A Satellite-based Approach to Investigating Eutrophication in Lakes Receiving Wastewater Treatment Effluent: A Case Study of Lake Windermere

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ABSTRACT

Excessive phosphorus from the sewer systems in the UK is a major contributor to eutrophication in freshwater bodies. Chlorophyll-a levels are widely used as a reliable indicator of phosphorus driven eutrophication, and satellite remote sensing provides an effective means of monitoring these dynamics at high spatial and temporal resolution. This study evaluated the utility of Sentinel-2 imagery in capturing the dynamics of eutrophication in Lake Windermere from 2017 to 2022. The Normalized Difference Chlorophyll Index (NDCI), calculated from the Sentinel-2 satellite imagery of the lake, was employed as a predictor for chlorophyll-a concentration. Statistical analysis revealed no significant temporal trend in NDCI values during the time period, indicating persistent eutrophication. Spatially, the southern parts of the lake showed elevated NDCI values, driven by the higher retention time and the presence of several treated sewage effluents along the lake's length. Notably, the NDCI values were positively correlated with the phosphorus content in the treated effluent from Ambleside WwTW, while the storm overflow showed a negative correlation, attributed to dilution effects from rainwater entering the combined sewer system.

1. INTRODUCTION

Lake eutrophication is a natural process of lake ageing; however, it can be accelerated by human activities such as pollution, which can ultimately shorten the life expectancy of the body of water. Eutrophication of aquatic ecosystems, defined as an increase in nutrient loading leading to the proliferation of primary producers such as phytoplankton, aquatic plants, and cyanobacteria, is a major cause of ecological degradation in inland and coastal waters worldwide (le Moal, Gascuel-Odoux, Ménesguen, Souchon, Étrillard, Levain, Moatar, Pannard, Souchu, & Lefebvre, 2019; Moss, 2012; Takolander et al., 2017; Yao et al., 2018). There is a also growing appreciation of the importance of Harmful Algal Blooms (HABs) and HAB-related illnesses to public health (Glibert et al., 2005). One of the major factors that contribute to water eutrophication is nutrient enrichment (Yang et al., 2008). Excessive nutrient input, particularly phosphorus, can lead to eutrophication and blooms of toxic cyanobacteria in freshwater systems and proliferation of green macroalgae in coastal areas (le Moal, Gascuel-Odoux, Ménesguen, Souchon, Étrillard, Levain, Moatar, Pannard, Souchu, & Lefebvre, 2019). Water residence time also plays a crucial role in the eutrophication process (Schindler, 2006). Controlling algal blooms and other eutrophication symptoms depends on reducing phosphorus inputs and control of point sources of phosphorus, such as discharge from wastewater treatment facilities (Schindler, 2006; Schindler et al., 2016b). Studies have demonstrated that the discharge of phosphorus from the UK sewer system into freshwater bodies may pose a greater risk to eutrophication compared to agricultural sources of phosphorus (Jarvie et al., 2006).

The measurement of chlorophyll-a levels has been widely recognised as an indicator of the presence and concentration of phosphorus (Dillon & Rigler, 1974; Filstrup & Downing, 2017; Jones & Bachmann, 1976). Therefore, measuring chlorophyll -a levels in a freshwater body can provide an indication of the presence and concentration of phosphorus in the water. Remote sensing technology, specifically the use of satellite imagery, is a valuable tool that can be utilized for monitoring chlorophyll levels in freshwater bodies (Ansper & Alikas, 2018; Chen et al., 2017; Kislik et al., 2022; Molkov et al., 2019; Pahlevan et al., 2020; Wang et al., 2020). Chlorophyll-a is commonly used as an indicator of phytoplankton biomass in remote sensing as it absorbs light in the blue and red regions of the electromagnetic spectrum (Porcar-Castell et al., 2014).

Sentinel-2 constellation is serving as a polar-orbiting optical mission for land and coastal region monitoring and emergency services. It offers a significant improvement in resolution compared to other freely available imagery such as SPOT and Landsat (Drusch et al., 2012). This comparatively high spatial and spectral resolution imagery can be used to detect changes in chlorophyll-a levels and identify areas of high chlorophyll-a concentration, which can help the management and conservation efforts of freshwater bodies (Ansper & Alikas, 2018; Bramich et al., 2021; Chen et al., 2017; Kislik et al., 2022; Molkov et al., 2019; Pahlevan et al., 2020; Quang et al., 2022; Wang et al., 2020) .

The Normalized Difference Chlorophyll Index (NDCI) has been used as an approach for estimating Chlorophyll-a concentration from remote sensing data (D. R. Mishra et al., 2014; S. Mishra & Mishra, 2012). The NDCI has been successfully used to predict chlorophyll-a concentration with a low overall bias of approximately 12% (S. Mishra & Mishra, 2012). In addition, the NDCI can be used to detect algal blooms in remote coastal waters where ground truth data is not available. It is a promising tool for monitoring chlorophyll-a concentration, and its potential applications in remote sensing studies of water quality and algal blooms are significant.

Lake Windermere, the biggest freshwater lake in England, was chosen as the study area for this study because of its ecological importance and the increasing concern over eutrophication due to the nutrient input in the lake coming from wastewater treatment effluents. This study aims to investigate the potential link between eutrophication and WwTW effluent in Lake Windermere. The objectives of this research include analysing changes in chlorophyll-a content over a period of six years in different parts of the lake using satellite data and determining the correlation between chlorophyll-a in the lake and both phosphorus content in the final treated effluent and storm overflow from the Ambleside WwTW. The results of this research can be used to inform management decisions and develop strategies for mitigating eutrophication in Lake Windermere and potentially other freshwater bodies.

2. DATA AND METHODOLOGY

2.1. Data

The present study utilized Sentinel-2 Multi-Spectral Instrument (MSI) Level-2A data from the period of 2017 to 2022, covering the months of July and August (Table 1). These two months were selected for this study because these months are typically considered the warmest with higher levels of eutrophication in freshwater bodies in the UK. The S2 cloud probability dataset, a widely utilized dataset in a multitude of academic studies, was also used for cloud detection (de Luca et al., 2022; Rahman et al., 2022; Roca et al., 2022).

Table 1: Number of images used.

Year	No. of images
2017	22
2018	48

2019	48
2020	52
2021	50
2022	50

The phosphorus data used in this study was obtained from the Environment Agency's water quality data archive, which contains information on the phosphorus content in the final effluent of the Ambleside Wastewater Treatment Work (WwTW). The data contains 95 samples collected between September 2016 and August 2022. The sample point is identified by the sampling point ID of NW-88004161.

The data for the overflow from the Ambleside WwtW were collected from multiple sources. Following a Freedom of Information Act request, Environment Agency provided yearly data for the years 2018-2021 (hours). The data (hours) for the year 2017 was obtained from the water quality archive of the Environment Agency. The sampling point referred to as "Ambleside STW Storm Tank Effluent" with the ID "NW-88009612".

Image Processing and Calculation of NDCI:

The Google Earth Engine platform (Gorelick et al., 2017) was employed to process all the images in this study.

2.1.1. Cloud Masking and Compositing

Firstly, the entire image collection was retrieved and filtered for the area of interest and the months of July and August. A scene-level cloud cover threshold of ≤65% was used to ensure adequate image availability, with residual clouds removed using the S2 cloud probability mask and median compositing to minimise contamination. The composite image was created by taking each pixel's median value, resulting in a single, representative image that could be used for further analysis.

2.1.2. Water Masking and NDCI Calculation

After the images had been pre-processed, the Normalized Difference Water Index (NDWI) was utilized to extract and crop the water's surface. It is widely utilized as a method for detecting water bodies in the field of remote sensing (Ali et al., 2019; Eid et al., 2020; Özelkan, 2020). The NDWI value for each pixel was calculated using Equation 1 (McFeeters, 1996), which allowed for the identification of water surfaces in the images. Upon completion of the water surface extraction process, the NDCI was computed utilizing Equation 2 (Buma & Lee, 2020; S. Mishra & Mishra, 2012; Shi et al., 2022).

Equation 1: Normalized Difference Water Index

$$NDWI = \frac{(B3 - B8)}{(B3 + B8)}$$

Equation 2: Normalized Difference Chlorophyll Index

$$NDCI = \frac{(B5 - B4)}{(B5 + B4)}$$

Here,

B3 or Band 3, central wavelength is 0.560 μm,

B4 or Band 4, central wavelength is 0.665 μm,

B5 or Band 5, central wavelength is 0.705 μm,

B8 or Band 8, central wavelength is 0.842 μm.

2.1.3. Spatial Segmentation

Finally, six yearly median composite images were exported and processed using QGIS version 3.22.3-Białowieża (QGIS Development Team, 2022) to cut each image into five sections from north to south (Figure 1).

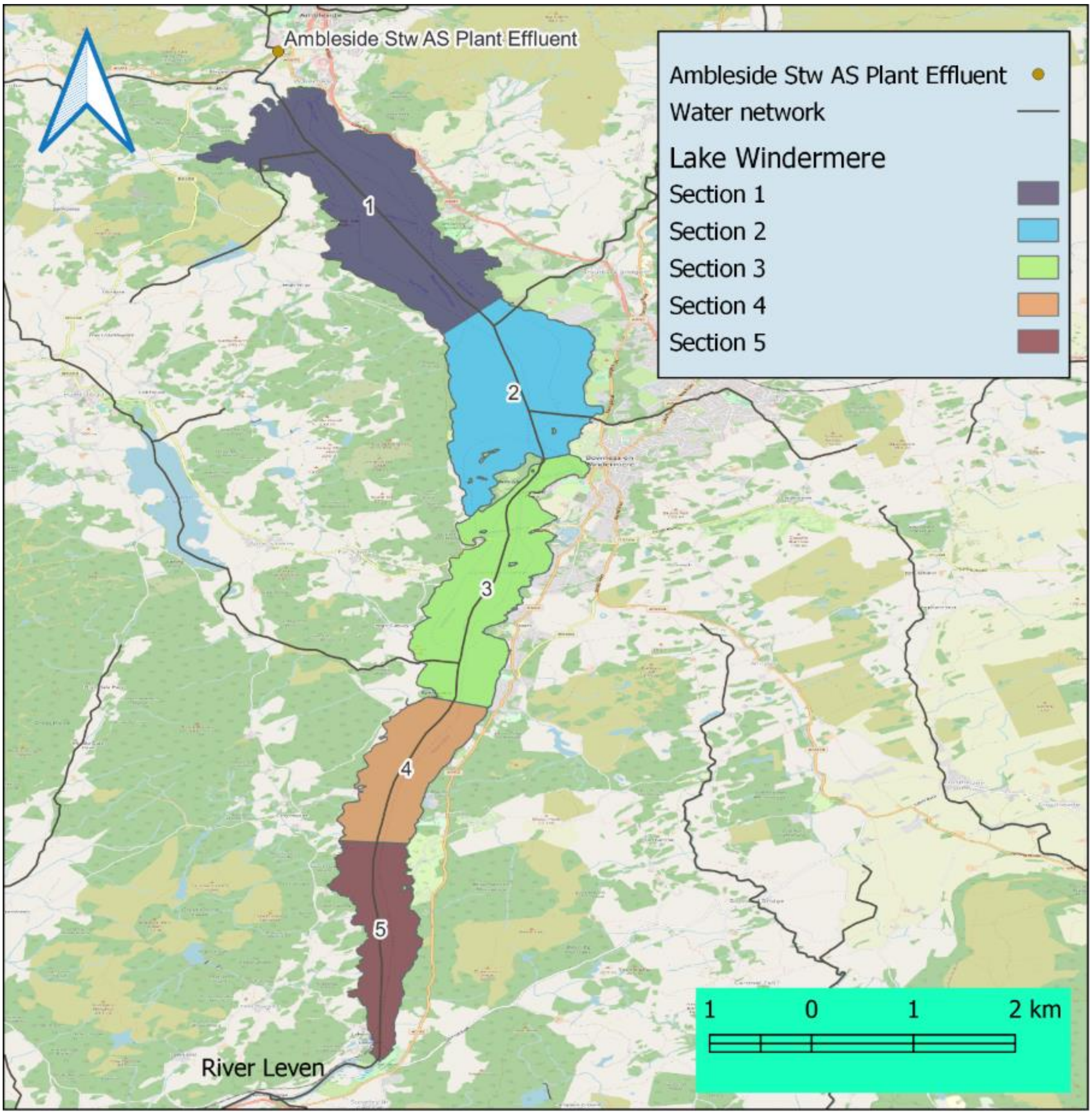

Figure 1: Studied sections of Lake Windermere

2.2. Statistical analysis

2.2.1. Temporal and Spatial Trend Analysis

The methodology for statistical data analysis involved the use of RStudio version 2022.7.1.554 (RStudio Team, 2022). For temporal trend analysis, the mean NDCI value for each year (Y_{17}- Y_{22}) in each section (S_1-S_5) was calculated (Table 2). Later, Pearson's, Spearman's Rank, and Mann-Kendall (MK) tests were conducted to determine if there was any parametric, monotonic, non-parametric trend over the years for any of the sections. The same tests were performed on the combined mean of all five sections

(S0), representing the entire lake, to determine the overall trend of the lake over the years. Additionally, hypothesis testing was done to find any variations in mean NDCI across the years. The means of the five sections were used to run the Shapiro-Wilk goodness of fit normality test and Leven's homogeneity of variance test. Based on the result of these tests, a one-way ANOVA or the Kruskal-Wallis test was performed on the data to see if there was any evidence of a difference in mean between the years.

Table 2: NDCI Data structure for spatial and temporal analysis. Each year's data (ex. S117- S517) represents one single image.

	2017 mean (Y_{17})	2018 mean (Y_{18})	2019 mean (Y_{19})	2020 mean (Y_{20})	2021 mean (Y_{21})	2022 mean (Y_{22})	Average combined mean Section data (Y_0)
Section 1 mean (S_1)	S_{117}	S_{118}	S_{119}	S_{120}	S_{121}	S_{122}	Average mean of Section 1
Section 2 mean (S_2)	S_{217}	S_{218}	S_{219}	S_{220}	S_{221}	S_{222}	Average mean of Section 2
Section 3 mean (S_3)	S_{317}	S_{318}	S_{319}	S_{320}	S_{321}	S_{322}	Average mean of Section 3
Section 4 mean (S_4)	S_{417}	S_{418}	S_{419}	S_{420}	S_{421}	S_{422}	Average mean of Section 4
Section 5 mean (S_5)	S_{517}	S_{518}	S_{519}	S_{520}	S_{521}	S_{522}	Average mean of Section 5
Average combined mean yearly data (S_0)	Average mean of 2017	Average mean of 2018	Average mean of 2019	Average mean of 2020	Average mean of 2021	Average mean of 2022	

A similar approach was taken to identify any spatial trend in the lake. The data from the five sections were combined into a single dataset for each year and analysed using same statistical tests described above to determine if there was any trend from north to south, as well as for the combined mean of all six years to determine the overall trend of NDCI in the lake from north to south.

2.2.2. Correlation Analysis:

The phosphorus data were collected by utilizing the Environment Agency's API (Application Programming Interface) from the RStudio platform and integrated into the yearly NDCI dataset. Phosphorus measurements were reported in mg/L and collected irregularly throughout the year. To ensure consistency with the annual NDCI composites, phosphorus concentrations were aggregated to a yearly mean for each year between 2017 and 2022. These annual means were then matched with the yearly mean NDCI values for correlation analysis. In addition to that, overflow data was also integrated into the dataset. Overflow was also aggregated at the yearly scale and paired with the corresponding annual mean NDCI values for each year. No sub-annual analysis was conducted due to the unavailability of higher-frequency data. Pearson's, Spearman's Rank, and Mann-Kendall (MK) tests were performed to evaluate the correlation between these variables.

The first set of analyses aimed at evaluating the correlation between Phosphorus and NDCI, as well as between Overflow and NDCI. The second set of analyses aimed at evaluating the relationship between Phosphorus and Overflow. The results from these tests were used to determine the significance of the relationship between the variables and to provide insight into the potential underlying mechanisms driving the trends observed in the data.

3. RESULTS

Because the statistical analyses in this study were based on annual mean values (six years) and a small number of spatial units (five sections), the correlation coefficients and trend statistics should be interpreted with caution. Small sample sizes reduce statistical power, increase uncertainty in correlation estimates, and make p-values less reliable. The findings presented here should therefore be considered indicative rather than conclusive, and future studies incorporating higher-frequency in-situ or satellite-derived chlorophyll measurements would allow more robust statistical inference.

3.1. Temporal Analysis:

The results of the Pearson and Spearman tests revealed negligible correlations for the north side of the lake in Sections 1 and 2. Nevertheless, they showed moderate negative correlations for the south side of the lake in Sections 3 to 5 and the combined data (Figure 2). However, the Mann-Kendall test only showed a moderate negative correlation for Section 5 and insignificant correlations for all other sections and the combined data. Despite the correlations being moderate in some cases, none of the p-values of these tests were less than 0.05 (Table 3). Based on this, it was concluded that the observed decrease in NDCI value was not statistically significant enough to be recognized.

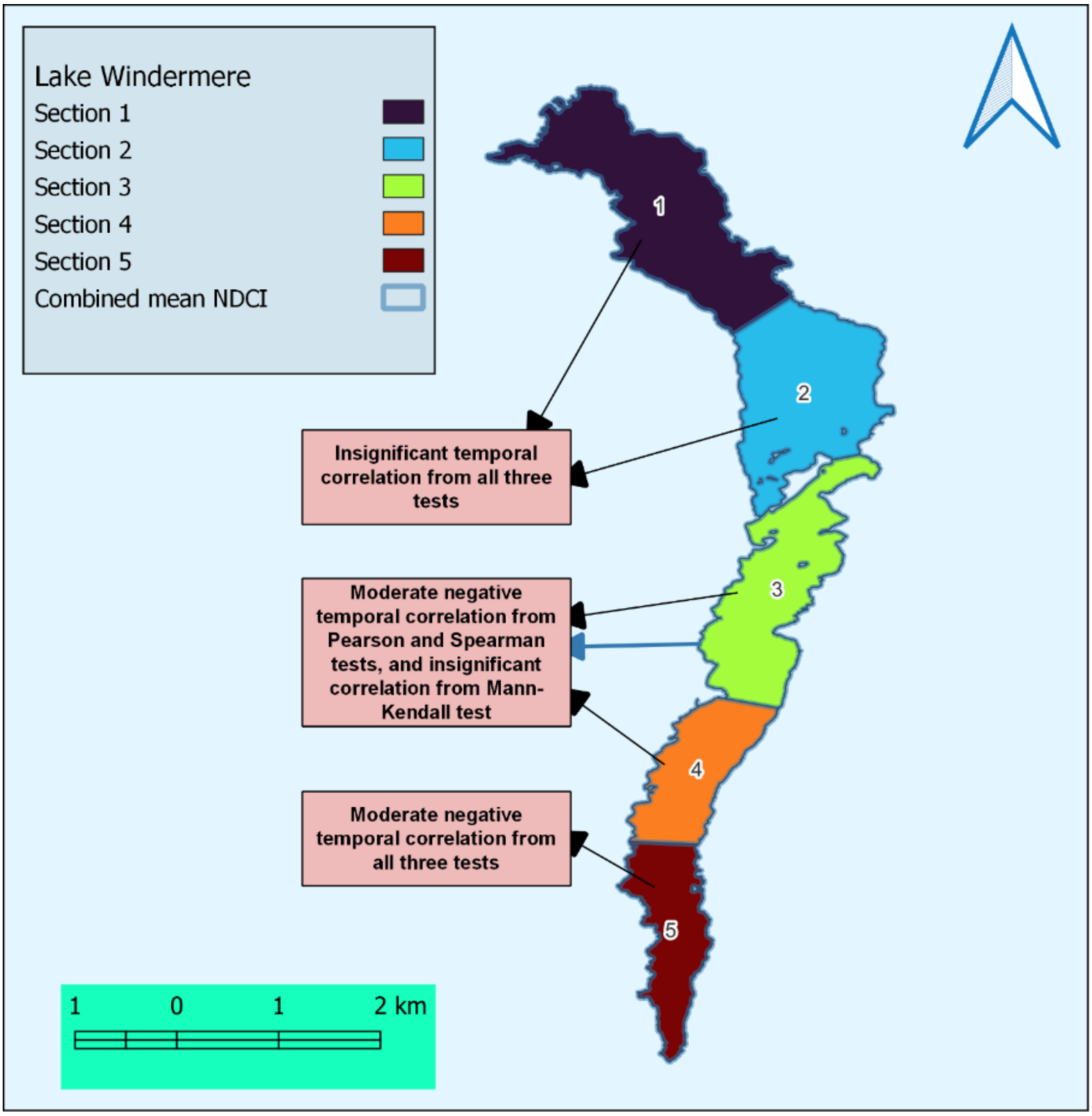

Figure 2: Temporal correlation of mean NDCI values

Table 3: Correlation coefficient and -values for all sections:

Section	Mann-Kendall	Pearson	Spearman

	tau	p-value	r	p-value	rho	p-value
Section 1	0.2	0.707	0.2	0.705	0.314	0.564
Section 2	0.2	0.707	-0.033	0.951	0.143	0.803
Section 3	-0.333	0.452	-0.551	0.257	-0.486	0.356
Section 4	-0.333	0.452	-0.526	0.283	-0.486	0.356
Section 5	-0.467	0.26	-0.573	0.235	-0.543	0.297
Combined	-0.333	0.452	-0.472	0.345	-0.486	0.356

Additionally, the Shapiro-Wilk goodness-of-fit test was carried out on the combined data, and the obtained p-value was 0.681, indicating the normal distribution of the data across all sections. Furthermore, Levene's test for homogeneity of variance was conducted and the p-value obtained was 0.024, indicating the presence of unequal variance in at least one of the sections. The Kruskal-Wallis test was then carried out to examine any notable differences in mean NDCI values between the years. However, the results showed no statistically significant difference between the years, with a p-value of 0.104. This is further reinforced by the boxplot of the yearly combined data (Figure 3), and a p-value of 0.064 from the One-Way ANOVA. Suggesting that there was no statistically significant difference in chlorophyll-a concentration between the years.

The statistical analysis revealed a lack of temporal trend in the chlorophyll index of the lake and established that there was no statistically significant difference between the mean NDCI values from 2017 to 2022. This suggests that the eutrophication conditions in the lake have remained unchanged over this time period.

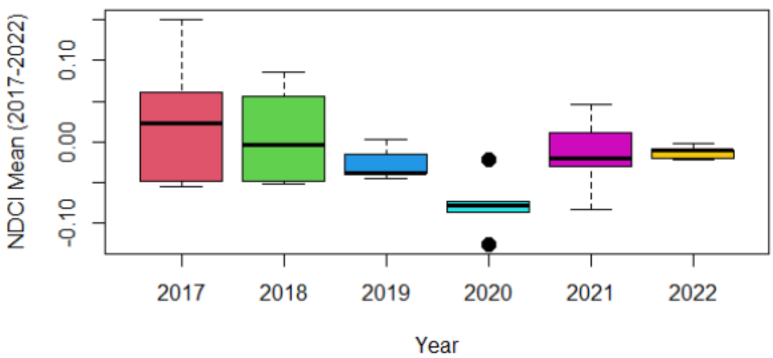

Figure 3: Boxplot for combined yearly NDCI data.

3.2. Spatial Analysis

The results of the spatial trend analysis of the NDCI between different years and sections of the lake revealed that the average NDCI value tends to increase from the northern (S_1) to the southern (S_5) part of the lake, indicating a rise in chlorophyll-a concentration towards the lake's southern region. The trend was determined by conducting Pearson, Spearman, and Mann-Kendall tests (Table 4). This positive correlation, indicating an increasing mean NDCI (chlorophyll-a concentration) value towards the south side of the lake, was found to be strong for the years 2017, 2018, and 2022. However, a strong negative correlation, indicating a decreasing mean NDCI value (chlorophyll-a concentration) towards the south side of the lake was observed for the year 2019. In 2020, the Spearman test showed a moderate positive correlation, while the other two tests showed no significant correlation. For the year 2021, the correlation was moderate to strong and positive in nature, suggesting an increase in chlorophyll-a concentration towards the south. Similarly, the combined data analysis revealed that both Pearson and Spearman tests showed a strong positive correlation, while the Mann-Kendall test showed a positive moderate correlation, suggesting an increase in chlorophyll-a concentration towards the south. Nevertheless, none of the Mann-Kendall tests had a statistically significant p-value (less than 0.05). On the other hand, the Pearson test showed significant p-values for the years 2017 and 2022, while the combined data had significant p-values for both Pearson and Spearman correlation.

Table 4: Correlation coefficient and -values for all years

Year	Mann-Kendall		Pearson		Spearman	
	tau	**p-value**	**r**	**p-value**	**rho**	**p-value**
2017	0.8	0.086	0.957	0.011	0.9	0.083
2018	0.8	0.086	0.821	0.088	0.9	0.083
2019	-0.8	0.086	-0.759	0.137	-0.9	0.083
2020	0.2	0.806	0.298	0.626	0.5	0.45
2021	0.6	0.221	0.705	0.184	0.8	0.133
2022	0.8	0.086	0.95	0.013	0.9	0.083
Combined	0.6	0.221	1	0	1	0.017

In addition, the Shapiro-Wilk goodness of fit test was conducted for all years of combined data with a p-value of 0.961, suggesting that the data was normally distributed. Levene's test for homogeneity of variance was performed with a p-value of 0.035, indicating that there were differences in the variance of the data across the sections. The Kruskal-Wallis test was performed to determine any significant differences between the sections. The One-Way ANOVA test was also performed to reinforce the finding from the Kruskal-Wallis test. The results of the Kruskal-Wallis test showed a p-value of 0.05, while the ANOVA showed a p-value of 0.03. Due to unequal variances, ANOVA results should be interpreted cautiously; the Kruskal–Wallis test provides a more robust assessment. These results suggest that the null hypothesis should be rejected, indicating that there was a statistically significant difference in chlorophyll-a concentration between the sections. Although the test suggested a statistically borderline difference, visual inspection shows substantial overlap between section distributions (Figure 4).

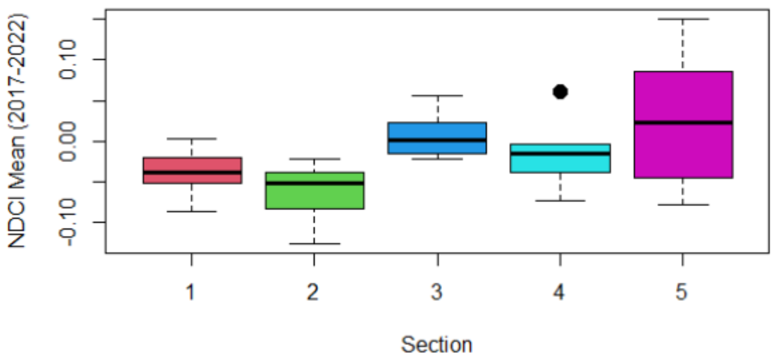

Figure 4: Boxplot for sections NDCI data

The results of the spatial analysis imply that the southern part of the lake is more vulnerable to eutrophication than the northern part. This phenomenon might be a result of the elongated geometry of the lake, with the south end connected to Morecambe Bay through a narrow river, Leven. The observed trend could be caused by multiple sources of treated sewage discharge effluent introduced into the lake from both water companies and private entities along its length, along with the downstream flow of dissolved and suspended phosphorus towards the lake's discharge point at the southern end. Nevertheless, spatial correlation patterns varied between years, suggesting high inter-annual variability and the need for cautious ecological interpretation.

3.3. Correlation of NDCI data, Phosphorus data, and overflow data:

The yearly data analysis revealed a robust positive correlation between Phosphorus and mean NDCI across all three correlation tests, suggesting the association between the chlorophyll-a concentration of the lake and the effluent of phosphorus from the Ambleside WwTW final treated effluent. The findings also indicated a negative correlation between Ambleside WwTW storm overflow and mean NDCI, which was observed to be strong with Pearson and Spearman and moderate with Mann-Kendall. Notably, the Pearson correlation showed the strongest correlation for all three pairs of variables and produced only statistically significant results among the three tests (Table 5). These findings suggest that the Pearson correlation method was most appropriate for analysing the relationship between the variables in this study.

The correlation test between NDCI, the phosphorus released in the Ambleside wastewater effluent, and the Ambleside WwTW storm overflow indicated that they are interconnected. As the phosphorus increases, so does the NDCI, directly affecting the eutrophication condition of the lake. However, an intriguing observation was made regarding the relationship between overflow, phosphorus, and NDCI values. A negative correlation was observed, with an increase in overflow leading to a decrease in both NDCI and phosphorus values, implying an inverse relationship between the overflow and chlorophyll-a concentration. A possible explanation for this could be the mixed plant used in the Ambleside WwTW. When overflow occurs due to heavy rainfall, the sewer gets diluted with all the rainwater coming in from other sources in the mixed tank, which could explain the negative relationship between effluent phosphorus and overflow. Additionally, because of the heavy load of water, a large proportion of the water coming from the plant runs off to the Leven river, which may further decrease the phosphorus concentration in the lake and in turn reduces the chlorophyll-a content. However, this interpretation is speculative and requires hydrodynamic data to confirm. Additionally, the extremely high correlation may be influenced by the small sample size and monotonic sampling structure; therefore, it should not be over-interpreted.

Table 5: Correlation tests between NDCI, Phosphorus, and Overflow

Variable	**Mann-Kendall**		**Pearson**		**Spearman**	
	tau	**p-value**	**r**	**p-value**	**rho**	**p-value**

Phosphorus vs NDCI	0.733	0.06	0.909	0.012	0.829	0.058
Overflow vs NDCI	-0.6	0.221	-0.89	0.043	-0.7	0.233
Overflow vs Phosphorus	-0.8	0.086	-0.997	0	-0.9	0.083

4. DISCUSSION

Satellite data has become an increasingly valuable tool for lake management and monitoring. Remote sensing of water quality using satellite data is effective and used extensively in providing frequent and spatially extensive measurements of key water quality parameters (Banks et al., 2012; Coimbra et al., 2021; Dörnhöfer et al., 2018; Gons et al., 2008; Huang et al., 2014; Xu et al., 2020). This has allowed for the identification of trends and patterns in water quality and has been used to inform management decisions for a variety of lakes around the world. Many researchers and organizations have used satellite data for lake monitoring, including NASA (Dörnhöfer et al., 2018; Ferral et al., 2018; Gons et al., 2008; Huang et al., 2014; Sayers et al., 2016; Zilioli et al., 1994). However, there are still limitations to the use of satellite data, such as issues with spatial resolution and the need for ground truthing. Further research and development in this area are needed to fully exploit the potential of satellite data for lake management and monitoring.

The analysis conducted on the NDCI data from Lake Windermere reveals several interesting insights into the state of eutrophication in the lake. One key finding is that there is a moderate negative correlation between the amount of overflow from the Ambleside WwTW and both the NDCI and phosphorus content in the final treated effluent from the Ambleside WwTW facility. Specifically, the increase in overflow from the Ambleside WwTW coincided with the decrease in both the level of phosphorus in the final treated effluent and the level of eutrophication as measured by NDCI. However, the study did not make use of field data to validate the accuracy of the NDCI in measuring the chlorophyll-a concentration in the water body. This means that the results of the study may not accurately reflect the true amount of chlorophyll-a in the water. Additionally, it is important to note that while Ambleside is a significant treatment plant in the region, treated sewage discharge from other private and water company sources also contributes to the overall phosphorus content and, thus, have an impact on the lake's eutrophication. Furthermore, the study did not consider other factors that could impact the changes in NDCI. These factors could include changes in water level or the presence of other water bodies in the vicinity, which could affect the NDCI readings and the results of the study. Nevertheless, this observation indicates that as the overflow from Ambleside WwTW increases, both the level of phosphorus and the level of eutrophication decreases. This outcome aligns with a prior investigation, which detected a negative relationship between rainfall duration and depth with phosphorus levels in an Italian lake, using both the Kendall rank correlation coefficient and Pearson linear correlation (Barone et al., 2019). The study also emphasizes the crucial role of WwTW in shaping the eutrophication status of Lake Windermere by introducing phosphorus through the final treated effluent, as previously suggested by Moorhouse et al., 2018. Furthermore, a 40-year overview of the water quality and phytoplankton trends in Grasmere lake, a small lake located north of Lake Windermere, indicated a threefold increase in annual areal phosphorus loading and a twofold increase in maximum chlorophyll-a concentrations after the commissioning of a wastewater treatment plant (Reynolds et al., 2012). Similarly, Little Mere, a small, hypertrophic, shallow lake, experienced a rapid decline of 92% in phosphorus concentration within three years following the diversion of sewage effluents (Beklioglu et al., 1999).

In addition to the correlation between NDCI, overflow, and phosphorus, the results of the analysis of the NDCI data from Lake Windermere also provide some important insights into the eutrophication condition of the lake. The analysis showed that there was no significant change in the NDCI values of the lake over the studied time, indicating that the state of eutrophication has remained unchanged since 2017. This finding is consistent with previous research that found little change in the phosphorus levels in the lake from 2015 to 2018 (LWA, 2018). Nonetheless, the study acknowledges that the limited temporal coverage of the dataset analyzed may not yield a comprehensive understanding of long-term trends. As the data analyzed spanned only seven years, it may not be adequate to infer trends that persist beyond this duration.

Moreover, the spatial analysis of the NDCI data revealed a distinct pattern, with increasing NDCI values from north to south of the lake. The utilization of directional analysis in this study facilitated a more comprehensive examination of NDCI data. Zhang et al. utilized this technique to investigate the spatial dependence of land surface temperature change data, to identify any potential spatial patterns or hot spots (Zhang et al., 2019). In this study such patterns of NDCI values contributed to a deeper understanding of eutrophication in the lake, thereby fostering a more comprehensive and refined perspective. The directional analysis technique was also implemented in several studies of lake Windermere (Fielding et al., 2020; LWA, 2018). In one such study, monthly samples were collected between April and August 2018, similar to the present study it found that the southern side of the lake had the highest mean phosphorus concentration, while the northern side had the lowest (LWA, 2018). A potential explanation for the increase chlorophyll-a concentration towards the southern section of the lake is the existence of multiple outlets that discharge treated sewage, thereby introducing dissolved and suspended phosphorus along the length of the lake, which subsequently flows downstream towards the south. In addition, the prolonged retention time of the elongated lake, which is connected to Morecambe Bay via the narrow Leven River, may contribute to this trend. Retention time has been identified as a significant contributor to eutrophication, which is known to introduce spatial heterogeneity in phytoplankton biomass (Soares et al., 2012). Additionally, retention time is a crucial factor in lake recovery, as higher retention times can impede the time required for the lake to recover (Scharf, 1998).

The management of phosphorus sources and delivery from WwTW represents a fundamental approach to controlling eutrophication in lakes. A key measure in this regard involves the reduction of phosphorus at the source, including in household products and diets (le Moal, Gascuel-Odoux, Ménesguen, Souchon, Étrillard, Levain, Moatar, Pannard, Souchu, Lefebvre, et al., 2019). This approach recognizes the importance of minimizing external nutrient inputs that can fuel excessive algal growth and ultimately lead to negative ecological consequences. As such, reducing phosphorus input represents a crucial step in mitigating the effects of eutrophication in lakes. In addition to regulating the amount of phosphorus entering the lake, it is crucial to introduce and sustain particular species in the lake to facilitate the recovery from eutrophication (Ibelings et al., 2007). The diversion of effluents from water bodies is also a viable strategy, but its implementation is dependent on the availability of an appropriate location for effluent disposal (Ahlgren, 1978; Beklioglu et al., 1999; Edmondson & Lehman, 1981).

The results of this study demonstrated that Ambleside WwTW plays a crucial role in the eutrophication of Lake Windermere and the introduction of treated effluent from the Ambleside WwTW is potentially a major factor influencing the chlorophyll-a concentration in the lake. These findings have significant implications for lake management and monitoring, emphasizing the need for a more holistic approach that considers the impacts of wastewater treatment plants on the lake ecosystem. In addition, the study highlights the potential of satellite data for monitoring and managing water quality in lakes, providing valuable information to inform management decisions.

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