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Monitoring Aquatic Debris in a Water Environment Using a Remotely Operated Vehicle (ROV): A Comparative Study with Implications of Algal Detection in Lake Como (Northern Italy)

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Abstract: This study investigates underwater debris in a freshwater lake using remotely operated vehicles (ROVs) during two distinct survey periods: 2019 and 2024. The primary objective was to count and document visible debris (metal and plastic) on the lakebed based on ROV video recordings. A total of 356 debris items were observed in 2019, while only 39 items were recorded in 2024. The notable decrease in debris visibility in 2024 is likely attributed to dense algal growth during the survey months, which hindered the visual identification of objects on the lakebed. The study highlights the challenges of monitoring underwater debris in freshwater systems, particularly during periods of high algal activity, which can significantly impact visibility and detection efforts. While ROVs have proven effective in identifying submerged debris in clear water, this research underscores their limitations under reduced visibility conditions caused by algal blooms, turbidity diminishing the video quality. The results provide valuable insights into the temporal variation in debris visibility and contribute to ongoing efforts to improve freshwater debris monitoring techniques.

Keywords: debris; ROV; lake; algal blooms

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1. Introduction

Aquatic debris poses a growing threat to biodiversity, ecosystem health, and water quality on a global scale. Traditionally, debris monitoring relied on manual methods such as visual inspections by motorboats, which are labor-intensive and limited in scale [1–3]. In recent years, remotely operated vehicles (ROVs) have emerged as valuable tools for underwater environmental monitoring [4–8]. They enable precise spatial and temporal surveys of marine ecosystems and scattered debris. However, challenges such as high manufacturing costs, significant weight, and large size can limit their effectiveness for broad-scale or dispersed area monitoring [4,5,8–13]. Despite these constraints, ROVs remain efficient for large-scale surveying due to their adaptability and accuracy [14–17].

However, advancements in ROVs have transformed underwater debris monitoring by providing automated, scalable solutions capable of real-time data collection and continuous video capture in different aquatic environments [18–20]. Despite these technological advancements, environmental factors such as water turbidity and light attenuation, particularly during algal blooms in summer and early autumn in Italy, can significantly impact ROV performance, leading to reduced detection efficiency [21,22].

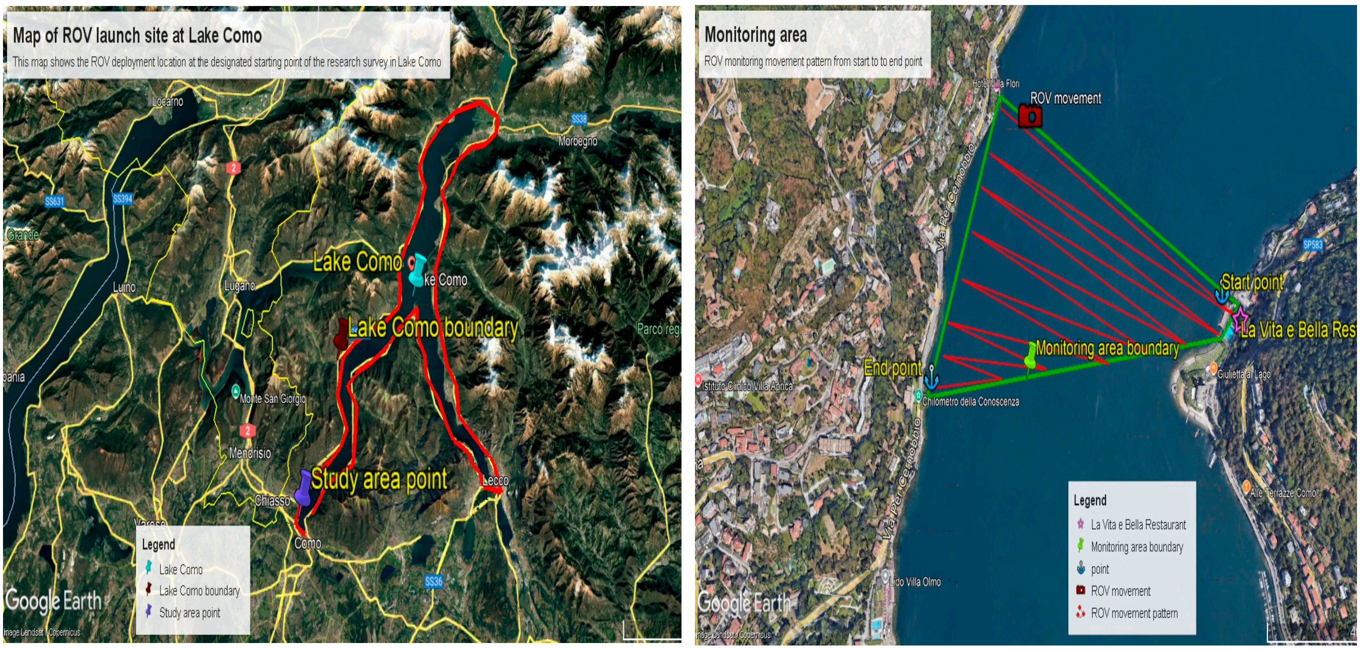
When densities of monospecific phytoplankton organisms are particularly high it is possible to refer to them as blooms that can distort the color spectrum and block light transmission, making underwater debris detection more difficult [4,23]. Algal development increases water turbidity and hinders light penetration, thereby degrading the effectiveness of electro-optical (EO) imaging systems used in ROVs [24–26]. The link between water transparency, algal growth, and underwater visibility is well documented. Kulshreshtha et al. [27] and Havens et al. [28] noted that algal growth directly impacts water clarity, which in turn affects underwater assessments, while González et al. [29] demonstrated the use of transparency as an indicator of eutrophication. Reduced clarity compromises the functionality of remote sensing technologies, particularly in turbid conditions [30–32], further complicating debris monitoring efforts. Similar to the challenges faced in our study of underwater debris monitoring in Lake Como, Yousefi et al. [33] conducted a comprehensive vulnerability assessment of road networks to landslide hazards in mountainous regions, highlighting the significant risks posed by environmental factors to infrastructure integrity, in a different context. Similarly, in our study in the context of Lake Como, the fluctuating environmental conditions, such as seasonal changes, algal blooms, and sedimentation, pose challenges to monitoring underwater debris and underscores the vulnerability of underwater debris visibility and detection in Lake Como, particularly during periods of high algal activity and turbidity. Šiljeg et al. [34] used ROVs for underwater debris detection, highlighting their effectiveness in shallow waters but noting limitations in obtaining morphometric data, especially without integrated systems like sonar. Similarly, our study faced challenges with visibility due to factors like algal blooms and turbidity, which hindered precise identification and measurement of submerged debris, underscoring the need for improved equipment and methods. Walia et al. [35] also identified difficulties in quantifying submerged waste, with factors such as light refraction, suspended particles, and color distortion complicating accurate detection. These challenges mirrored those in our study, where reduced visibility impacted debris identification and quantification. Ioakeimidis et al. [36] categorized debris materials, finding plastics (55%) and metals (36%) as the most common. However, their study also faced issues with detecting buried items and poor visibility, issues that were similarly observed in our study due to algal growth and turbidity. Lake Como, in a temperate region, experiences seasonal temperature changes and thermal stratification in summer, affecting debris visibility. In winter, the isotherm promotes vertical mixing of nutrients and oxygen, influencing debris distribution. The lake's Y-shaped structure, with three sub-basins (northern, southeastern, and southwestern), complicates water movement. Seasonal shifts and wind patterns influence northern inflows, affecting the northern and southwestern basins. These hydrodynamic conditions impact sediment transport, nutrient distribution, and debris visibility during ROV surveys [37,38].

This study addresses the gap in understanding how environmental visibility challenges—specifically algal blooms—affect the performance of ROV-based debris detection in real-world conditions. Unlike prior research conducted under controlled or optimal settings, this study compares the effectiveness of ROVs in detecting submerged debris during two distinct years—2019 and 2024—in Lake Como, Northern Italy. The observations revealed that reduced water clarity caused by algal blooms in 2024 significantly impacted the visibility of debris on the lakebed, which was not as challenging in 2019. By documenting these visibility challenges and comparing the debris counts between the two survey periods, the study highlights the limitations of ROV-based debris monitoring in freshwater systems under reduced visibility conditions. This research further provides valuable insights into the types of debris observed and emphasizes the need to consider environmental factors such as algal growth when conducting underwater debris assessments.

2. Materials and Methods

2.1. Study Site

Figure 1 describes the study area and investigation points. Lake Como is situated in Lombardy, Italy, with its approximate center at latitude 46°00′ N and longitude 9°16′ E. The study site is a peninsula in Lake Como known as Villa Geno, located slightly toward the center of the first part of the Lake Como basin in Northern Italy, 1 km north of the city of Como. Lake Como is located in a temperate region, while its surrounding catchment area predominantly experiences a cold climate. This results in distinct seasonal temperature patterns, where summer is warmer at low altitudes, and cooler at middle to high altitudes. The lake experiences thermal stratification during summer, with warmer surface water and cooler deeper layers. In winter, the lake undergoes isothermal, where water temperatures become uniform, promoting vertical mixing of oxygen and nutrients. This dynamic process is critical in shaping underwater habitats and debris distribution [37]. In shallow littoral zones, the absence of stratification results in uniform temperatures from the surface to 8 m (around 24 °C), while deeper areas (1.5–10 m) play a key role in sedimentation and debris deposition. These thermal and hydrodynamic conditions significantly influence the visibility and detection of submerged debris, as sedimentation, turbidity, and algal blooms may obscure debris during ROV surveys [39].



(**a**) (**b**)

Figure 1. (**a**) Launch site of the ROV at Lake Como; (**b**) the ROV's movement path is shown as a zigzag pattern.

The ROV's movement path is shown as a zigzag pattern, which was followed consistently throughout the 2019 and 2024 survey periods. The length of the ROV survey routes was approximately 50 m each month, as estimated based on the duration of operation and maintaining a consistent speed under the surface. Due to the absence of geolocation systems during the survey, precise control over the route length was not possible. Instead, the survey relied on standardizing the time of flight for each session to ensure consistency in coverage. This methodology ensured that the same approximate area was covered during each survey; the green path in Figure 1 represents the general movement of the ROV, covering the study area each time. The path is consistent in both years and across different months. To ensure consistency across surveys conducted in different months and years, physical markers on the lake bottom were utilized as reference points to recognize and repeat the route. These markers, visible in the ROV footage, allowed the operators to follow a similar path during each survey period. While this approach did not provide precise geospatial measurements, it was sufficient to maintain consistent coverage of the survey area. By relying on these visual cues, the ROV surveys ensured a comparable dataset across months and year. This method also helped to identify recurring patterns in debris distribution and accumulation. This consistency allows for meaningful comparisons of debris counts and patterns between months and years, despite potential variations in visibility conditions or environmental factors. The surveys were conducted at shallow depths within the nearshore zone of Lake Como. While precise depth measurements were not recorded during the surveys, the study area is estimated to range between 2 and 10 m in depth based on general observations and the typical characteristics of the lake's nearshore zone. The depth distribution at the testing ground was consistent across all months, allowing for meaningful comparisons of debris observations over time. This site provides convenient access to the lake, making it easier to handle the ROV. The monitoring area is near the shore and features several restaurants, hotels, coffee houses, resorts, and parks, making it a popular place for visitors. The surface of the lake is slightly tilted but is level at the end of the location where most of the accumulation gathers. The ROV surveys were conducted under varying water conditions, which influenced visibility and debris detection.

2.2. Methodology

A remotely operated vehicle (ROV) was used to record debris objects. Given its reasonable price, it is a feasible device for underwater videography, as represented in Figure 2.

Figure 2. Remotely operated vehicle (ROV).

Details of the ROV

The system called Trident, developed by Open Rov snc, is based on a Raspberry Pi shield programmed to record video from a CCD sensor and manage input from a controller. It is cabled to the surface with a 100 m tether and is equipped with LED lights (with a brightness of 200 lumens), a thermometer, a depth sensor, and an internal digital compass for navigation support. An ABS 3D-printed shell maintains water pressure resistance up to 100 m below the surface, and a LiPo battery provides an actual autonomy of 3 h. A smartphone (iPhone) was attached to a device as the main device, which was used to record observations and control the application. Data such as depth, temperature, direction, and battery life were displayed in real-time on the application via onscreen display (OSD). The device was assembled with three motors capable of propelling the Trident at speeds of up to two meters per second, a reliable speed for its size. The navigation system is similar to that of a radio-controlled airplane, using a single vertical motor for pitch adjustment, enabling vertical navigation while maintaining high speed. This system was secured with a sturdy rope cable.

The underwater survey was conducted in the months of April, May, June, August, and November 2019 and in January, February, March, April, May, and June 2024 to count the number of objects in the same area to understand the pattern of accumulation. The ROV used in this study has an estimated field of view of approximately 2 m in the initial meters of sight, based on its technical specifications. While the precise width of the surveyed area depends on water turbidity and lighting conditions, this estimate was used as a reference for assessing debris visibility. However, the device's exact height above the bottom varied slightly due to operator adjustments to avoid obstacles and optimize visibility during the survey. These variations were minimal and did not significantly impact the data collection process.

ROV Video Data Collection: High-definition (HD) littoral videos were considered for the evaluation as high quality. The debris counts were manually recorded by reviewing video footage captured by the ROV.

This study employed the remotely operated vehicle (ROV) to capture underwater video footage in the littoral zone of Lake Como, focusing on monitoring aquatic debris and environmental conditions. The ROV led the underwater transects to a depth of 10 m depth below the water surface. A total of 36 high-definition video clips were recorded across two distinct periods: 2019 and 2024. Each video varied in duration, ranging from short clips (<1 min) to longer recordings (up to 10 min), depending on environmental conditions and the objectives of each survey. The ROV operated consistently within the same general area of Lake Como, ensuring reliable spatial coverage for comparative analysis.

2.3. Data Logging and Categorization

The video footage was systematically organized and analyzed using Microsoft Excel version 2411, where relevant parameters were recorded for each video clip. The following attributes were logged:

Location: All videos were captured within the same littoral zone of Lake Como.

Year and Date: Each video was labeled with the specific year (2019 or 2024) and the date of recording for temporal analysis.

Video Number: A unique identifier was assigned to each video clip (e.g., Video 1, Video 2, etc.) for easy reference.

Notes: Observational notes were made for each video, detailing environmental conditions such as water clarity, visibility issues, or weather conditions.

Month: The month of recording was documented to analyze seasonal variations in debris accumulation.

Turbidity: Turbidity was qualitatively assessed based on the clarity of the water in each video. Instances where high turbidity or algal blooms hindered object identification were noted. Water turbidity was visually assessed based on photographs obtained using the ROV. Due to the absence of direct turbidity measurements (e.g., NTU values), water clarity was categorized into three qualitative levels based on visual observations:

Clear water: Water appeared transparent with no visible cloudiness or suspended particles.

Slightly turbid water: Minor cloudiness observed with very few suspended particles visible.

Highly turbid water: Water appeared visibly cloudy with significant suspended particles or sediment reducing water clarity. These categories were applied to all photographs to classify and compare water turbidity conditions across different months and years. Turbidity in the water was affected by sedimentation and biological activity, particularly algal blooms, which fluctuated throughout the study period.

Object Identification and Timestamping: Debris items were identified based on distinct colors and shapes. For example, objects such as blue candy wrappers, orange soda cans, and disposable glass were categorized accordingly. The timestamp of each object's appearance was recorded, along with notes indicating any difficulties encountered in identifying objects. The ROV captured video at varying levels of resolution, which allowed for the identification of debris based on size, shape, and distinct features. Large objects, such as plastic chairs, were easily identifiable, even with the moderate video resolution. Smaller objects, such as candy wrappers, posed a greater challenge due to their size and the potential for being obscured or hidden under larger debris, such as plastic chairs or rocks. While smaller items may have been partially obscured, they were only counted if clearly visible in the footage. In cases where such objects were not visible due to being covered by larger debris or sediment, their absence was noted.

Object Type and Quantity: Each identified object was categorized by type (e.g., plastic bottles, metal cans) and documented by its distinct characteristics (color and shape) to ensure accurate identification. The quantity of each type was recorded when possible.

Observations started from a fixed reference point (an iron pipe structure) across multiple months in 2019 and 2024, ensuring consistency in the surveyed area. Debris types were categorized into:

Direct sources: Items likely deposited directly into the lake, such as beach furniture and large metallic objects.

Indirect sources: Lighter debris, such as packaging material, likely transported via surface currents or runoff. This analysis aimed to establish a baseline inventory of debris types and their potential origins, providing insights into the mechanisms of debris accumulation in the lake.

Data Analysis Approach

The compiled data was structured in an Excel spreadsheet, allowing for a comprehensive analysis of aquatic debris and environmental conditions over time. Each row represented a unique video, while columns documented relevant attributes such as the presence and type of debris, notes on turbidity, and other observations. This organization facilitated comparisons between videos recorded in 2019 and 2024, providing insights into both seasonal and long-term temporal changes.

Temporal and Monthly Variations: The analysis focused on both years to examine changes in debris counts over time. Monthly variations in debris presence were assessed by grouping data by month, highlighting periods of increased or decreased debris counts in different months and years.

Pollutant Distribution: The frequency and types of debris (e.g., plastic, metal) were quantified for each video, when possible. Observations of visibility challenges due to turbidity or algal blooms were documented to explain instances where identification was difficult. While specific spatial distribution patterns of debris accumulation were not systematically mapped, general observations suggest that debris was often found near flat or sloping areas of the lakebed. Seasonal variations in the visibility of pollutants were noted, and these trends contribute to understanding the challenges of monitoring underwater debris in dynamic freshwater environments.

2.4. Statistical Analysis

A paired *t*-test was conducted using Microsoft Excel to compare the mean quantity of aquatic debris collected during the same months in 2019 and 2024. The paired *t*-test was selected to account debris levels in the overlapping months for the months of April, May, and June for both years to be compared between two years. A paired *t*-test was employed to assess whether the difference in debris counts between these two years was statistically significant. The analysis was conducted to compare debris data collected during the same months (April, May, and June) across two years (2019 and 2024). A paired *t*-test was selected as the appropriate statistical method for this analysis, as it compares data collected from the same periods (i.e., identical months across two years). The paired *t*-test controls for intraseasonal variations and enables us to evaluate changes within the same sample over time. The statistical test resulted in a p-value of 0.061, suggesting a trend toward a difference in debris counts between the two years, though it did not reach statistical significance at the 0.05 level. While the sample size is limited to three months per year, the paired *t*-test remains the best approach given the available data and the seasonal focus of the study. We acknowledge that increasing the sample size in future studies would enhance statistical power and allow for a more robust comparison across broader temporal scales. The null hypothesis (H_0) assumed there was no significant difference in debris levels between 2019 and 2024.

3. Results

The debris collected in Lake Como during 2019 and 2024 comprised two primary material types: metal and plastic. Metal objects included soda tins, door couplings, and metal sheets, while plastic debris consisted of wrapping packaging, plastic bottles, and tires. The items varied in shape, size, and color, with rusted metals contrasting with vibrant plastic hues, such as blue candy wrappers and orange soda cans.

3.1. Monthly Distribution of Metal Objects in 2019

Figure 3 presents a stacked graph showing the monthly counts of various metal object categories observed in Lake Como in 2019 highlighting the consistent predominance of soda tins, particularly in May, August, and November, while the presence of other metal objects varied throughout the year. During April 2019 a total of 25 metal objects were recorded, with beach beds (9) and soda tins (12) being the most frequently observed. Other categories included iron cylinder (1), metal piece of boat (1), metal sheet (1), and table (1). Whereas, in May 2019, the total count was 65 metal objects, with a notable presence of soda tins (48) and iron chairs (4). Additional counts included beach beds (8), metal star objects (1), stand (1), iron bed (1), and camera stand (1). Upon further analysis of the ROV video footage, it was observed that heavier objects, such as beach beds, tend to become partially or fully buried in bottom sediments over time. This likely explains the discrepancy in counts, as one of the beach beds may have been obscured by sediment accumulation during the May survey and was therefore not visible. Sediment burial of heavy debris is a well-documented phenomenon in aquatic environments, particularly in areas with active sediment deposition. In June 2019, the recorded total was 31 metal objects, with soda tins (19) being the predominant category. Other objects included beach beds (5), metal wire (2), iron bed (2), and camera stand (1). In August 2019, a total of 43 metal objects were counted, including soda tins (37) and iron beds (2). Other categories included beach beds (3) and stands (2). Similarly, in August, the turbidity levels were high due to sediment disturbance, which further obscured visibility and hindered debris identification. In November 2019, the total count was 39 metal objects, with soda tins (30) being the most frequently observed. Additional objects included beach beds (7) and iron cylinders (1). In general, smaller objects were particularly challenging to detect during these months due to increased water turbidity and camera movement.

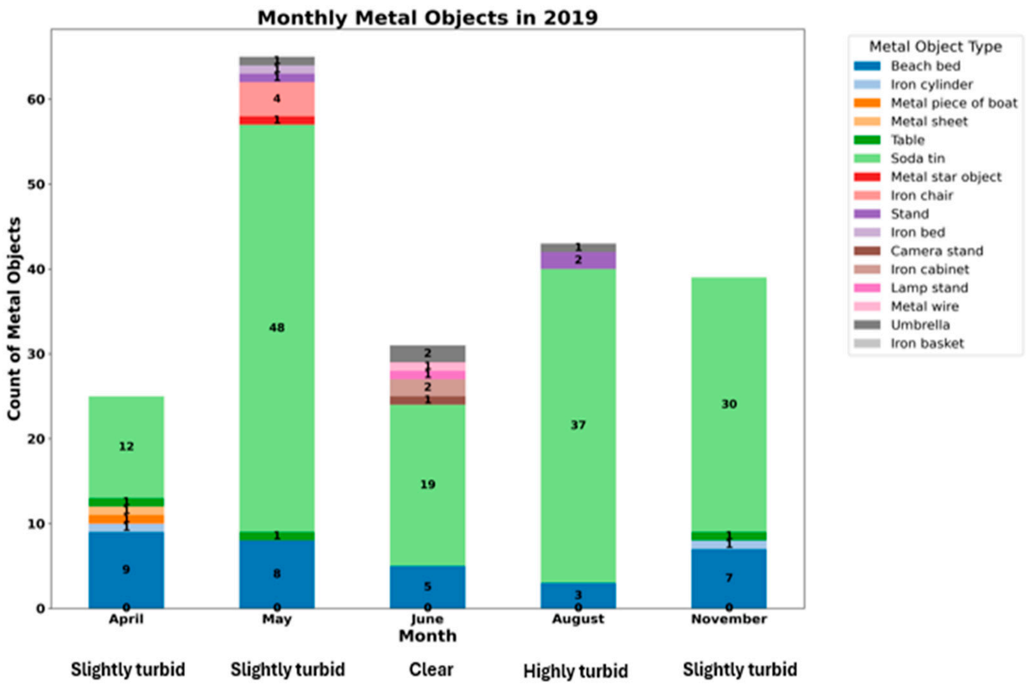


Figure 3. Stack representation of monthly metal objects in year 2019.

3.2. Monthly Distribution of Metal Objects in 2024

The stacked graph (Figure 4) visually summarizes the distribution of metal debris, highlighting that soda tins were primarily observed in January and March, while other metal objects were either rarely detected or absent in subsequent months.

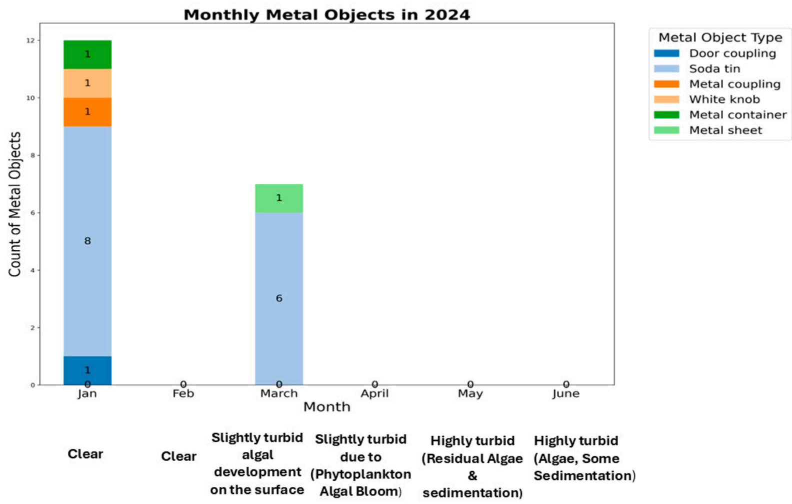


Figure 4. Stack representation of monthly metal objects in year 2024.

In January 2024, the most frequently observed items were soda tins (8) followed by white knobs (1), door couplings (1), metal couplings (1), and metal containers (1). No metal sheets were recorded. In February 2024, no metal objects were detected across any category, with all counts recorded as 0. In March 2024, the count was dominated by soda tins (6), with a single metal sheet (1) observed. No other metal objects were recorded. In April 2024, there were no metal objects observed, with all categories showing 0 counts. In May 2024, all categories showed 0 counts, indicating no detected metal debris. Similarly, in June 2024, no metal objects were detected, with counts remaining at 0 for all categories. The observed disappearance of certain metal objects in February and April–June 2024 may be attributed to several factors. It is possible that some debris was buried due to sedimentation or moved due to water currents, which could account for their nonvisibility in subsequent surveys. Based on video observations, it was noted that in some months, turbidity and sediment disturbance led to the partial or complete burial of objects, particularly larger debris like metal pieces. Additionally, in March 2024, dense algal blooms and higher turbidity obscured the objects' visibility, making it difficult to identify debris, which might have led to an undercount. Furthermore, it is not confirmed whether any cleaning of the lakebed occurred between the surveys, as this was outside the scope of the study. However, the lack of visible debris in specific months may reflect natural processes, such as the movement of debris due to currents or sedimentation, rather than any active removal or cleaning efforts. No organized efforts to collect or remove underwater debris were documented in the study area during the survey period. The variation in observed debris counts between surveys may result from natural factors such as sedimentation burying objects, changes in visibility conditions, and debris movement influenced by lake currents and turbulence. These natural processes could obscure the detection of certain items over time, contributing to variability in debris counts across months.

3.3. Monthly Distribution of Plastic Objects in 2019

The stacked graph (Figure 5) visually summarizes these distributions, emphasizing the prevalence of candy wrapping throughout the year, particularly in April and November, while other plastic items showed variable counts across months.

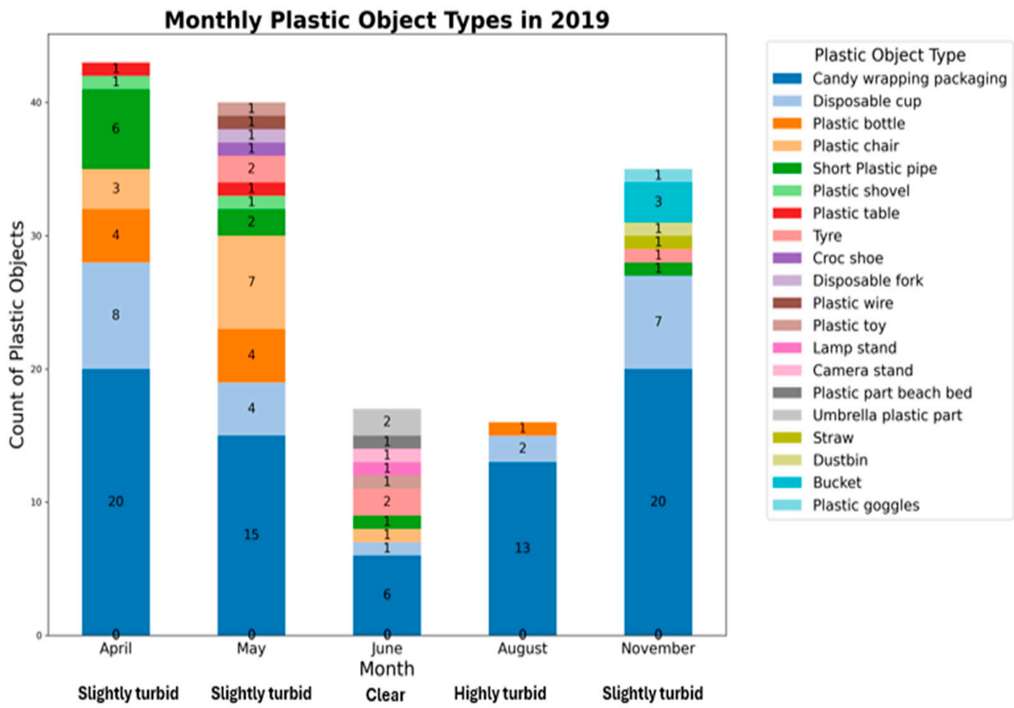


Figure 5. Stack representation of monthly plastic objects in year 2019.

The categories of plastic debris included candy wrapping packaging, disposable cups, plastic bottles, plastic chairs, short plastic pipes, plastic shovels, plastic tables, tires, croc shoes, disposable forks, plastic wires, plastic toys, lamp stands, camera stands, plastic parts of beach beds, umbrella plastic parts, straws, dustbins, buckets, and plastic goggles. During April 2019, the total count was 43 plastic items, with significant contributions from candy wrapping packaging (20), disposable cups (8), and plastic bottles (4). Other items included plastic chairs (3) and short plastic pipes (6). In May 2019, a total of 40 plastic items were recorded, including candy wrapping packaging (15), disposable cups (4), and plastic bottles (4). Additional items included plastic chairs (7) and tires (2). Whereas, in June 2019, the total count was 17 plastic items, with notable observations of candy wrapping packaging (6) and plastic shovels (1). Other items recorded were plastic tables (2) and plastic toys (1). In August 2019, a total of 16 plastic items were observed, predominantly candy wrapping packaging (13). In November 2019, the count was 35 plastic items, with notable counts of candy wrapping packaging (20) and disposable cups (7). Additional items included plastic chairs (1) and plastic goggles (3).

3.4. Monthly Distribution of Plastic Objects in 2024

Figure 6 effectively visualizes the monthly distribution of plastic debris types throughout 2024. The data highlight variations in the presence of different plastic objects, with wrapping packaging being most frequently observed in March, while other categories such as tires and plastic bags appeared in different months.

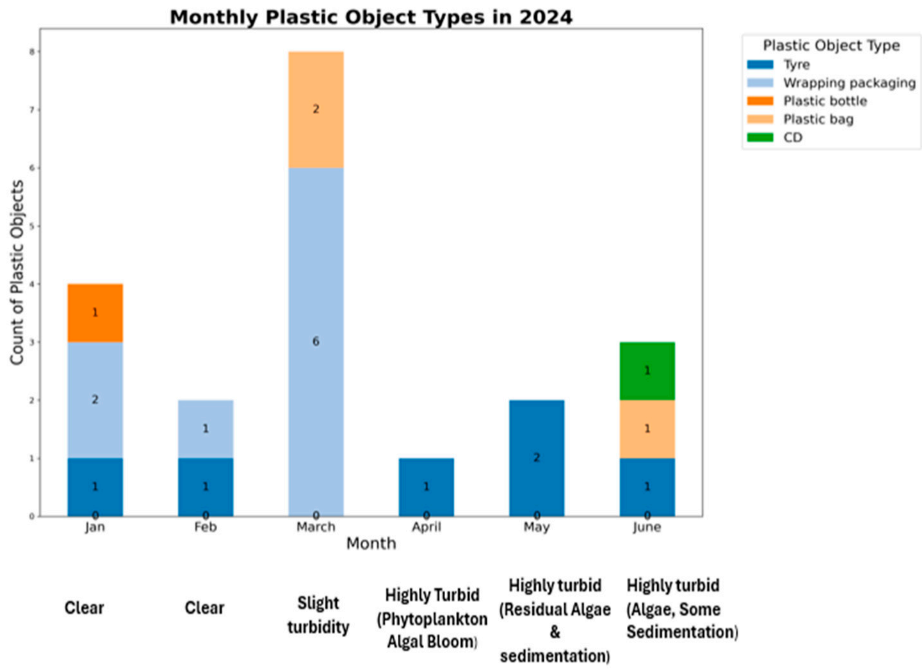


Figure 6. Stack representation of monthly plastic objects in year 2024.

During January 2024, a total of 4 plastic objects were recorded, including 1 tire, 2 wrapping packaging, and 1 plastic bottle. No plastic bags or CDs were observed. In February 2024, the total count was 2 plastic objects, comprising 1 tire and 1 wrapping packaging. No other categories were detected. In March 2024, a total of 8 plastic objects were observed, with 6 wrapping packaging and 2 plastic bags. No tires, plastic bottles, or CDs were recorded. In April 2024, the count was 1 plastic object, specifically a tire, with no other categories detected. In May 2024, a total of 2 plastic objects were recorded, both of which were tires. No wrapping packaging, plastic bottles, plastic bags, or CDs were observed. Whereas, in June 2024, the total count was 3 plastic objects, including 1 tire, 1 plastic bag, and 1 CD. No wrapping packaging or plastic bottles were detected.

3.5. Comparison of Debris Presence: 2019 vs. 2024

A comparative analysis of total debris counts in Lake Como revealed significant differences between 2019 and 2024. In 2019, a total of 356 items (metals and plastic) were detected and in 2024 only 39 items (metal and plastic) were detected In April, the total debris count was 66 items in 2019, while only one item was recorded in April 2024. Similarly, the total counts for May and June were 111 and 48 in 2019, compared to 2 and 3 in 2024, respectively. The results of the paired *t*-test for total debris counts indicated no statistically significant difference between the years ($p = 0.061$).

Figure 7 illustrates the yearly aggregation of the monthly variations, showing an overall decrease in debris across all months monitored in 2024. A paired *t*-test comparing total debris counts for 2019 and 2024 yielded a *p*-value of 0.061, indicating that although there was a clear reduction in debris, it was not statistically significant at the 0.05 level. This trend suggests potential improvements in environmental conditions or waste management practices over the five-year period. Although a clear visual reduction in debris was observed between 2019 and 2024, statistical testing using a paired *t*-test did not indicate a significant difference ($p = 0.061$) at the 0.05 significance level. This result is due to the fact that the total number of debris items in both years (2019 and 2024) was relatively low in certain months, particularly in 2024. A few months in 2024, such as April, May, and June, recorded an extremely low number of debris items (1, 2, and 3 items, respectively), which may have caused a higher variance and reduced statistical power in detecting a significant difference. Despite this, the visual trend of a decrease in debris is apparent and aligns with broader environmental or waste management changes that could have occurred over the years, such as improvements in waste collection efforts or natural factors such as sedimentation.

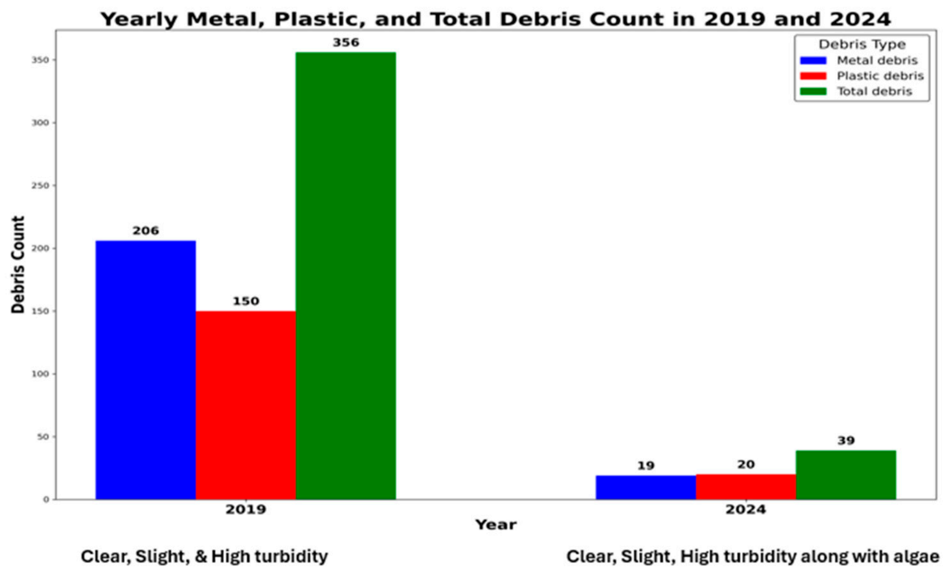


Figure 7. Bar graph representation of yearly breakdown of plastic and metal count in 2019 and 2024.

4. Discussion

4.1. Influence of Algal Growth on Debris Detection

In 2024, algal growth during warmer months likely reduced water clarity in Lake Como, hindering the ROV's ability to detect debris. Thus, the decreased debris counts may reflect visibility challenges rather than a true decline in debris accumulation. Hansen et al. [40], Upadhyay and Papadakis [41], Watanabe et al. [42] used ROVs for underwater monitoring and highlighted the disturbances caused by algae. While algal blooms complicate ecosystem monitoring [43–45], our focus was on debris detection. For instance, in our study, visibility declined from March to June 2024, coinciding with peak algal activity, whereas data from January to February, when algal levels were lower, likely provides a more reliable measure of debris. This emphasizes the need for timing in monitoring and suggests using alternative detection technologies or scheduling surveys during low algal periods. These results align with other reports of clarity issues in water caused by algae [46,47].

4.2. Interpretation of Debris Count Differences and Statistical Significance

In this study, all data were collected using a remotely operated vehicle (ROV), not an underwater drone. This distinction is important, as the ROV was specifically suited for detailed underwater surveys, while drones are typically used for aerial surveys. The statistical analysis was performed using a t-test to compare the data from the same months across different years (2019 and 2024). The significant decrease in visible debris in 2024, as indicated by the t-test results, likely reflects the impact of algal blooms and increased turbidity, which hindered visibility. Although the total debris counts in 2024 were visibly lower than in 2019, the paired t-test result ($p = 0.061$) suggests that this difference is not statistically significant at the 0.05 threshold. This outcome might seem surprising given the large numerical difference, but several factors may explain the result:

Small Sample Size: The analysis was based on data from just three months (April, May, and June), which limits the statistical power of the test. With such a small dataset, even large differences in observed counts may not reach statistical significance.

High Variability in 2019 Data: The debris counts in 2019 varied significantly, particularly the high count recorded in May (111 objects). This variability contributes to a higher standard deviation in the 2019 dataset, which reduces the statistical strength of the observed decline in 2024.

Environmental Factors in 2024: The reduced water clarity in 2024, likely caused by algal blooms, may have affected the ROV's ability to detect debris, leading to potential underreporting. This introduces a detection bias that complicates direct comparisons between the two years.

While the p-value (0.061) is close to the significance threshold, it remains insufficient to reject the null hypothesis. Therefore, additional data collection is necessary to better understand whether the observed reduction represents a genuine trend in debris accumulation or is influenced by environmental and methodological factors. Since this p-value exceeds the conventional significance threshold of 0.05, it suggests that the difference in metal and plastic object counts between the two years is not statistically significant. However, the proximity of the p-value to the significance level indicates a potential trend toward reduced metal and plastic object accumulation, which could be explored further with additional data or extended monitoring periods.

This dramatic decrease in both metal and plastic debris suggests that external factors influenced debris levels. However, the reduced debris count in 2024, especially the near absence of metal items in later months, may not be solely attributed to an actual reduction in debris. The observed decline coincides with reduced water clarity in 2024 due to algal blooms, which significantly impacted the visibility of debris during underwater monitoring using the ROV. This complicates the interpretation of the data, as the visibility challenges likely contributed to underreporting, particularly in areas where debris was likely buried under sediment or obscured by a higher density of algae.

During the 2024 monitoring period, dense algal growth and turbidity reduced water transparency, causing signal interference and image degradation [21,22,48]. This aligns with previous studies highlighting the critical role of water clarity in underwater assessments [27,29,49]. Natural factors such as algal migration and underwater turbulence further degraded the ROV's electro-optical imaging [21,22,30,50], while turbidity, low light transmittance, and light scattering led to blurred imaging [31,51]. Suspended sediments also worsened light attenuation, reducing the visual range and detection accuracy [52,53].

This study highlights the challenges and opportunities of using ROVs in fluctuating aquatic environments. Current ROV technology struggles with reduced visibility in turbid conditions, underscoring the need for adaptive monitoring strategies. Integrating auxiliary sensors like sonar can enhance detection reliability in such environments [54–57]. Additionally, miniature ROVs offer a cost-effective alternative for large-scale debris monitoring, maintaining high-resolution imaging while reducing costs and complexity [14–17,58]. Beyond debris detection, advanced ROVs support continuous ecosystem monitoring, offering valuable insights into water quality and pollution control strategies [59,60].

Our data do not analyze algal composition or toxicity, but the visibility challenges align with findings on algal blooms' effects on water transparency [61–64]. Comparing 2019 and 2024, debris decreased significantly, from 356 to 39 items, suggesting potential improvements in management or environmental conditions that require further investigation.

4.3. Visual Evidence of Turbidity and Algal Growth: Comparison Between 2019 and 2024

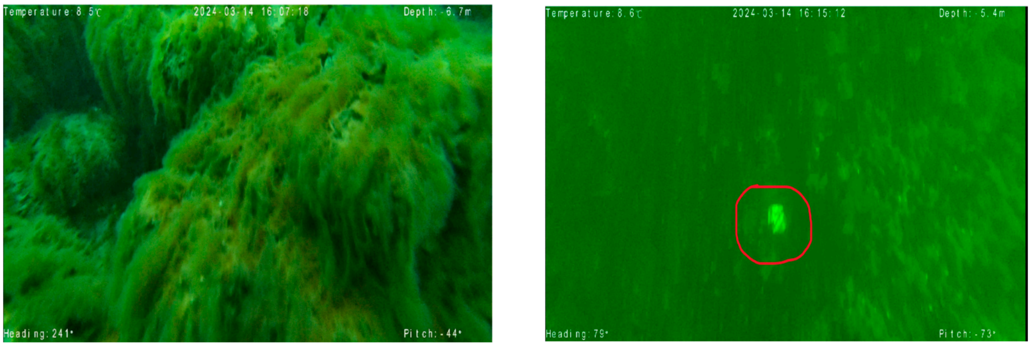
This section presents a visual analysis of water turbidity and algal presence in Lake Como during the survey periods of 2019 and 2024. Screenshots captured from ROV video recordings highlight the differences in water clarity and algal development across various months, providing a clearer understanding of the environmental conditions that impacted debris detection efforts. These visual comparisons aim to support the findings on the influence of algal blooms on underwater visibility. Figure 8 visually represents the clear underwater visibility observed in January and February 2024, where objects were easily identifiable and countable. Both months exhibit similar conditions for object detection, as indicated by the red markers highlighting the debris presence.

(**a**) Image 22 January 2024 represents clear water (**b**) Image 15 February 2024 represents clear water

Figure 8. (**a**) Encircled objects are clearly visible to count, with a clear lake bottom surface free of turbidity from algae, sedimentation, or color (January 2024). (**b**) Encircled objects are clearly visible to count, with a clear lake bottom surface free of turbidity from algae, sedimentation, or color (February 2024).

Figure 9 illustrates the dense algal development observed in March 2024. The algal growth caused slight turbidity and altered the watercolor, significantly reducing visibility. This hindered the ability to detect and count objects on the lakebed, as much of the bottom was largely covered with dense algae. As a result, only a few objects could be identified and counted.

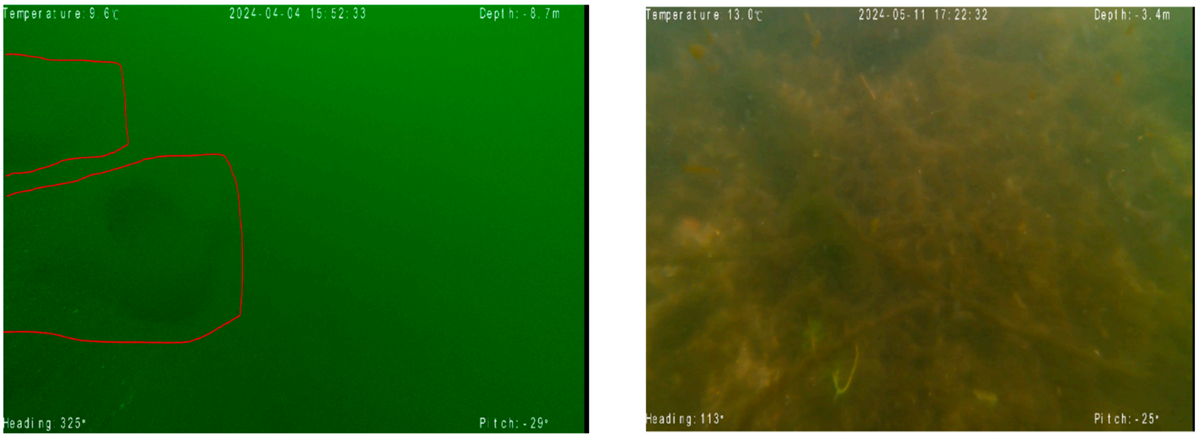
Figure 10 shows that the water in April 2024 was highly turbid due to a phytoplankton algal bloom, which caused cloudiness in the water. Despite the absence of sedimentation, the algal growth and change in watercolor made it difficult to detect objects. Similarly, in May 2024, both algae and sedimentation contributed to high turbidity, further obscuring the visibility of objects on the lakebed.



(**a**) Image 14 March 2024 represents slight turbidity

(**b**) Image 14 March 2024 represents object marked in slight turbid water

Figure 9. (**a**) Dense algal development. (**b**) The encircled object is present in algal development conditions.



(**a**) Image 4 April 2024 represents objects marked in highly turbid water

(**b**) Image 11 May 2024 represents highly turbid water

Figure 10. (**a**) Encircled objects in highly turbid water (April). (**b**) Highly turbid water in May.

Figure 11 shows that while the watercolor in June 2024 was less green compared to previous months, significant sedimentation caused cloudiness, making it difficult to locate objects. The reduced visibility due to sedimentation hindered the identification of debris on the lakebed.

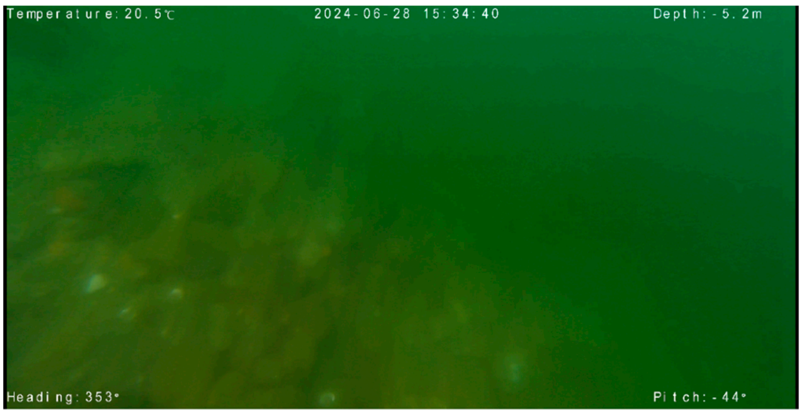


Figure 11. Image 28 June 2024 represents highly turbidity.

Figure 12 shows that in April 2019, the objects were clearly visible with minimal interference from algal development. While sedimentation caused mild turbulence, it did not significantly affect the visibility of the objects. Water turbidity was relatively low during this period.

Figure 12. Image 2 April 2019 represents slight turbidity due to sedimentation.

Figure 13 shows that in May 2019, there was no noticeable color change or algal development. While slight turbidity was observed in some parts of the lake, it did not significantly impact the visibility of the objects. In contrast, June 2019 saw clear water with no turbidity caused by sedimentation or algal development.

(**a**) Image 7 May 2019 represents slightly turbid water

(**b**) Image 6 June 2019 represents clear water

Figure 13. (**a**) The scenario of slight turbidity in May. (**b**) Clear water with a marked object (June).

Figure 14 shows that in August 2019, the water was highly turbid due to sedimentation, which likely limited the ability to count objects as they were partially buried beneath the sediment. In contrast, clear water can be seen in November 2019, with no algal development or sedimentation, making the objects clearly visible.

As the surveys progressed, increased turbidity due to sediment disturbance and biological activity, such as fish movements and camera-induced sediment disturbance, impacted visibility, particularly in the months of August, particularly during the tilted path.

The observed reduction in visible debris, especially large metal objects, could be explained by turbidity and sedimentation effects. During the surveys, larger debris items were often covered by sediment layers, particularly in areas with higher turbidity, making them difficult to detect. Additionally, the camera movement itself likely disturbed sediments, causing further visibility challenges. The reduction in the number of visible debris items could potentially be attributed to cleaning activities in the study area, though no such activities were officially documented during the survey period. Alternatively, sedimentation and turbidity are likely to have played a more prominent role in obscuring debris, as evidenced by video observations showing objects becoming progressively buried under sediment layers. Given the lack of information about potential garbage collection efforts, the role of natural processes in debris dynamics remains the primary focus of this study. Seasonal variations, particularly during intense algal growth in summer, can greatly influence the visibility and distribution of underwater debris in Lake Como. Algae can transport debris, such as plastics and metals, from the water column to the lakebed, further complicating debris detection efforts. Additionally, evaporation rates during the warmer months may alter the visibility of submerged waste [65]. These climatic patterns underscore the challenges of monitoring debris, as both stratification and isothermy can obscure the detection of debris by ROVs.

(**a**) Image 20 August 2019 represents highly turbid water due to sedimentation

(**b**) Image 6 November 2019 represents clear water

Figure 14. (**a**) Marked objects in highly turbid water (August). (**b**) Clearly visible object (November).

In temperate lacustrine ecosystems, winter climatic fluctuations significantly affect nutrient enrichment and algal growth, contributing to more intense algal blooms in the summer. As observed in the 2024 survey, these blooms can significantly reduce the visibility of underwater debris, making it more difficult to accurately assess debris accumulation in the lake [6]. This highlights the importance of understanding seasonal climate influences on freshwater monitoring efforts, especially in regions with dynamic thermal and hydrodynamic patterns.

4.4. Study Limitations

This study encountered several limitations that impacted the findings and interpretation of results. First, the visibility of debris was significantly affected by environmental conditions, particularly dense algal blooms in 2024, which reduced the accuracy of visual detection. Second, sedimentation played a role in partially or fully burying debris items, complicating their identification and classification over time. Third, the quality of ROV video footage varied between surveys due to differences in turbidity, lighting conditions, and equipment performance, limiting the precision of observations, particularly for smaller debris. Additionally, the study did not include quantitative measurements of turbidity, sedimentation rates, or algal density, which could have provided more robust insights into the factors affecting debris detection. The lack of detailed ROV movement tracking, such as the exact distance travel or areas covered during each survey, posed challenges for comparing debris accumulation across different months and years. Despite these limitations, the study underscores the need for improved methodologies, such as integrating advanced imaging systems, quantitative turbidity analysis, and precise route tracking, to enhance the reliability of underwater debris monitoring in freshwater environments. Another challenge in this study was using ROV video footage to identify and count heterogeneous plastic objects, such as candy wrappers and plastic chairs. While larger items, such as plastic chairs, were easily identified due to their size and shape, smaller objects, such as candy wrappers, were sometimes difficult to detect, especially when they were hidden under larger objects or sediments. The moderate resolution of the video footage impacted the visibility of smaller debris. For instance, candy wrappers could be hidden beneath larger objects or covered by sediment, which made them harder to spot. However, we made every effort to count all visible debris and note their absence when they could not be identified. While the route length was estimated at approximately 50 m based on time and speed, the absence of a geolocation system may introduce some variability. This limitation was mitigated by maintaining a consistent time of operation for each survey, ensuring comparable coverage across months and years. In this study, debris was categorized based on material type (plastic, metal, etc.), which provided valuable insights into the composition of debris in Lake Como. However, a limitation of this approach was the lack of measurement of debris size. Size differentiation is important for understanding the full environmental impact of different types of debris. For instance, small plastic particles (microplastics) may pose different ecological risks than larger items, such as plastic bottles or metal cans. Although categorizing by material type was informative, future research would benefit from incorporating size measurements, which would enhance the understanding of how debris size and material interact to affect ecosystems. Such additions could improve the accuracy of debris monitoring and offer better guidance for management strategies to reduce the environmental impact of debris.

Despite these challenges, the methodology used provided valuable insights into the presence and distribution of debris. It is important to acknowledge that the limitations of video quality may have led to an undercount of smaller objects, but this was the best available data for the study period as shown in Table 1.

Table 1. List of limitations, impacts, and recommendations from this study.

Limitation	Impact	Recommendation
Algal Blooms (2024)	Confounded ROV assessments, leading to underestimation of debris levels	Employ sonar detection systems for improved accuracy [34].
Undetectable Suspended Debris	Smaller debris may be suspended, affecting overall assessment	Investigate methods for detecting suspended debris [35].
Visual Count Methodology	Lacked differentiation between debris sizes and types, limiting environmental impact conclusions	Classify debris by size and type in future studies [36].

4.5. Future Research Directions

Future research should focus on enhancing ROV technology to better address the visibility challenges identified in this study, particularly those caused by environmental factors such as algal blooms and turbidity. The development of advanced imaging and sensing technologies that mitigate light attenuation could improve the quality of video footage captured by ROVs in turbid waters. Innovations like low-light cameras or multi-spectral imaging could greatly enhance debris detection in conditions where traditional ROV cameras struggle. Moreover, integrating ROV data with remote sensing tools, such as satellite imagery and autonomous underwater vehicles (AUVs), would provide broader spatial coverage and deeper insights into the distribution of debris, particularly in remote or difficult-to-access areas [53,66,67].

Additionally, combining sonar technology with ROVs could improve debris assessments in turbid conditions, where sonar systems, which do not rely on light, can map the underwater environment more effectively and detect debris buried or obscured by sediment [55,68]. To further enrich debris detection and monitoring, integrating water quality sampling could provide valuable data on factors such as algae concentrations and sedimentation rates.

5. Conclusions

This study provides valuable insights into the aquatic debris present in Lake Como by comparing debris counts and types between 2019 and 2024 using remotely operated vehicle (ROV) technology. The significance of this research lies in its ability to highlight the dynamic changes in debris composition and the challenges of monitoring aquatic environments over time. Our findings show a noticeable reduction in both plastic and metal debris in 2024 compared to 2019, suggesting potential improvements in waste management, natural sedimentation processes, or changes in environmental conditions. In 2019, metal items like soda cans and plastic debris such as candy wrappers were the most common, with counts peaking in the spring months (April and May). In contrast, 2024 saw a marked decrease in these items, with a total of only 39 debris items recorded during the same period. This change underscores a possible trend toward cleaner aquatic conditions, though it is important to note that the environmental factors, such as algal blooms and increased water turbidity in 2024, significantly impacted visibility. These conditions made it difficult to detect smaller or submerged debris, potentially leading to undercounts, particularly in March and April 2024.

Despite the visual differences, statistical analysis using a paired *t*-test showed no statistically significant difference between debris counts in 2019 and 2024 ($p = 0.061$). This lack of statistical significance suggests that while there were clear visual reductions in debris, the ability to accurately detect debris in 2024 was hindered by challenging environmental conditions. This finding highlights the complexity of debris monitoring and the need to account for such factors when interpreting the results. The study contributes to the field by emphasizing the critical role of environmental factors, such as turbidity, sedimentation, and algal blooms, in influencing the effectiveness of debris detection methods, particularly when using ROVs. The results indicate the need for continuous improvement in monitoring techniques to overcome these challenges, including the integration of complementary technologies, such as sonar, to enhance debris detection in low-visibility conditions. In conclusion, this research provides important insights into the debris dynamics of Lake Como and stresses the necessity for ongoing monitoring of freshwater systems to track the trends in aquatic pollution. Although the study did not find statistically significant differences between the two years, the observed reduction in debris points toward positive environmental changes and improved waste management. Continued research with enhanced methodologies will be crucial for addressing the challenges of aquatic debris and guiding effective conservation strategies in freshwater ecosystems.

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