Depth vs. Development: Evaluating the Accuracy of 'At Capacity' Designations in Predicting Water Quality in Haliburton Lakes

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A-25

AMOD 5640Y

12th December 2025

Abstract

Ontario’s “At Capacity” lake designation system relies on mass-balance models to limit shoreline development, yet its effectiveness in morphologically complex regions remains debated. This study evaluated the validity of these designations across 31 lakes (61 sites) in Haliburton County using a reproducible Python-based analytical pipeline. By integrating water chemistry data (2022–2024) with morphometric and development metrics, we assessed whether administrative capacity status aligns with observed trophic conditions.

Results from ANCOVA models revealed that maximum depth is the primary driver of phosphorus variability (p < 0.005$), whereas capacity status showed no significant predictive power (p = 0.99) once morphometry was accounted for. While regional patterns appeared stable, short-term trajectory analysis identified localized enrichment hotspots in Gull, Stocking, and Kashagawigamog lakes ($\beta > 0.0008$ mg/L/yr), likely driven by the synergistic effects of legacy loading and climate-mediated internal release.

These findings indicate that binary capacity designations mask the ecological reality of deep-lake resilience and shallow-lake vulnerability. We recommend transitioning to "Anthro geomorphic" assessment models that explicitly integrate basin geometry and internal loading potential to better protect headwater systems from emerging cumulative stressors.

Introduction

Freshwater lakes act as living systems that shift and respond to their surroundings, and at the same time, they hold an important place in human communities. In the glaciated regions of the Canadian Shield—especially in areas like Haliburton, Ontario—lakes shape local identity, support tourism and property value, and anchor the region's ecology. Yet these systems are facing a growing risk of decline as eutrophication becomes more common. As phosphorus accumulates, often faster than the lake can settle it out, the whole system starts leaning away from its natural rhythm. For the people responsible for managing these waters, the difficult part is figuring out how much of that change comes from natural conditions and how much is the result of human activity. Basin shape, depth, and hydrology all dictate how a lake naturally processes nutrients, while shoreline development, septic systems, and resource use introduce disturbances that do not occur on their own. Ontario's "At Capacity" designation is built on this distinction; it aims to limit development on lakes where phosphorus levels are predicted to surpass what the ecosystem can handle. However, the reliability of these designations is still questioned. The standard predictive models often struggle when they confront the real variation in lake shapes, flushing patterns, and the layered pressures brought on by modern environmental change.

The Natural Template: Morphometry and Nutrient Dynamics

Determining whether a lake is approaching its natural capacity for nutrient assimilation requires a clear understanding of its baseline conditions. Dillon and Rigler (1975) established a mass-balance framework in which trophic status reflects the interaction among phosphorus loading, hydraulic flushing, and sedimentation. Their formulation remains central to Canadian

Shield lake management. Long-term observations at the Turkey Lakes Watershed support this view; Jeffries et al. (1988) reported that phosphorus persists as the dominant limiting nutrient in these headwater systems, with concentrations typically within the range of 8–16 μg L^{-1}, even during recovery from historical acid deposition.

External loading, though critical, is not the sole determinant of nutrient behaviour; basin morphometry exerts a comparable influence on phosphorus fate and transport. As shown by Håkanson (2005), mean depth and the area-to-depth ratio govern internal hydrodynamic processes such as sedimentation, resuspension, and mixing. These physical constraints regulate the extent to which phosphorus becomes sequestered in sediments or remains available in the water column. Fee's (1979) work expanded this perspective by linking primary production to the ratio of sediment surface area relative to epilimnetic volume, demonstrating that internal nutrient recycling is strongly conditioned by basin geometry rather than external inputs alone.

Morphometric effects also shape the nutrient limitation regime. Qin et al. (2020), drawing on a global dataset of 573 lakes, identified depth as a decisive parameter: deeper basins tend to remain phosphorus-limited because they store nutrients efficiently in sediments, whereas shallow systems experience continuous resuspension that promotes co-limitation by nitrogen and phosphorus. Similar patterns were documented by Kebedew et al. (2020) in Lake Tana, where shallow bathymetry maintained near-constant sediment disturbance, causing phosphorus concentrations to reflect internal stores more strongly than external loading. Consequently, deeper lakes generally exhibit greater resilience to enrichment, whereas shallow lakes respond more rapidly and more intensely to comparable external pressures.

The Anthropogenic Pressure: Shoreline Development and Land Use

Human activity imposes a distinct pressure on lake ecosystems, often altering nutrient pathways in ways that amplify or obscure natural controls. In regions such as Haliburton, shoreline development—cottages, septic systems, and the removal of riparian vegetation—represents the dominant disturbance. Rosenberger et al. (2008) demonstrated that even modest residential density can restructure littoral communities in large, deep oligotrophic lakes; periphyton assemblages shifted toward filamentous green algae and detritivore dominance while offshore water chemistry remained comparatively unchanged. These results show that whole-lake averages may conceal localized eutrophication signals emerging within the nearshore zone.

Quantifying the magnitude of development-driven effects is confounded by temporal lags and spatial heterogeneity. Van Heyst et al. (2022) described how legacy phosphorus persists in soils long after historical agricultural practices have ceased, producing a mismatch between present-day land use and measured loading. Basins with complex shoreline morphology further complicate assessment. Campbell and Chow-Fraser (2018) found that the Lakeshore Capacity Model consistently overestimated phosphorus concentrations in Georgian Bay embayments because key model assumptions—uniform mixing and simple export coefficients—did not hold in systems with restricted circulation or concentrated human activity. Incorporating metrics such as dock and building counts, along with measures of morphometric resistance to mixing, substantially improved model performance.

These outcomes point to a broader limitation in capacity frameworks that rely on well-mixed reactor assumptions. Such formulations tend to perform adequately in simple basins yet prove unreliable in lakes where shoreline alteration generates spatially uneven nutrient pressures. Without site-specific validation, resulting classifications risk imposing unnecessary constraints on morphometrically resilient lakes while failing to protect systems where localized development exerts disproportionate ecological influence.

Modelling Capacity: Successes and Failures

The Lakeshore Capacity Model (LCM) has long served as the primary tool for determining development capacity in Ontario, yet its performance depends heavily on assumptions that do not hold uniformly across lakes. Paterson et al. (2006) noted that the model relies on phosphorus export and retention coefficients derived from datasets that may not represent contemporary conditions or lakes with atypical morphometry. Shifts in climate, land-use intensity, and watershed hydrology raise additional concerns about whether these coefficients remain valid for present-day management. The reliance on steady-state conditions is especially problematic in lakes experiencing fluctuating water levels or episodic loading events, circumstances in which the equilibrium framework breaks down.

Brett and Benjamin (2008) further challenged the retention component of the model by showing that hydraulic retention time was a far stronger predictor of phosphorus loss than the settling velocity parameters commonly used. Their analysis indicated that lakes with short flushing times may export nutrients more efficiently than the model assumes, while those with prolonged retention may accumulate phosphorus even when predicted to be within acceptable limits. Such discrepancies create uncertainty in capacity classifications, with the potential to misidentify vulnerable lakes as stable or, conversely, to restrict development where morphometric resilience could accommodate additional loading.

Fundamentally, the application of generalized mass-balance models for regulatory decision-making is precarious without continuous recalibration against empirical observations.

Lakes with complex basin geometries, substantial internal loading, or climate-driven shifts in stratification often fall outside the domain where LCM assumptions hold, and model outputs may diverge markedly from observed system behaviour. Under such conditions, capacity designations risk underestimating or overestimating a lake's assimilative potential, underscoring the need for validation across a wide range of morphometric and climatic contexts.

The Complicating Factors: Multiple Stressors and Climate Change

Environmental change rarely operates through isolated pathways; multiple stressors acting simultaneously can produce ecological outcomes that diverge substantially from single-factor predictions. Orr et al. (2024), synthesizing nearly 2,400 experimental studies, reported that while additive responses are common, synergistic interactions remain a significant and often underestimated risk. These interactions can amplify nutrient enrichment effects, accelerate shifts in biological structure, or destabilize communities beyond the range anticipated by traditional stressor-specific assessments. Christensen et al. (2006) provided empirical support for this complexity in Boreal lakes, documenting how drought, warming, and acidification combined to generate non-additive responses in plankton biomass that could not be inferred from the behaviour of individual stressors.

Climate change introduces an additional set of pressures that modify baseline lake function and complicate capacity-based evaluations. Nelligan et al. (2019) demonstrated coherent increases in hypolimnetic oxygen deficits across Boreal Shield lakes, driven by climate-mediated alterations in stratification phenology and rising dissolved organic carbon. These shifts influence nutrient retention and internal loading, thereby reducing the assimilative capacity upon which phosphorus-based management models rely. Bănăduc et al. (2024) expanded the scope of known stressors, identifying invasive species, thermal pollution, and conflict-driven resource alteration as emerging drivers that may intensify nutrient-related degradation, particularly in systems already sensitive to hydrological or morphological change.

When these stressors coincide, their combined influence can deviate sharply from trajectories predicted by legacy phosphorus models. Lakes classified as "At Capacity" under historical assumptions may already exceed functional limits once warming-induced stratification changes, increased organic inputs, and new biological pressures are incorporated. Conversely, systems previously considered resilient may rapidly lose buffering capacity when exposed to multiple co-occurring disturbances. Consequently, accurate capacity designations require a framework that incorporates contemporary environmental complexity, moving beyond the static assumptions of equilibrium-era nutrient models.

Modernizing Assessment: Data, Indicators, and Analytics

Validating capacity classifications requires assessment frameworks that extend beyond single-parameter phosphorus measurements and instead capture the broader causal structure linking human activity to ecological response. Suresh et al. (2023) positioned the Driver–Pressure–State–Impact–Response (DPSIR) framework as an effective means of structuring these linkages by identifying the pathways through which socio-economic drivers—such as cottage development or land-use change—translate into ecological pressures and measurable shifts in lake condition. Employing such a framework demands data streams capable of resolving variation at temporal and spatial scales far exceeding the resolution of traditional monitoring programs.

Advances in open-source software and reproducible workflows have begun to meet these requirements. Horsburgh et al. (2015) emphasized the importance of standardized data architectures for managing continuous sensor networks, enabling integration of high-frequency measurements that capture short-lived events often missed by manual sampling. Yenni et al. (2019) demonstrated that automated data pipelines reduce uncertainty introduced by ad hoc processing and improve reproducibility across long-term monitoring efforts—an essential feature when evaluating ecological change over climatic timescales.

Analytical sophistication has evolved alongside these data infrastructures. Schreiber et al. (2022) showed that multilevel statistical models provide more reliable inference from noisy environmental datasets by explicitly accounting for temporal autocorrelation, a persistent confounder in lake monitoring programs. Spatial heterogeneity requires complementary approaches: structured designs such as the ANOVA-based frameworks employed by Hassan et al. (2024), and machine-learning tools like PyLEnM (Meray et al. 2022), allow pollution hotspots, contamination gradients, or emergent spatial patterns to be resolved even when datasets are sparse or unevenly sampled.

Together, these methodological developments enable assessment systems that reflect the heterogeneity and dynamic behaviour of contemporary lake environments. Such systems provide the foundation required to evaluate whether capacity classifications remain aligned with observed ecological trends in regions where climatic pressures and shoreline development interact to reshape nutrient regimes.

Problem Statement and Research Questions

Despite extensive research on individual stressors and modelling approaches, a persistent gap remains in evaluating whether policy designations reflect observed lake conditions at a regional scale. Haliburton provides an instructive setting for such an assessment: the region contains deep glacial lakes, shallow embayments, and a wide gradient of development intensity, creating substantial variation in morphometry and external loading. These features establish a natural testbed for determining whether "At Capacity" designations correspond to functional resilience or whether they fail when confronted with spatial heterogeneity, internal loading, or climate-mediated change. The disconnect between theoretical capacity limits and measured water chemistry motivates a systematic evaluation of how development pressure interacts with basin form to shape nutrient dynamics.

Objective.

The primary objective of this study is to determine whether Haliburton's "At Capacity" classifications align with observed water chemistry and to assess the extent to which morphometric resilience modifies the influence of development on nutrient enrichment.

Hypothesis.

It is hypothesized that development intensity—indexed through cottage density or shoreline disturbance—will correlate positively with phosphorus enrichment, but that this relationship will be strongly mediated by depth. Deep lakes are expected to exhibit greater resilience than shallow systems, potentially rendering the capacity designation conservative for some basins, whereas shallow lakes may experience degradation even when theoretical thresholds are not exceeded.

Research Questions.

1. **How do development intensity and basin morphometry (e.g., area, depth, residence time) relate to present water-quality status and long-term trends?**

   This question integrates morphometric principles from Håkanson (2005) and Qin et al. (2020) with development-driven impacts documented by Rosenberger et al. (2008), enabling a joint assessment of physical and anthropogenic controls.

2. **What physical and chemical differences emerge when comparing lakes of similar morphometry that differ in development pressure?**

   By pairing lakes with comparable basin structure but contrasting shoreline alteration, the analysis isolates the anthropogenic signal from background morphometric variation, drawing on comparative frameworks outlined by Schreiber et al. (2022) and Suresh et al. (2023).

By addressing these questions, the study seeks to refine capacity assessments so that they reflect the conditions of contemporary lake environments—where multiple stressors, complex bathymetry, and varied development intensities jointly determine nutrient behaviour and ecological resilience.

Method

This study implemented a reproducible Python-based workflow (Python 3.10) to integrate the multiple data sources required for evaluating lake capacity classifications in Haliburton. The pipeline consolidated heterogeneous inputs—including CSV sensor logs, Excel files, and manually digitized morphometric tables originally embedded in PDF reports—into a uniform analytical structure while maintaining full provenance of all data transformations. By minimizing manual intervention within the computational stages and logging each processing step, the workflow ensured auditability and scalability, consistent with best practices for reproducible environmental data science (Yenni et al. 2019). This computational framework supported all subsequent statistical analyses linking morphological characteristics, development intensity, and measured water chemistry.

Dataset

The primary dataset was compiled by the Woodland Waterways and Ecowatch (WWEW) program and the U-Links Centre for Community-Based Research. Limnological measurements were collected from 61 sampling sites across 31 lakes between 2022 and 2024 by academic partners and trained volunteers. Sampling occurred seasonally (spring overturn, mid-summer stratification, autumn overturn) to capture key phases of nutrient dynamics characteristic of temperate Shield lakes.

The dataset comprises four primary categories of attributes:

1. **Location Attributes**
   - Unique site identifier
   - Lake name
   - Georeferenced coordinates (latitude/longitude)
2. **Morphometric & Hydrologic Attributes**
   - Lake surface area (A_0, ha)
   - Watershed area (A_d, ha)
   - Maximum depth (z_{max}, m)
   - Mean depth ($\hat{z}$, m)
   - Shoreline length (L, km)
   - Drainage ratio (A_d / A_0)
   - Theoretical residence time (τ_w)

These variables were selected for their mechanistic influence on internal loading potential, sediment resuspension, and phosphorus retention.

3. Water-Quality Parameters

- Total Phosphorus (TP, μg L^{-1})
- Secchi depth (m)
- Specific conductivity (μS cm^{-1})
- Dissolved oxygen (mg L^{-1})
- Temperature (°C)
- Nitrogen species:
    - Total Kjeldahl Nitrogen (TKN)
    - Nitrate (NO_3^-)
    - Nitrite (NO_2^-)
    - Ammonia (NH_3/NH_4^+)

Sampling Protocol — Please confirm or edit the bracketed lines below:

- TP sampling
- DO/Temperature profiling
- Secchi depth

4. Development Metrics

- Shoreline property counts
- Binary "At Capacity" designation (Yes/No), obtained from municipal planning documentation

Another dataset, CHA technical reports, provided morphometric variables and development capacities not included in the primary monitoring logs. These reports served as the authoritative reference for validating input parameters required for assessing “At Capacity” status.

Preprocessing

A structured data-harmonization and QA/QC workflow was implemented in Python to reconcile substantial inconsistencies across the raw datasets. The pipeline addressed heterogeneity in file naming, directory structure, variable formatting, and data integrity, ensuring that all subsequent analyses were conducted on a unified and fully traceable dataset.

1. **Data Extraction and Standardization**

The raw inputs were stored within a decentralized directory system in which folder names and file structures lacked standardized conventions (e.g., *“Lake [Name]”* vs. *“[Name] Lake”*). A custom Python script—using **os**, **pathlib**, and **re**—recursively traversed all directories, normalized naming conventions, and extracted the relevant CSV and Excel files into a structured repository.

Morphometric data from “CHA Reports” required additional processing. Key variables were embedded as rasterized images within PDF documents, preventing direct machine-readable extraction. Initial OCR attempts using **pytesseract** produced low-fidelity outputs due to table boundaries, shading, and spatial artificing. To preserve data integrity, these values were manually digitized and independently cross-verified against the original reports before being ingested into the workflow.

All extracted files were reformatted to consistent encodings and standardized data types prior to merging.

2. Cleaning and Harmonization

Using **pandas** and **openpyxl**, the heterogeneous files were merged into a master dataset with standardized column names and measurement units (e.g., unifying "Total P," "TP," and "Phosphorus (µg/L)" into *total_phosphorus*). Lake naming inconsistencies—such as multiple entries for connected basins in the Kashagawigamog system ("Head Lake," "Grass Lake")—were resolved using a controlled vocabulary.

Outliers and transcription anomalies were identified using rule-based filters (e.g., TP values exceeding **limnologically plausible thresholds**). Missing values were retained as NA rather than imputed, preventing the inflation of statistical significance in downstream analyses. A comprehensive QA/QC log documenting all transformations was maintained to ensure reproducibility and auditability.

3. Feature Engineering

Derived variables were constructed to support morphometric and hydrologic analyses using standardized limnological notation:

Drainage Ratio ($A_d : A_0$): Drainage Ratio = A_d / A_0

A proxy for external loading potential and watershed-driven hydrologic forcing.

Hydrologic Class

Categorized as:

- **Headwater**: No upstream inflow

- **Throughflow**: Upstream inflow present
- **Mixed**: Multiple or ambiguous inflow–outflow pathways

Classifications were based on inlet–outlet configurations documented in CHA technical reports.

Lake Size Class

Lakes were grouped into Small / Medium / Large categories to enable size-stratified analyses, following the size-dependent nutrient dynamics described by Håkanson (2005).

Analytical Approach

The analytical workflow was structured to evaluate whether observed water chemistry aligns with Haliburton's "At Capacity" designations and to quantify the relative influence of morphometric and development variables on nutrient dynamics. All analyses were conducted in Python using **pandas**, **numpy**, **scipy**, **statsmodels**, and **scikit-learn**.

1.Descriptive and Comparative Statistics

Summary statistics (mean, median, standard deviation, interquartile range) were computed for all water-quality parameters and stratified by:

- Capacity status (At Capacity vs. Not At Capacity)
- Morphometric attributes (depth class, lake size category, hydrologic class)
- Development intensity (shoreline property counts)

These descriptive metrics established baseline contrasts among lake groups and contextualized water-quality variation within the region.

2. Short-Term Trajectory Analysis and Regression

Because continuous monitoring data were available only for 2022–2024, inter-annual change was evaluated as a **short-term trajectory** rather than a long-term trend. Ordinary least squares (OLS) regressions were fit to seasonal or annual TP and Secchi depth values to estimate directional change over the three-year period, acknowledging that these slopes (β) reflect short-term variability rather than statistically robust decadal trends.

Morphometric influences on trajectory direction were assessed by regressing β against lake depth, surface area, and residence time. Development effects were evaluated using:

- Pearson correlation coefficients between TP and property counts
- Univariate OLS models relating nutrient concentrations to development intensity
- Multivariate OLS models including morphometric covariates

This structure allowed evaluation of whether deeper lakes showed dampened short-term sensitivity to development pressure.

3. Group Difference Testing (ANOVA)

A one-way ANOVA was used to test whether mean nutrient concentrations differed between lakes designated At Capacity and those not designated as such. Because ANOVA cannot adjust for morphometric heterogeneity directly, analyses were additionally **stratified by depth class and hydrologic type**, allowing comparisons to be made within more morphometrically uniform groups.

This stratified ANOVA approach parallels hotspot identification frameworks used in watershed assessments such as Hassan et al. (2024), where grouping by physical characteristics compensates for the inability of ANOVA to accommodate covariates.

Tools and Technologies

All data processing, statistical analysis, and visualization were conducted in Python (v3.10), using an environment configured to support reproducibility and modular workflow design. The following libraries formed the core analytical stack:

pandas & NumPy

Used for high-performance data handling, including table restructuring, type casting, merging heterogeneous datasets, and performing vectorized numerical operations required for morphometric and water-quality calculations.

scipy & scikit-learn

Employed for statistical computations such as Pearson correlations, OLS regression (where implemented in scikit-learn), and non-parametric tests. These libraries also supported diagnostic assessments of model assumptions.

statsmodels

Used for inferential statistical modelling—particularly the extraction of regression coefficients, p-values, confidence intervals, and goodness-of-fit metrics. This package provided the formal statistical outputs required for hypothesis evaluation.

matplotlib & seaborn

Used to generate publication-ready visualizations, including time-series plots, capacity-group boxplots, and correlation heatmaps. Figures were exported in high-resolution formats for integration into thesis chapters and supplementary materials.

Jupyter Notebooks

Served as the development platform, enabling interleaving of code, outputs, narrative explanation, and versioned analysis steps. This facilitated peer review and reproducibility consistent with modern open-science workflows.

Microsoft Excel

Used for preliminary inspection of raw datasets, manual verification of digitized values, and the preparation of structured input templates. Excel was limited to non-analytical tasks to avoid introducing undocumented transformations.

All tools were selected for their transparency, interoperability, and ability to support an auditable environmental data analysis pipeline.

Evaluation Metrics

The performance of the statistical models and the validity of the “At Capacity” designations were evaluated using a set of standard limnological and statistical metrics. These metrics quantify explanatory power, statistical significance, and directional change in water-quality parameters.

1. Coefficient of Determination (R^2)

R^2 values from OLS and multivariate regression models were used to assess the proportion of variance in nutrient concentrations explained by morphometric variables (e.g., depth, residence time) and development intensity. Interpretation emphasized effect size rather than absolute thresholds, given the ecological noise typical of short-term datasets.

2. P-values and Significance Testing

P-values were extracted from **statsmodels** outputs to evaluate whether observed relationships or group differences were statistically significant at $\alpha = 0.05$. Significance was interpreted cautiously, recognizing the limited temporal extent of the dataset and the heterogeneity among lake types.

3. Trajectory (Slope) Estimates

For each lake, the slope parameter (β) derived from short-term OLS fits to TP and Secchi depth measurements served as an indicator of directional change over the 2022–2024 interval. Positive β values were interpreted as short-term enrichment or reduced clarity, while negative values indicated improving or stabilizing conditions. These slopes were treated as descriptors of **inter-annual trajectories**, not long-term trends.

Together, these metrics provided a quantitative basis for determining whether "At Capacity" classifications aligned with observed trophic conditions and whether morphometric attributes moderated lake sensitivity to development pressure.

Results

The analysis of water-quality data from 31 Haliburton lakes revealed clear patterns associated with morphometric structure, development status, and short-term phosphorus trajectories. Measurements collected between 2022 and 2024—including total phosphorus, Secchi depth, and conductivity—were evaluated alongside shoreline development metrics and administrative capacity classifications.

Morphometric Controls on Water Quality

Correlation analysis demonstrated that vertical morphometry exerts the strongest influence on nutrient concentrations. Maximum depth showed a pronounced negative relationship with total phosphorus, indicating that deeper lakes consistently maintained lower TP levels than shallow basins.

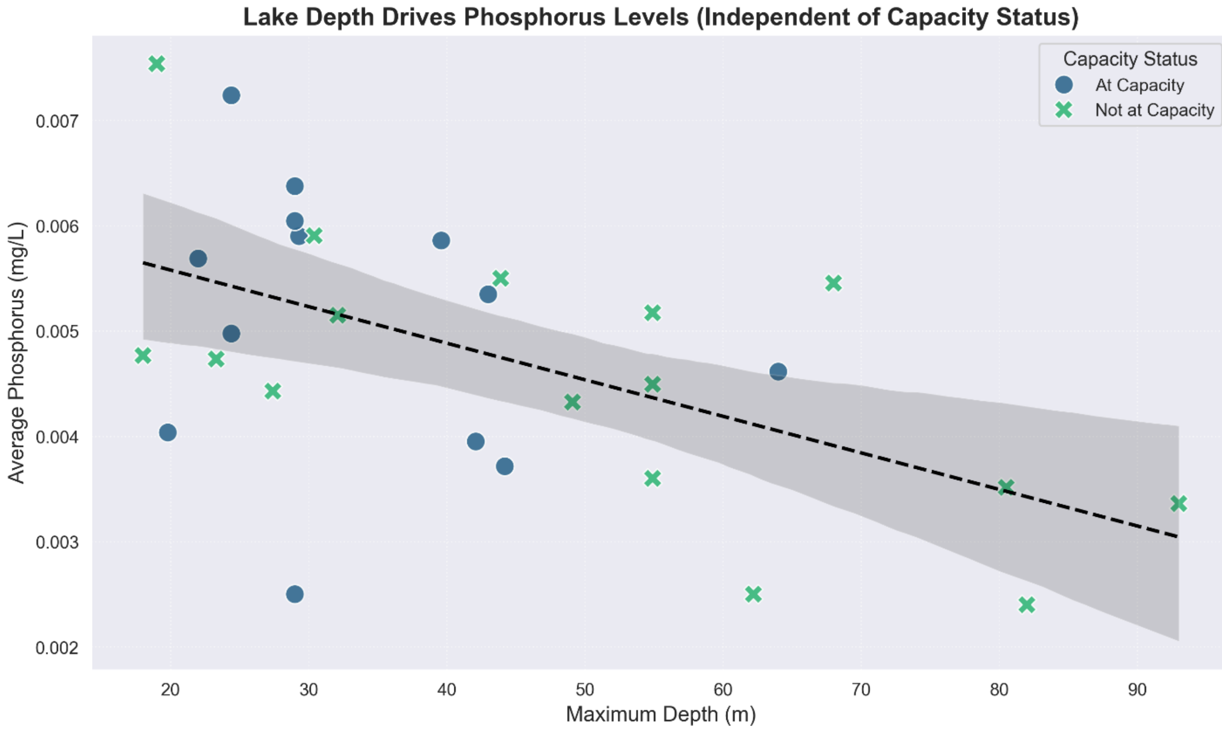

Figure 1: Relationship Between Lake Depth and Average Total Phosphorus

This pattern supports the hypothesis that depth confers resilience by suppressing internal loading mechanisms such as sediment resuspension, which are more prevalent in shallow systems.

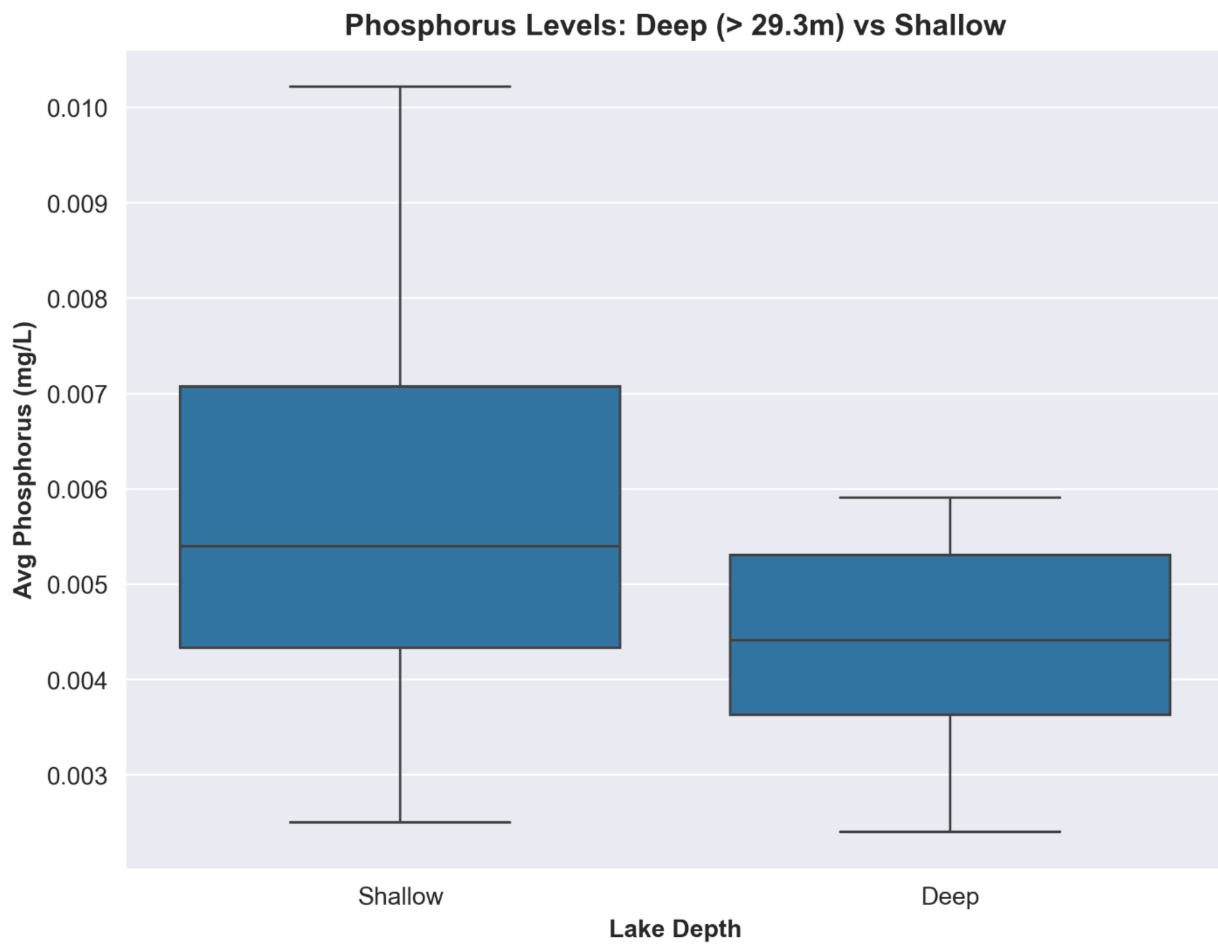

Figure 2: Comparison of Phosphorus Levels in Deep vs. Shallow Lakes

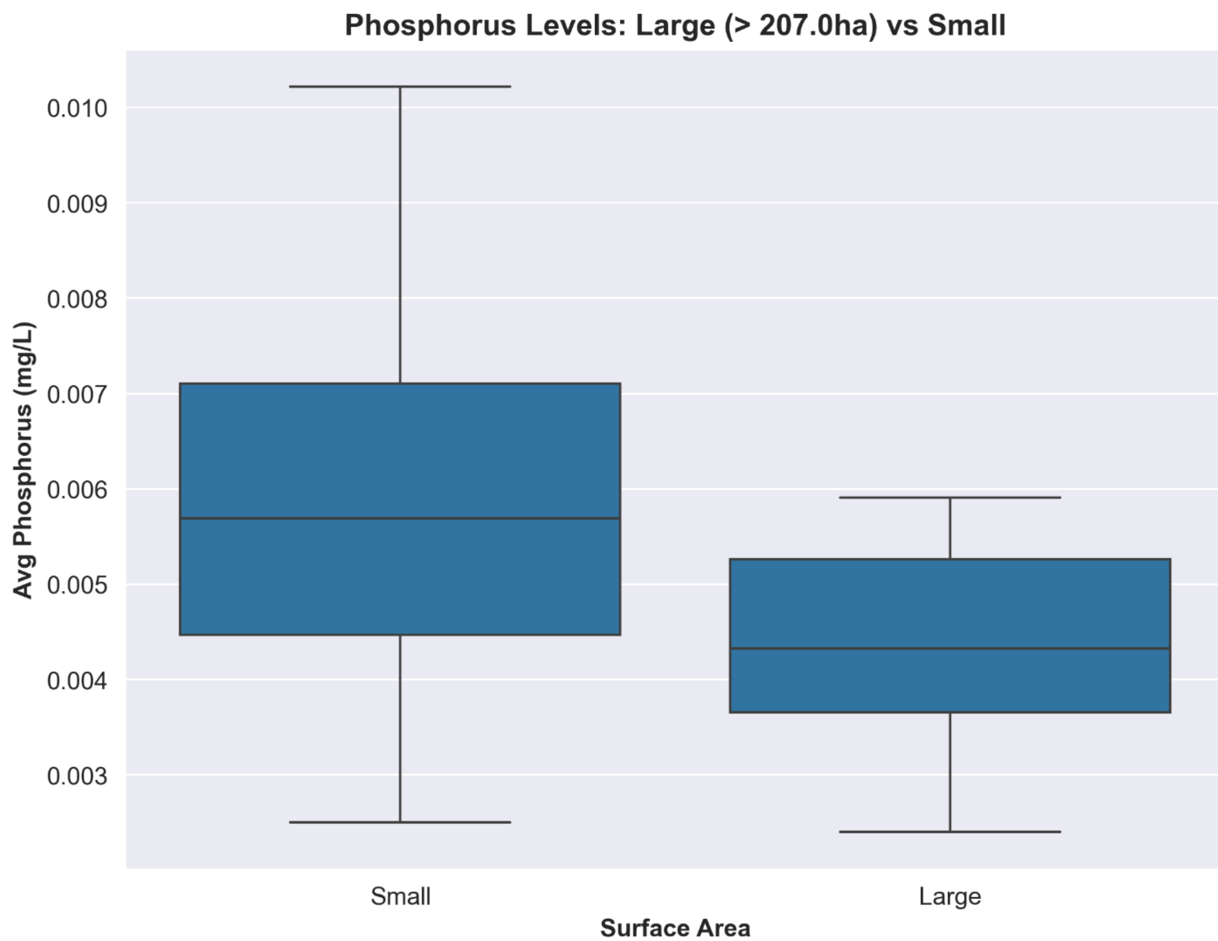

Figure 2: Comparison of Phosphorus Levels in Large vs. Small Lakes

In contrast, surface area and watershed size exhibited weaker associations with phosphorus, suggesting that depth-driven internal processes dominate nutrient dynamics in this region more than horizontal spatial extent.

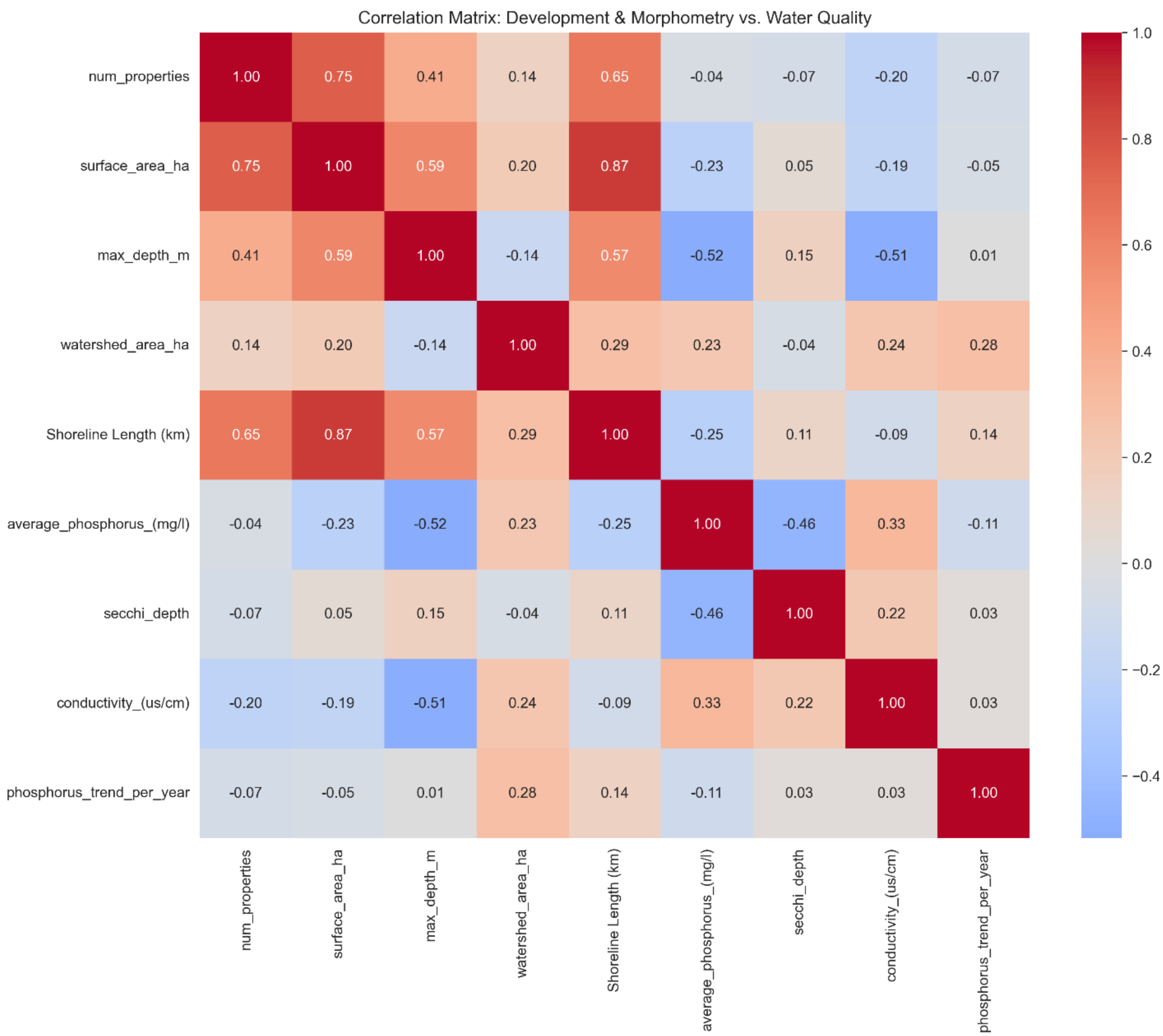

Figure 4. Correlation Matrix Linking Development, Morphometry, and Water-Quality Indicators

Capacity Designations and Phosphorus Concentrations

A one-way ANOVA comparing mean TP between lakes designated **At Capacity** and those classified as **Not At Capacity** yielded a significant difference ($F = 5.566$, $p = 0.0097$). However, the adjusted R^2 for the model (0.246) indicated that capacity status explained only a modest proportion of variance in phosphorus concentrations.

Additional nuance emerged when depth was incorporated through ANCOVA. After controlling for maximum depth, capacity status was no longer a significant predictor of TP. The coefficient for **Not At Capacity** lakes (5.57×10^{-6}, $p = 0.99$) was effectively zero, while maximum depth remained a significant negative predictor ($\beta = -3.48\times10^{-5}$, $p = 0.0048$). These results corroborate earlier findings: administrative designations do not consistently distinguish lakes by nutrient condition once morphometric variability is accounted for.

Table 1. ANCOVA Results for Total Phosphorus

Predictor	Coefficient	Std. Error	t-Value	p-Value
Intercept	0.0063	0.0005	12.68	< 0.001
Capacity Status (Not At Capacity)	5.57e−06	0.0005	0.012	0.990
Maximum Depth (m)	−3.48e−05	0.00001	−3.08	0.005

Short-Term Trajectories in Total Phosphorus (2022–2024)

Short-term trajectory analysis indicated that most lakes displayed relatively stable TP levels over the three-year period. However, three systems—**Gull Lake, Stocking Lake, and Kashagawigamog Lake**—exhibited statistically significant increasing trajectories.

- **Gull Lake**: $\beta = 0.0028$ mg/L/yr, $p = 0.038$, $R^2 = 0.63$
- **Stocking Lake**: $\beta = 0.0011$ mg/L/yr, $p = 0.027$, $R^2 = 0.75$
- **Kashagawigamog Lake**: $\beta = 0.0008$ mg/L/yr, $p = 0.010$, $R^2 = 0.40$

These slopes signal localized phosphorus enrichment, even as regional patterns remain comparatively stable.

Lakes such as **Mountain Lake** and **Little Hawk Lake** showed no significant directional change ($p = 0.81$ and 0.62, respectively), underscoring the heterogeneity of lake responses to watershed pressures.

Table 2. Significant Phosphorus Trajectories (2022–2024)

Lake	**Slope (mg/L/yr)**	**p-Value**	**R^2**
Gull Lake	0.0028	0.038	0.63
Stocking Lake	0.0011	0.027	0.75
Kashagawigamog Lake	0.0008	0.010	0.40

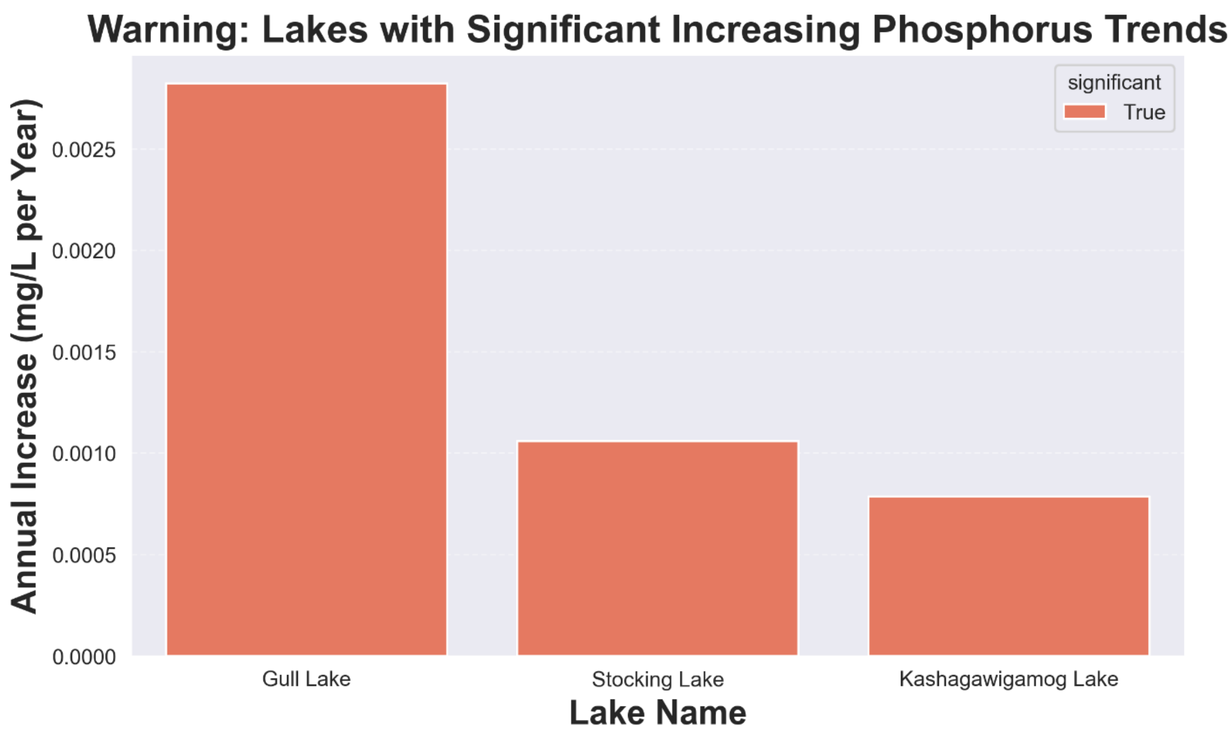

Figure 5. Lakes Exhibiting Significant Increases in Phosphorus Concentrations (2022–2024)

Multivariate Analysis of Water Quality

A MANOVA including conductivity, dissolved oxygen, and Secchi depth found no multivariate difference between **At Capacity** and **Not At Capacity** lakes (Wilks' $\lambda = 0.80$, $F = 2.04$, $p = 0.13$). This aligns with the ANCOVA results and indicates that capacity designations do not consistently separate lakes by their broader water-chemistry profiles.

Summary of Findings

The results demonstrate that:

- **Maximum depth** is the most reliable predictor of nutrient condition across the region.

Capacity designations alone do not strongly predict phosphorus concentrations, especially after accounting for morphometric differences.

- **Localized enrichment** is occurring in several lakes—most notably Gull, Stocking, and Kashagawigamog—indicating emerging risks not captured by administrative classifications.

These findings support the broader conclusion that morphometric context, rather than development status alone, governs nutrient sensitivity in Haliburton lakes.

Discussion

Interpreting the Morphometric Imperative

The most prominent result emerging from this study is the dominant influence of maximum depth on nutrient dynamics across Haliburton lakes. Depth showed a strong negative association with total phosphorus (TP), outperforming both shoreline development intensity and the regulatory *At Capacity* classification as a predictor of trophic status. These finding challenges management frameworks that rely primarily on development caps and is consistent with the morphometric theory articulated by Håkanson (2005), who emphasized the regulating role of basin geometry—particularly the ratio of area to depth—in controlling sedimentation, resuspension, and internal nutrient transport.

The resilience of deeper lakes documented here aligns with the global synthesis by Qin et al. (2020), which identified depth thresholds that govern phosphorus retention. In strongly stratified basins, separation between the epilimnion and the sediment–water interface inhibits continuous mixing, reducing the recycling of sediment-bound phosphorus. Instead, phosphorus is transferred into the hypolimnion, where it becomes effectively sequestered through sediment burial rather than fueling primary production in the photic zone. This mechanism likely explains why Mountain Lake and Little Hawk Lake maintain low nutrient concentrations despite notable shoreline development; the depth of these systems provides a functional buffer against both external loading and internal nutrient release.

Shallower systems, by contrast, displayed elevated baseline phosphorus levels. This pattern mirrors observations from Kebedew et al. (2020) in Lake Tana, where persistent wind-induced mixing prevents the stabilization of sediment–phosphorus interactions, generating a self-reinforcing internal loading loop. Fee's (1979) finding that primary production scales with the ratio of sediment area to epilimnetic volume further reinforces the centrality of vertical morphometry: shallow basins with expansive sediment contact relative to water-column volume are predisposed to higher productivity and greater sensitivity to disturbance. Collectively, these insights establish depth not merely as a correlational variable, but as a functional driver of trophic state in the Haliburton region.

The 'At Capacity' Paradox

The absence of a significant difference in phosphorus concentrations between *At Capacity* and unconstrained lakes, once depth is accounted for, exposes a fundamental mismatch between policy designations and limnological processes. The *At Capacity* framework, derived from the mass-balance reasoning of Dillon and Rigler (1975), assumes a predictable and proportional relationship between external phosphorus loading and in-lake concentrations. Yet the results of this study indicate that this assumption does not consistently hold in the Haliburton context.

Two mechanisms likely contribute to this decoupling. First, as outlined by Paterson et al. (2006), the Lakeshore Capacity Model (LCM) relies on generalized export and retention coefficients that do not adequately reflect the hydrologic and morphometric diversity of individual basins. Lakes with rapid flushing or substantial depth may receive high theoretical loads but exhibit limited in-lake responses—a pattern exemplified historically by the "Cameron Lake paradox" (Dillon, 1975), in which predicted concentrations diverged from empirical observations due to substantial hydrologic dilution.

Second, the *At Capacity* designation is a binary administrative construct imposed upon systems that respond along a continuum of ecological pressure. Shoreline development generates heterogeneous effects depending on basin shape, mixing regime, and littoral complexity. Campbell and Chow-Fraser (2018) demonstrated this in Georgian Bay, where predictive models failed in nearshore embayments until recalibrated with metrics explicitly incorporating building density, shoreline configuration, and morphometric resistance. Their work underscores the need for "anthro-geomorphic" approaches—models that integrate both human activity and basin-specific physical constraints. The patterns observed in Haliburton are consistent with this framing: capacity categories alone fail to differentiate trophic conditions because they omit the structural features that govern how a lake processes anthropogenic inputs.

Localized Enrichment and Ecological Surprises

Although regional phosphorus patterns appeared broadly stable, the significant upward trajectories observed in Gull, Stocking, and Kashagawigamog lakes indicate the presence of localized enrichment "hotspots." These cases illustrate what Christensen et al. (2006) termed *ecological surprises*: non-linear system responses arising from the convergence of multiple stressors. The steep increase in TP in Gull Lake, for example—a large system with extensive shoreline development—suggests that its assimilative capacity may be approaching a threshold at which external loading and internal processes interact synergistically.

Legacy phosphorus provides one plausible explanation. As described by Van Heyst et al. (2022), long-term septic inputs and historical land use can saturate terrestrial retention zones, shifting lakes into a delayed enrichment phase as accumulated phosphorus gradually mobilizes into surface waters. Such a lagged response would be consistent with the trajectories observed here, particularly in lakes with decades of shoreline occupancy.

Climate-mediated internal loading may be compounding this effect. Orr et al. (2024) demonstrated that stressor interactions tend to be additive under moderate pressure but can become synergistic when systems are pushed beyond morphometric thresholds. In Boreal Shield lakes, Nelligan et al. (2019) found that warming prolongs stratification and increases hypolimnetic oxygen depletion, conditions that accelerate the release of iron-bound phosphorus from sediments. If lakes such as Gull or Kashagawigamog are experiencing longer anoxic intervals due to warming, internal loading may be amplifying the contribution of legacy external loads, generating the sustained positive trajectories detected in this study.

These cases illustrate a critical limitation of the *At Capacity* framework: enrichment risk is not solely a function of shoreline density but emerges from the interaction between development history, morphometry, and climate-driven shifts in physical structure. Localized, non-linear responses therefore warrant focused monitoring and management attention, independent of administrative designation.

The Role of Emerging Stressors

The general stability observed across most lakes in the dataset should not be interpreted as evidence of long-term resilience. The suite of stressors affecting freshwater systems is expanding rapidly, and Haliburton lakes are increasingly subject to pressures that extend beyond traditional nutrient inputs. Bănăduc et al. (2024) emphasize that contemporary stressors now include thermal pollution, invasive species, and emerging contaminants such as nanoparticles, each of which can alter biogeochemical pathways in ways not captured by current monitoring programs.

Invasive species represent a particularly salient risk. The introduction or upstream presence of taxa such as *Bythotrephes longimanus* or zebra mussels has the potential to restructure food webs, modify nutrient cycling, and obscure the relationship between external loading and pelagic nutrient concentrations. Such biological alterations may either mask enrichment (e.g., via benthic filtering) or amplify it by modifying grazing pressure or sediment interactions, complicating the interpretation of phosphorus trends in both *At Capacity* and unconstrained lakes.

Concurrently, increasing dissolved organic carbon (DOC) inputs—part of the broader browning trend documented across the Canadian Shield by Jeffries et al. (1988) and Nelligan et al. (2019)—pose an additional confounding factor. Elevated DOC reduces light penetration and compresses the photic zone, potentially shifting systems from nutrient limitation to light limitation. Under such conditions, lakes predicted to express eutrophic symptoms may instead exhibit muted algal responses, not because external loads are low, but because light availability constrains phytoplankton growth. This mechanism likely explains cases where predicted high-load lakes fail to develop pronounced blooms, underscoring the limits of phosphorus-centric assessment models.

These emerging pressures reinforce the need for a broader indicator suite within monitoring programs. As Suresh et al. (2023) argue through the DPSIR framework, effective management requires distinguishing between ecological symptoms and underlying causal drivers. Integrating biological indicators—such as periphyton assemblages or plankton community composition—alongside chemical metrics would provide a more comprehensive picture of ecological condition and improve the diagnostic capacity of lake assessments in Haliburton.

Implications for Monitoring and Analysis

The methodological challenges encountered in this study—particularly the heterogeneity of data formats and the reliance on manual extraction from static reports—underscore a broader limitation in the region's monitoring infrastructure. As Horsburgh et al. (2015) and Yenni et al. (2019) argue, reproducible and automated workflows are now essential for managing the volume and frequency of environmental data required to detect subtle or emergent changes. While the QA/QC pipeline developed here ensured data integrity, it is not scalable for real-time or near-real-time decision-making, nor is it efficient enough to support rapid reassessment of lake capacity classifications.

Advances in computational limnology illustrate the value of modernization. Machine-learning frameworks such as PyLEnM (Meray et al. 2022) demonstrate that automated ingestion, interpolation, and validation pipelines can substantially reduce latency between monitoring and management intervention. For Haliburton, transitioning from static annual reporting to a centralized, continuously updated database—capable of integrating sensor data, volunteer monitoring, and administrative records—would allow for dynamic recalibration of capacity models and earlier detection of deviations such as those observed in Gull and Stocking lakes.

The statistical behaviour of the dataset also highlights opportunities for methodological refinement. As Schreiber et al. (2022) note, OLS regression often struggles with environmental datasets due to temporal autocorrelation and nested sampling structures. While ANOVA provided robust group comparisons despite unequal sample sizes, future analyses would benefit from hierarchical or multilevel modelling approaches that explicitly account for sampling nested within lakes, seasons, and years. Such models may reveal trends currently obscured by interannual variability, particularly in lakes classified as "stable" in this short-term dataset.

Collectively, these findings argue for an integrated monitoring strategy—combining automated data systems, advanced statistical tools, and multiscale indicators—to improve both the accuracy and timeliness of lake management decisions in the Haliburton region.

Limitations

Several limitations constrain the interpretation and generalizability of these findings. Foremost, the study period (2022–2024) represents a narrow temporal window in limnological terms. As Brett and Benjamin (2008) note, retention dynamics, sediment–water interactions, and watershed loading processes often unfold over decadal scales. Consequently, many lakes classified as "stable" may simply be exhibiting delayed responses, particularly deeper systems in which phosphorus accumulation or release occurs slowly relative to external inputs.

Second, variability inherent in multi-partner and volunteer-supported data collection introduces differences in sampling consistency. Although the Water Quality and Environmental Watch program achieves exceptional spatial coverage, field methods—such as Secchi depth deployment, sampling depth precision, or handling of TP bottles—can vary across observers. This variability may elevate within-lake variance and reduce the sensitivity needed to detect subtle, early-stage changes.

Third, the study used total phosphorus as the principal indicator of trophic status. While TP is a widely accepted regulatory metric, it may not capture early shifts occurring in the littoral zone. Rosenberger et al. (2008) demonstrated that periphyton communities respond to shoreline disturbance long before pelagic nutrient concentrations change, suggesting that our open-water sampling protocol may have missed the first signs of ecological stress in vulnerable lakes.

Finally, internal loading was not explicitly modelled for all lakes due to incomplete dissolved oxygen profiles. In stratified lakes, late-summer hypolimnetic anoxia can dominate phosphorus dynamics (Nürnberg 2004, cited in Van Heyst et al. 2022). Without full seasonal DO datasets, the relative contribution of internal versus external loading remains uncertain, potentially leading to underestimation of risk in deeper basins with emerging anoxic conditions.

These limitations do not invalidate the study's conclusions but highlight the need for longer-term datasets, standardized sampling protocols, expanded indicator suites, and improved characterization of internal loading processes.

Future Directions and Recommendations

Aligning planning policy with the ecological realities revealed in this study requires a shift toward models and monitoring frameworks that explicitly account for basin geometry, internal loading potential, and emerging stressors. Three avenues appear particularly important for advancing both research and management in the Haliburton region.

1. Refinement of Capacity Models

The current "At Capacity" designation should be recalibrated to incorporate morphometric controls rather than relying almost exclusively on external loading estimates. Testing the Anthro-Geomorphic Model (AGM) developed by Campbell and Chow-Fraser (2018) on the Haliburton dataset is a logical next step. Their work in Georgian Bay demonstrated that integrating basin shape, building density, and circulation constraints substantially improved predictive accuracy. If similar performance (<20% prediction error) can be achieved here, the AGM could offer a defensible replacement—or at minimum, a complementary tool—to the legacy mass-balance framework used in regional planning.

2. Targeted Monitoring of Identified Hotspots

The lakes exhibiting significant upward trends in total phosphorus—Gull, Stocking, and Kashagawigamog—require intensified, high-frequency monitoring to identify the mechanisms driving these increases. Sediment core analyses and detailed inlet–outlet load assessments would help differentiate between recent watershed-derived loading and the delayed release of legacy phosphorus, as described by Van Heyst et al. (2022) and Christensen et al. (2006). Such differentiation is essential for designing effective interventions, since management responses diverge sharply depending on whether the dominant driver is contemporary land use or historical accumulation.

3. Expansion of Monitoring Indicators

Chemical indicators alone are insufficient to capture early ecological change. Incorporating biological metrics—such as nearshore periphyton biomass (Rosenberger et al. 2008) and shifts in plankton assemblages—would provide a more sensitive assessment of littoral stress. Likewise, monitoring programs should begin integrating socio-economic data (e.g., the pace of cottage conversion to permanent residency), enabling a more comprehensive Driver–Pressure–State–Impact–Response (DPSIR) analysis. Expanding the indicator suite would also help disentangle cases in which high predicted phosphorus loading does not correspond to observed algal growth, a discrepancy that may arise from increased DOC inputs and associated light limitation.

Together, these directions underscore the need for a more dynamic, morphometrically informed management framework—one capable of adapting to both legacy pressures and emerging stressors in Haliburton's lakes.

Conclusion

This study illustrates that although the "At Capacity" designation was developed as a practical planning instrument, it lacks the resolution needed to anticipate water quality outcomes across Haliburton's morphologically diverse lakes. The consistent influence of depth observed throughout the analysis indicates that basin geometry confers substantial resilience in some systems while leaving shallow lakes disproportionately exposed to legacy loading, internal nutrient release, and emerging stressors. These dynamics reveal a fundamental mismatch between the static assumptions embedded in traditional capacity models and the ecological processes governing phosphorus behaviour in Shield lakes.

Recognizing these limitations is essential for moving toward management approaches that reflect contemporary environmental conditions rather than historical modelling conventions. Incorporating morphometric controls, internal loading potential, and site-specific stressor interactions into capacity assessments would provide a more defensible basis for decision-making. By adopting a framework that is both dynamic and grounded in lake-specific characteristics, regional planners and stewardship groups will be better positioned to safeguard Haliburton's freshwater systems against the cumulative pressures of development and climatic change.

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