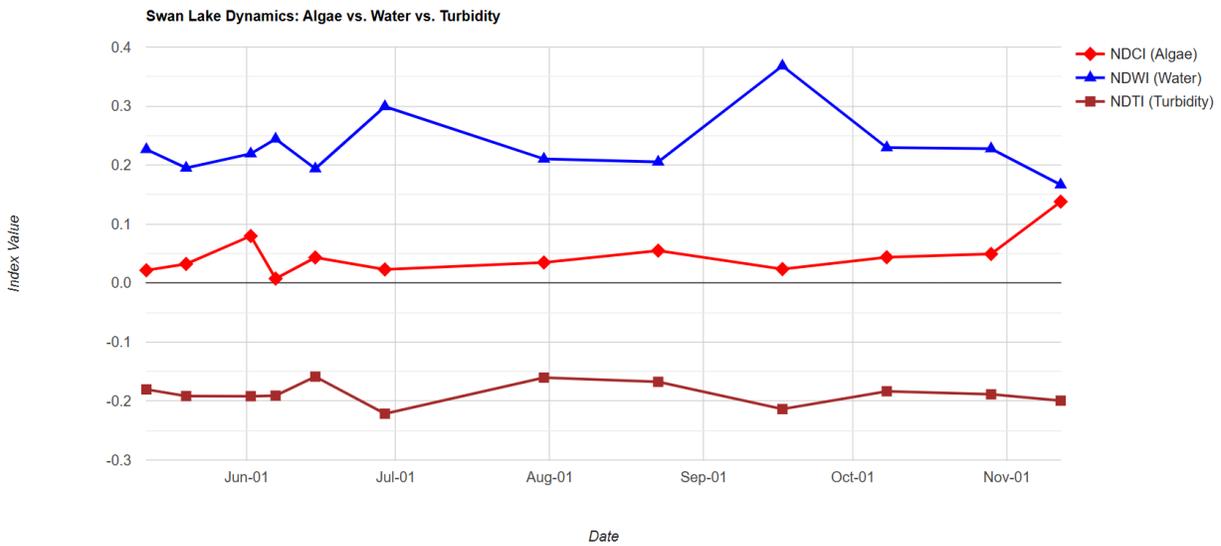


Fig. 11 Overall NDCI, NDTI, and ANWI trends in Swan Lake during the study period

Since NDCI is the most informative index in this context, histograms of pixel values were generated for the entire lake across the full study period to represent the mean, maximum, variability, and temporal trend (Fig. 12).

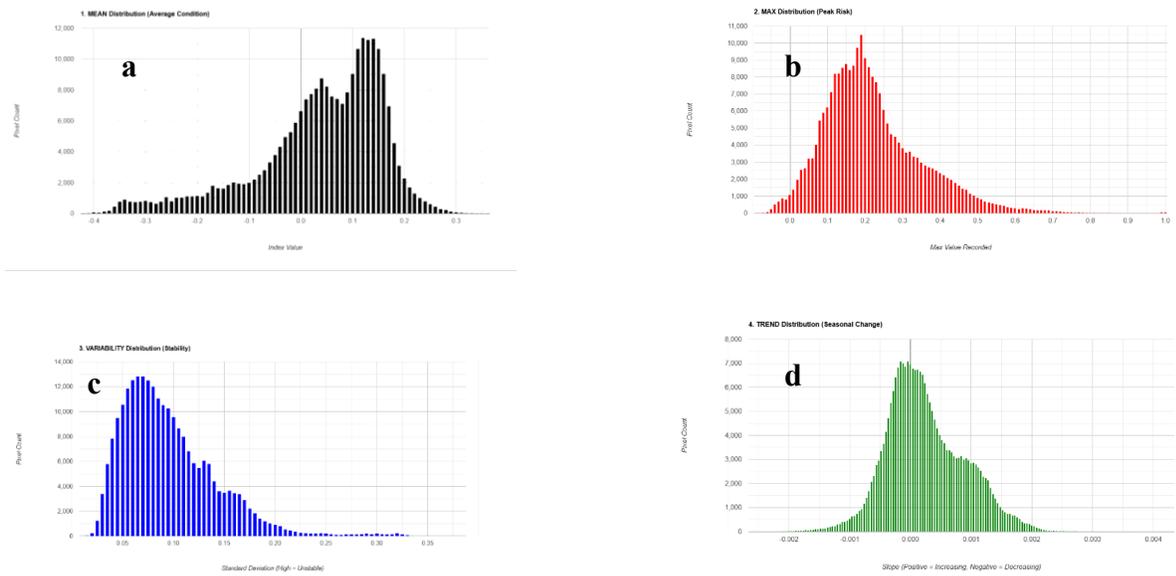
The histogram of mean NDCI values exhibits a pronounced positive skew. This indicates that the lake experienced widespread algal activity during the monitoring period. The unimodal distribution suggests persistent chlorophyll-a levels across much of the lake surface. Although a minor tail of negative values reflects localized areas of clearer water, the high concentration of pixels within the positive range suggests that the lake's baseline condition was biologically active, with relatively few consistently clear zones.

The distribution of maximum NDCI values highlights the occurrence of localized high-risk events that are often masked by average statistics. While the histogram peaks around approximately 0.20, suggesting that most of the lake experienced at least moderate bloom conditions, a substantial proportion of pixels are in the extreme positive range (>0.40). This confirms the presence of

intense surface scums and bloom hotspots. The long right-skewed tail (0.50 up to 0.80) indicates that severe algal accumulation was not an isolated anomaly but a recurring feature.

The NDCI variability (standard deviation) histogram is unimodal, with a peak near 0.06, suggesting that much of the lake exhibited relatively stable temporal behavior. However, the pronounced right-skewed tail extending to approximately 0.25 indicates the presence of localized regions with high temporal variability. These areas likely correspond to bloom initiation zones identified in the spatial maps, where water quality rapidly oscillates between clear and bloom states.

The histogram of NDCI trends (slope) displays a quasi-normal distribution centered near zero, indicating that the seasonal trajectory of chlorophyll-a levels remained relatively stable across a large portion of the lake. Nevertheless, a distinct positive shoulder between 0.0005 and 0.0015 reveals a sub-population of pixels exhibiting sustained increases in NDCI over time. This pattern confirms the presence of spatially concentrated zones undergoing progressive deterioration in water quality.



**Fig. 12. Distribution of NDCI Mean, Max, Variability, and Trend for Swan Lake based on Drone data: a.** NDCI MEAN distribution in Swan Lake during the study period (May to November 2025), **b.** NDCI MAX distribution in Swan Lake during the study period (May to November 2025), **c.** NDCI VARIABILITY distribution in Swan Lake during the study period (May to November 2025), **d.** NDCI TREND distribution in Swan Lake during the study period (May to November 2025)

#### 4.5. Results of Satellite Data

To quickly illustrate the differences between drone-based and satellite-based data, we display the NDCI, NCTI, and NDWI maps of key statistical indicators (Mean, Max, Variability, and Trend) (Fig 13) along with overall trends (Fig. 14). Although satellite results are close to those from drones, the drone data are more detailed. These charts clearly demonstrate the "resolution gap" between drones and satellites, emphasizing why the drone study is essential. It captured a biological event that satellite data could not accurately characterize. The satellite data shows higher algal values ( $\sim 0.15\text{--}0.20$ ) than the drone ( $\sim 0.03\text{--}0.05$ ), mainly due to the lower satellite resolution (10m per pixel) causing the Mixed Pixel Effect and atmospheric noise, which blend water signals with bottom reflectance and artificially inflate the green signal, respectively.

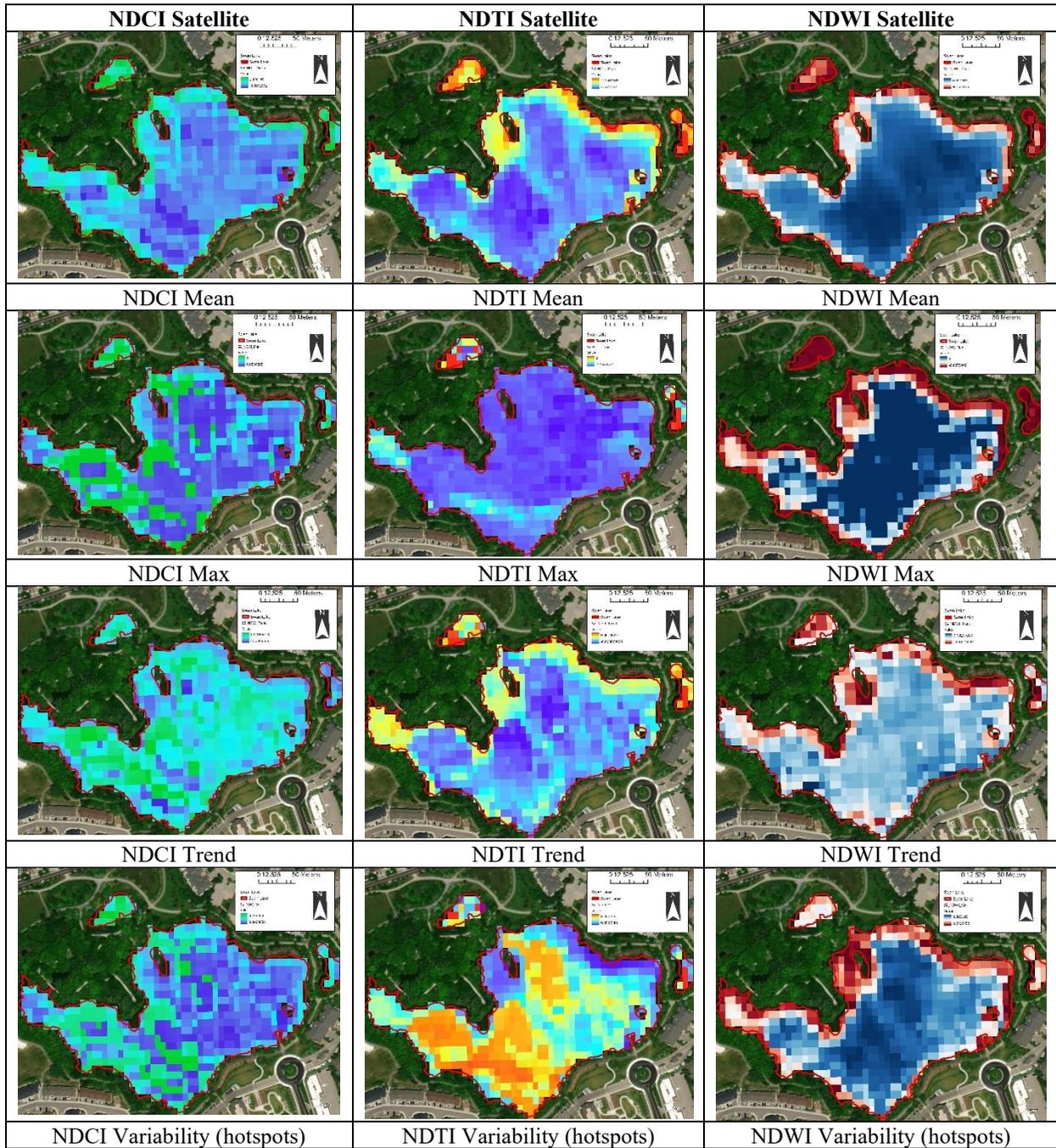
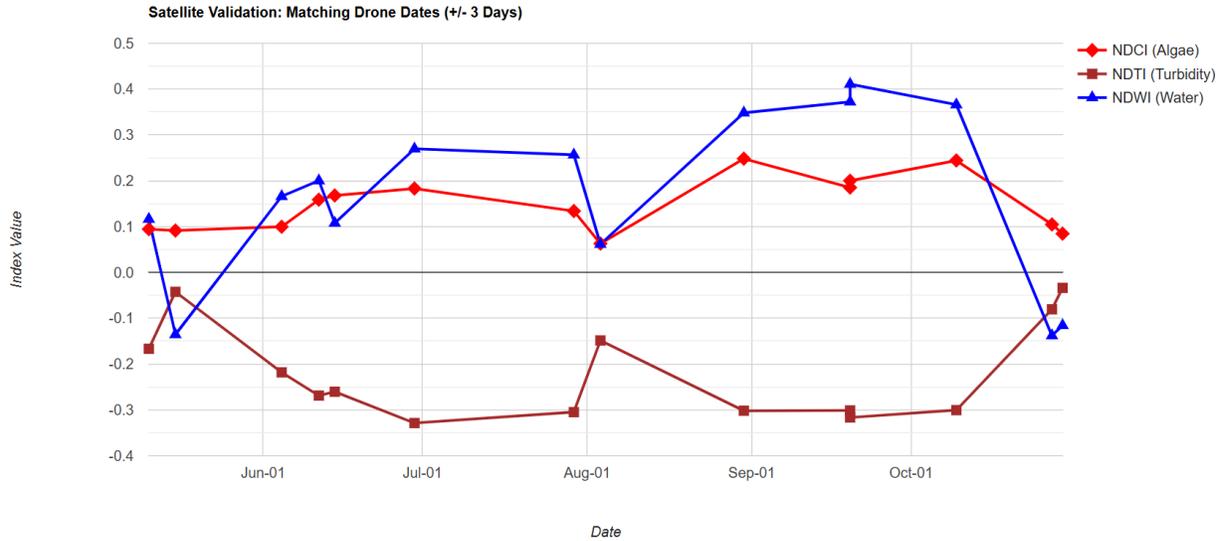


Fig. 13 NDCI, NDTI, and NDWI Mean, Max, trend, and Variability mapping of Swan Lake between May to October 2025 using Sentinel 2 Satellite data



**Fig. 14 Results of NDCI, NDTI, and NDWI using Sentinel 2 Multispectral sensor data**

The Drone Max values consistently surpassed 0.50, indicating the presence of intense, localized surface scums that were diluted in the averaged satellite data. In early spring (May), drone data revealed high-intensity hotspots ( $\sim 0.75$ ), while satellite data significantly underreported these ( $\sim 0.35$ ). However, the alignment of maximum values from both the drone and the satellite in October confirms the bloom's spatial expansion.

Similarly, analyzing spatial variability uncovers a notable resolution gap between the two datasets. The drone data show high variability in spring ( $\sim 0.28$ ), indicating a patchy bloom distribution. In contrast, satellite data exhibit lower variability ( $< 0.15$ ) throughout the season, reflecting a smoothing effect. Additionally, in November, the average algal concentration increased, while the spatial variability in drone data decreased significantly. This inverse relationship indicates a shift in bloom phenology, from patchy, localized scums in spring to a more uniform, widespread bloom in fall.

## 5. Conclusion

This study demonstrates that drone-based multispectral sensors can effectively collect remote sensing data for environmental assessments, including water-quality analysis of small water

bodies. Satellite data often fall short in providing on-demand, fine-tuned, high-resolution data, which are crucial for implementing environmental protection and water quality improvement efforts. The analysis of chlorophyll-a concentration, turbidity, and water clarity using NDCI, NDDI, and NDWI reveals interesting and important spatiotemporal variations in these remote-sensing-based water-quality indicators.

The primary conclusion about Swan Lake's water quality is that NDCI, NDTI, and NDWI clearly identify it as a eutrophic system, with turbidity mainly caused by algal biomass rather than suspended sediment. The observed spatiotemporal correlations between chlorophyll-a and turbidity peaks confirm that dense, floating algal scums impair water clarity. The simultaneous recovery of all three indices in late autumn may suggest a decrease in turbidity that water temperature is an important control factor in the lake's biological activity.

While comparisons of drone results with satellite data confirm the overall validity of the findings, they also demonstrate that drone data can provide significantly more detailed information, crucial for a better understanding of the patterns, distributions, and temporal and spatial changes in these factors.

Integration of this data with other physical, chemical, environmental, and behavioural data through the field investigations can improve planning and decision-making to enhance water quality in Swan Lake and similar small urban water bodies. Drone-based data and analyses can also help with more accurate, targeted field sampling, since water quality appears to vary significantly across the lake. Knowing the current spatio-temporal patterns of the key indicator values, future drone data collection can also seek to obtain even higher-resolution data from hotspots.

## **Statements and Declarations**

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None

### **Disclosure statement**

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