Geospatial Analysis of Flood Impacts on Surface Water Quality Using Google Earth Engine: A case study in Feni, Bangladesh

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Statement of Approval

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Declaration

It is hereby declared that this thesis titled "**Geospatial Analysis of Flood Impacts on Surface Water Quality Using Google Earth Engine: A case study in Feni Bangladesh**" or any part of it has not been submitted elsewhere.

It is also declared that, this book contains no materials previously published or written by any other person, except where due reference has been added in the text.

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Abstract

This research investigates the impact of flooding on surface water quality in Feni, Bangladesh, through a geospatial analysis using Google Earth Engine (GEE). Flooding events have a significant effect on water quality by increasing turbidity and altering nutrient concentrations, particularly chlorophyll levels. This study utilizes satellite data from Sentinel-1 and Sentinel-2 to monitor changes in turbidity and chlorophyll-a concentration before and after the flood. The Normalized Difference Turbidity Index (NDTI) and Normalized Difference Chlorophyll Index (NDCI) were employed to assess water quality. The results show a notable increase in turbidity following the flood, likely due to suspended sediments, and a reduction in chlorophyll concentration, suggesting disruption to aquatic ecosystems. The flood mapping process revealed that the eastern region of Feni remained waterlogged even a week after the peak of the flood event, indicating slow drainage and prolonged waterlogging. This research highlights the effectiveness of remote sensing for large-scale, real-time monitoring of water quality during flood events, especially in areas that are difficult to access or lack ground-based monitoring infrastructure. The findings suggest that the integration of GEE with satellite data can provide critical insights into flood-related water quality changes and contribute to improved flood management and water resource planning.

Keywords: Remote Sensing, Google Earth Engine, Flood Mapping, Surface Water Quality, NDCI, NDTI

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Chapter 1: Introduction

1.1 Background of the study

In recent decades, the ability to monitor and manage environmental changes has become more crucial than ever, especially with growing concerns about climate change, urbanization, and natural disasters. Understanding the dynamics of environmental processes, particularly those related to water resources, has gained significant attention as our planet experiences rapid changes. Traditional methods of environmental monitoring are increasingly being supplemented or replaced by innovative technologies that provide more timely, accurate, and comprehensive data(Manfreda et al., 2018). Remote Sensing and Geospatial analysis have become invaluable tools in environmental monitoring, offering an unprecedented ability to capture and analyze large-scale spatial and temporal data(Li et al., 2020). These technologies have proven to be particularly promising in assessing environmental phenomena, such as land use changes, forest cover loss, and water quality degradation. By utilizing satellite imagery and sophisticated analytical techniques, Remote Sensing allows for the continuous, real-time monitoring of environmental conditions across vast areas(Li et al., 2020). This capability is essential for understanding dynamic environmental processes, especially in areas that are difficult to access or experience frequent changes due to natural disasters.

Bangladesh, a country located in the South Asian region, has long been known for its vulnerability to flooding. The country is situated in the delta of three major rivers—the Ganges, Brahmaputra, and Meghna—which makes it highly susceptible to seasonal floods, tropical cyclones, and storm surges(Dewan et al., 2003). In recent years, however, the frequency and severity of these floods have significantly increased due to climate change, urbanization, and deforestation. This escalation poses serious threats to the country's infrastructure, agriculture, and most notably, its water resources. Surface water quality, in particular, is severely impacted during flood events, as the floodwaters often bring with them a range of pollutants(Zou et al., 2023). These include sedimentation, agricultural runoff containing pesticides and fertilizers, untreated sewage, and industrial waste(van Vliet et al., 2023). These contaminants not only degrade the physical and chemical quality of water but also make it unsafe for drinking, irrigation, and aquatic life, leading to a public health crisis and environmental degradation.

Traditional water quality monitoring techniques, which involve manual sampling and laboratory testing, face substantial limitations, especially during flood events. One of the primary challenges is that floodwaters often make it difficult or even impossible to access water bodies in affected areas, hindering the collection of timely and relevant data. Furthermore, the conventional method of water quality monitoring is resource-intensive, requiring significant manpower, equipment, and time to conduct fieldwork and analyze water samples. The data obtained from these methods are also often limited in both spatial and temporal coverage, making it difficult to capture the full extent of water quality changes across large flood-prone areas. These limitations make it a challenge to manage water resources effectively during flood events and to respond quickly to changes in water quality.(Masse-Dufresne et al., 2021)

The integration of Remote Sensing and Geospatial analysis provides a transformative solution to these challenges. Through satellite imagery, Remote Sensing enables the continuous monitoring of surface water bodies in real-time, even in remote or flood-affected areas that are difficult to access by conventional means(Jaywant & Arif, 2024). By capturing data such as surface temperature, suspended sediments, chlorophyll concentrations, and turbidity, Remote Sensing allows for the identification of water quality indicators that are directly impacted by flooding(Chawla et al., 2020). This data can be analyzed to assess how floods affect water quality over large regions, providing a comprehensive view of water conditions during and after flood events. Additionally, Geospatial analysis enhances the interpretation of these data by providing spatial context, enabling the identification of flood-prone areas, pollution sources, and patterns in water quality changes across geographic regions.

Using Remote Sensing and Geospatial tools not only improves the efficiency and timeliness of water quality monitoring but also aids in better flood management strategies. By providing real-time data on the condition of water bodies, authorities can make informed decisions regarding flood control measures, water treatment, and resource allocation. These technologies also support the development of early warning systems and predictive models that can forecast potential water quality deterioration based on flood patterns. Ultimately, the use of Remote Sensing and Geospatial analysis can enhance disaster preparedness, ensure better management of water resources, and safeguard public health by providing accurate, up-to-date information on surface water quality during flood events. This approach promises to be a valuable tool in mitigating the adverse effects of floods on water resources in Bangladesh and other flood-prone regions around the world.

1.2 Research Gap

Despite the significant advancements in water quality monitoring technologies, there remain substantial gaps in effectively assessing surface water quality during flood events. Traditional methods of water quality monitoring, such as manual sampling and laboratory analysis, are often insufficient in flood-affected areas due to several limitations(Masse-Dufresne et al., 2021). These conventional techniques are not only time-consuming and labor-intensive but also limited in their ability to provide real-time data over large geographic areas. Additionally, the difficulty in accessing flooded regions further hampers the collection of representative water quality samples during such events. As a result, these methods fail to offer a comprehensive, timely, or spatially extensive assessment of water quality during and after floods, leaving crucial gaps in flood management and water resource planning.

In this context, Remote Sensing, particularly through the use of satellite imagery, provides a promising alternative. Remote Sensing technologies can continuously monitor water quality indicators such as turbidity, suspended sediments, chlorophyll concentration, and temperature, all of which are directly affected by flood events(Yang et al., 2022). By leveraging satellite data, Remote Sensing enables the detection of changes in water quality over vast areas, even in regions that are difficult to access due to floodwaters. This capability is critical for timely and accurate assessment of water conditions during floods, providing decision-makers with the information needed to implement effective flood management strategies and mitigate the impacts on water resources.

Google Earth Engine (GEE), a cloud-based geospatial analysis platform, offers an especially powerful tool for addressing the challenges associated with flood-related water quality monitoring. With its vast repository of satellite imagery and robust analytical capabilities, GEE enables the processing and analysis of large volumes of geospatial data in real time. GEE can be used to monitor changes in surface water quality, analyze trends over time, and assess the spatial extent of water quality degradation caused by floods(Z. Chen & Zhao, 2022). The platform’s ability to handle vast datasets efficiently allows for the continuous, real-time monitoring of flood-prone regions, providing valuable insights into how floods affect water bodies and facilitating the development of better flood management strategies. In particular, GEE's integration of satellite data, such as Landsat and Sentinel imagery, allows for detailed and precise analysis of water quality at a scale that is not possible with conventional monitoring methods(Pizani et al., 2020a). This positions GEE as a critical tool in addressing the gaps in flood-related water quality monitoring, offering an innovative and scalable solution for real-time environmental assessment during flood events.

1.3 Research Objective

The primary objective of this research is to utilize Google Earth Engine (GEE) as a tool for monitoring and analyzing changes in water quality, specifically turbidity and chlorophyll-a concentrations, in surface water bodies before and after flood events. The specific objectives are as follows:

1. To assess the changes in turbidity levels in surface water bodies before and after flood events: This objective aims to quantify how turbidity, an important indicator of water quality, is affected by floodwaters. Turbidity will be monitored using the Normalized Difference Turbidity Index (NDTI), which is sensitive to changes in suspended sediments and turbidity. The study will utilize satellite imagery in GEE to track turbidity levels in flood-prone regions and identify fluctuations before and after flood events.

2. To monitor the variations in chlorophyll-a concentration in surface waters due to flood-induced changes: Chlorophyll-a concentration is a key parameter for understanding water quality, as it indicates the presence of phytoplankton and the overall health of the aquatic ecosystem. This objective will focus on detecting changes in chlorophyll-a levels using the Normalized Difference Chlorophyll Index (NDCI), which is specifically designed to estimate chlorophyll-a concentrations in water bodies. Satellite data processed through GEE will be used to observe how floods impact these concentrations in the affected areas.

3. To evaluate the potential of GEE as an efficient tool for real-time monitoring and assessment of water quality during flood events: This objective focuses on demonstrating how GEE can be leveraged to monitor water quality parameters in near real-time.

1.4 Limitations

This research was subjected to several limitations, primarily associated with the use of satellite remote sensing data for monitoring surface water quality during flood events. One significant constraint was the unavailability of cloud-free satellite imagery during the flooding period. Flood events are typically accompanied by persistent cloud cover, which impedes the acquisition of clear optical images. This limitation affected the temporal continuity of the dataset, particularly during critical periods when water quality conditions are most likely to change rapidly. As a result, it was challenging to capture and analyze the immediate impact of flooding on surface water quality with high temporal precision.

Additionally, the study was limited by the inherent inability of remote sensing techniques to detect optically non-reactive water quality parameters. While satellite-based observations are effective for monitoring optically active substances—such as turbidity, suspended sediments, and chlorophyll-a—they cannot directly measure parameters that do not exhibit a detectable spectral signature, such as pH, BOD, DO, nutrient concentrations (e.g., nitrate, phosphate), heavy metals, or microbial contaminants(Pizani et al., 2020a). In the absence of concurrent in-situ water quality sampling, it was not possible to validate or complement the remotely sensed data with physical measurements. This limitation restricted the scope of the analysis to a subset of water quality indicators, potentially overlooking important physicochemical and biological dynamics during and after the flood event.

Chapter 2: Literature Review

2.1 Definition of the terms

2.1.1 Remote Sensing

Remote sensing is the science of obtaining information about the Earth's surface without direct physical contact, typically through satellite or airborne sensors that detect and measure electromagnetic radiation reflected or emitted by surface features. This technology enables consistent, large-scale, and repeatable observations, making it particularly valuable for environmental monitoring. Satellite imagery, the primary data source in remote sensing, is captured across multiple spectral bands—such as visible, near-infrared (NIR), and shortwave infrared (SWIR)—each sensitive to specific surface properties(NASA, 2025). These bands can be processed individually or in combination to derive biophysical indicators relevant to surface water quality, including turbidity, suspended sediments, and chlorophyll concentration. By utilizing these spectral characteristics, remote sensing provides an effective means to analyze spatial and temporal variations in water bodies(Jaywant & Arif, 2024). In this study, satellite data processed through the Google Earth Engine platform was employed to assess the impact of flooding events on surface water quality, demonstrating the potential of remote sensing for dynamic and scalable water resource monitoring.

2.1.2 Geospatial Analysis

Geospatial analysis refers to the process of gathering, visualizing, and interpreting spatial data to understand patterns, relationships, and trends across geographic spaces. It integrates data with spatial attributes—such as coordinates, elevation, or administrative boundaries—allowing researchers to analyze the spatial distribution and interaction of environmental variables(UMW, 2025). In the context of water quality assessment, geospatial analysis enables the examination of how surface water characteristics vary across regions and over time, particularly in response to external influences such as flooding. By combining satellite-derived indicators with spatial datasets in platforms like Google Earth Engine and GIS software, it is possible to detect changes, identify affected areas, and quantify the extent of impact. This analytical approach enhances the precision and scalability of environmental studies, providing critical insights for effective water resource management and disaster response planning.

2.2 Definition of the Indices

2.2.1 AWEI

The Automated Water Extraction Index (AWEI) is a remote sensing-based index developed to enhance the accuracy of surface water body detection in satellite imagery, particularly in environments where traditional indices struggle due to the presence of shadows, built-up areas, or dark surfaces. Unlike earlier indices such as the Normalized Difference Water Index (NDWI), AWEI incorporates multiple spectral bands and empirically derived coefficients to minimize the misclassification of non-water features that exhibit similar reflectance properties to water. There are two main variants of AWEI: AWEI_sh, which is designed to correct for shadow effects using a combination of green, near-infrared (NIR), and shortwave infrared (SWIR) bands; and AWEI_ns, which is optimized for environments where shadows are not a significant issue. By leveraging the distinct absorption and reflection characteristics of water across the visible and infrared spectrum, AWEI improves the robustness and reliability of water detection, especially in urban and heterogeneous landscapes. This makes it particularly useful for applications such as flood monitoring, wetland mapping, and hydrological modeling. The index has proven effective in a wide range of geographic settings and is widely used in both research and operational environmental monitoring(Feyisa et al., 2014)

2.2.2 NDTI

The Normalized Difference Turbidity Index (NDTI) is a spectral index used to estimate water turbidity levels from multispectral satellite imagery. It is particularly effective in identifying and monitoring suspended sediment concentrations and surface water quality in inland and coastal water bodies. The index is calculated using the red and green bands, following the formula: (Red – Green / Red + Green)(Org & Tripathi). This formulation leverages the spectral response of turbid water, where increased sediment loads typically result in higher reflectance in the red band compared to the green. As turbidity increases, the reflectance difference between these bands becomes more pronounced, allowing NDTI to serve as a proxy for relative turbidity. Higher NDTI values generally indicate more turbid conditions, while lower values are associated with clearer water. Owing to its simplicity and reliance on visible bands, NDTI is especially useful for rapid, large-scale monitoring of water quality using sensors such as Landsat-8, Sentinel-2, and MODIS. It plays a critical role in environmental monitoring, watershed management, and the assessment of anthropogenic impacts on aquatic systems.

2.2.3 NDCI

The Normalized Difference Chlorophyll Index (NDCI) is a spectral index developed to estimate chlorophyll-a concentrations in surface waters using multispectral satellite imagery. It is particularly useful for assessing phytoplankton biomass and monitoring algal blooms in lakes, rivers, and coastal environments. The index is calculated using reflectance values from the red and near-red spectral bands, typically following the formula: NDCI = (NIR − Red) / (NIR + Red)(Org & Tripathi). This formulation exploits the characteristic absorption of chlorophyll-a in the red band and its reflectance in the red-edge region, making it sensitive to variations in algal concentration. As chlorophyll levels increase, the reflectance difference between these bands becomes more pronounced, resulting in higher NDCI values. The index has proven effective for use with sensors like Sentinel-2 MSI, which provides a dedicated red-edge band, enhancing the precision of chlorophyll detection. NDCI is widely employed in water quality monitoring, eutrophication assessment, and the early detection of harmful algal blooms. Its simplicity, sensitivity to biological activity, and compatibility with freely available satellite data make it a valuable tool for environmental research and aquatic ecosystem management.

2.3 Remote Sensing for Water Quality Monitoring

The comparative analysis of the various studies on remote sensing for water quality monitoring reveals both commonalities and notable distinctions in methodologies, applications, and findings. These studies illustrate the growing potential of remote sensing technologies in addressing water quality issues, such as turbidity, chlorophyll-a, and other key water parameters. However, there are critical differences in the approaches used by the authors, as well as inherent limitations within the various models.

One prominent feature shared by several studies is the application of Landsat 8 imagery for water quality monitoring. For instance, Sharaf El Din & Zhang's study on the estimation of optical and non-optical water quality parameters using Landsat 8 provides robust results with an R^2 value greater than 0.85 for turbidity and dissolved oxygen (DO) estimation. Similarly, González-Márquez et al., (2018) employed Landsat 8 images to model water quality parameters like total suspended solids (TSS) and turbidity in Playa Colorada Bay. The findings in both studies highlight the accuracy of optical parameters, particularly those that interact with satellite sensors, like turbidity and TSS. While these studies confirm the utility of Landsat 8 in large-scale water quality monitoring, they also point out the challenge of capturing nonlinear relationships between optical and non-optical parameters, which complicates the modeling of water quality indicators like biochemical oxygen demand (BOD) and chemical oxygen demand (COD). To address this, Sharaf El Din & Zhang suggest that future research should incorporate artificial neural networks to better capture these nonlinear dynamics.

The effectiveness of Sentinel-2 imagery in comparison to Landsat 8 is also a recurrent theme. Pizani et al. (2020) found that Sentinel-2 MSI outperformed Landsat 8 OLI for parameters like chlorophyll-a and turbidity, particularly in the context of the Três Marias Reservoir in Brazil. This aligns with the findings of the study by Caballero et al. (2019), which demonstrated Sentinel-2's superiority in detecting harmful algal blooms (HABs) due to its higher spatial and temporal resolution compared to Landsat 8. However, as with Landsat 8, the Sentinel-2 imagery comes with challenges. In the case of Caballero et al. (2019), the sun glint effect and the spatial resolution limitations of Sentinel-3 were identified as factors that could degrade the quality of satellite-derived data for small HAB detection. Similarly, Pizani et al. (2020) mentioned that discrepancies between field sampling times and satellite overpasses made temperature estimation using Sentinel-2 challenging.

Despite the promise of remote sensing, several studies acknowledge the limitations in temporal and spatial resolution. The study by Pereira et al. (2020) on water pH estimation in the Pantanal wetland region using Landsat data highlights how atmospheric correction, cloud coverage, and inconsistent field sample collection can skew results. Similarly, studies on chlorophyll-a concentration estimation, like that of Barraza-Moraga et al. (2022) in Lanalhue Lake, identified the seasonal variation in satellite data performance, with some models performing better in certain seasons than others. These findings stress the importance of continuous model calibration and validation, especially when working with remote sensing data that is subject to seasonal or environmental variations.

In terms of methodological diversity, a notable strength lies in the incorporation of machine learning and regression techniques. For instance, L. Chen et al. (2025) reviewed various inversion models, including machine learning approaches like XGBoost and deep neural networks (DNN), which were found to enhance the estimation of water quality parameters. However, the study also highlighted the ongoing challenges related to atmospheric interference and model generalization across different regions. In a similar vein, the study by (Akbarnejad Nesheli et al., 2024) employed Google Earth Engine (GEE) and regression models to predict cyanobacteria concentrations, showcasing the power of cloud-based solutions and automated tools for large-scale environmental monitoring. However, they also pointed to cloud contamination and the limited scope of in situ data as constraints.

In conclusion, the studies reviewed reveal that remote sensing technologies, especially Landsat and Sentinel satellites, offer significant advantages over traditional water quality monitoring methods, including broader spatial and temporal coverage and cost-effectiveness. However, challenges remain, particularly in terms of model accuracy, seasonal variations, atmospheric interference, and the complexity of predicting non-optical parameters. The integration of machine learning and artificial intelligence, as suggested in several studies, holds promise for improving model performance and expanding the applicability of remote sensing in water quality monitoring. Future research should focus on refining atmospheric correction techniques, enhancing temporal and spatial resolution, and incorporating more diverse data sources to overcome the limitations observed in the current studies.

2.4 Use of Google Earth Engine in Water Quality Monitoring

The comparative analysis of the various studies on use of Google Earth Engine for water quality monitoring showcase diverse studies on environmental monitoring, emphasizes the increasing reliance on remote sensing for continuous, large-scale monitoring of natural environments, addressing critical issues like water pollution, ecological degradation, and resource management. The integration of satellite imagery, especially from Sentinel-2 and Landsat, and the use of GEE's cloud-computing capabilities, emerge as a central theme across the works.

The work by Xiong et al. (2021) offers a substantial contribution in assessing spatial-temporal ecological changes in the Erhai Lake Basin, China. The use of Remote Sensing-based Ecological Index (RSEI) and Google Earth Engine (GEE) for large-scale ecological assessments is a notable strength, as it provides timely data crucial for sustainable development policies. However, its reliance on only a few ecological factors limits the breadth of ecological analysis. Future studies could integrate socio-economic data to enhance the understanding of land-use impacts on ecological health. A similar approach can be seen in the research by Wang et al. (2020), which combines multi-sensor satellite observations to monitor harmful algal blooms (HABs). This approach benefits from using multiple satellite sensors to improve prediction accuracy but suffers from issues like sensor calibration and temporal resolution mismatches, issues also highlighted in the Xiong's study.

In the realm of water quality monitoring, several studies demonstrate the power of spectral indices like NDTI, NDCI, and TSS in assessing parameters such as turbidity and chlorophyll concentrations. Das et al. (2024)'s work in Chilika Lake and Kwong et al. (2022)'s study in Hong Kong use GEE in similar ways to develop efficient, cost-effective monitoring methods. Both studies face limitations related to the spatial resolution of satellite data. Das's work also acknowledges the absence of depth-related variations in water quality, a challenge that could be addressed by integrating higher-resolution imagery or advanced machine learning models, as suggested in Kwong's research on marine water quality monitoring.

The research conducted by Kolli & Chinnasamy (2024), focusing on turbidity in the Godavari River, faces similar challenges with spatial resolution. However, their use of Sentinel-2's red-edge band proves effective for estimating turbidity, and their method is a good example of how remote sensing data can be utilized for cost-effective water quality assessments. The focus on a specific region also limits the generalizability of the results, as seen in other studies like that of Sherjah et al. (2023), who also focus on specific water bodies for their TSI estimations.

The research by Kislik et al. (2022) on algal bloom detection in small reservoirs also stands out for its innovation in applying Sentinel-2 imagery to monitor algal blooms, an area often overlooked in remote sensing studies. The study's use of NDCI as the most effective spectral index is a valuable insight. However, the temporal mismatch between satellite and in-situ data is a common issue in remote sensing research, as highlighted in other studies such as Wang's and Kolli & Chinnasamy's works. Future research could address this by integrating hyperspectral satellite data for more accurate species identification, as suggested in Kislik's work.

Moreover, Jin et al. (2023)'s work on surface water mapping in Zhejiang Province underscores the value of long-term satellite data for large-scale water resource management. However, errors introduced during data synthesis and challenges in detecting smaller water bodies remain a concern, as noted in other studies. This challenge is particularly apparent in Jin's study, where detecting smaller water bodies could be improved with more advanced machine learning techniques or higher-resolution data, as also suggested for other studies.

Overall, while each study highlights the growing capability of remote sensing technologies, the common limitations across these studies—such as spatial resolution, temporal resolution, data integration, and model accuracy—underline the need for future research to explore advanced algorithms, higher-resolution satellite imagery, and multi-sensor data integration. Each paper provides valuable insights into regional water quality and ecological health assessments, but there is room for further refinement in methodologies to improve monitoring accuracy, scalability, and applicability to different environmental contexts.

Chapter 3: Methodology

3.1 Methodology Diagram

The methodology displayed in Figure 1 for this work outlines a systematic approach for flood mapping and water detection and quality analysis using remote sensing data from Sentinel 1 and Sentinel 2 satellites. The process begins with the selection of the study area, followed by Sentinel 1 radar and Sentinel 2 optical image collection. Flood mapping and detection of permanent water are then performed. The next steps involve water source selection, extracting water pixels, and image filtration and cleaning to refine the data. Index calculation and data collection are carried out for further analysis. The results are then analyzed to draw conclusions on change of water quality and flood dynamics in the region.

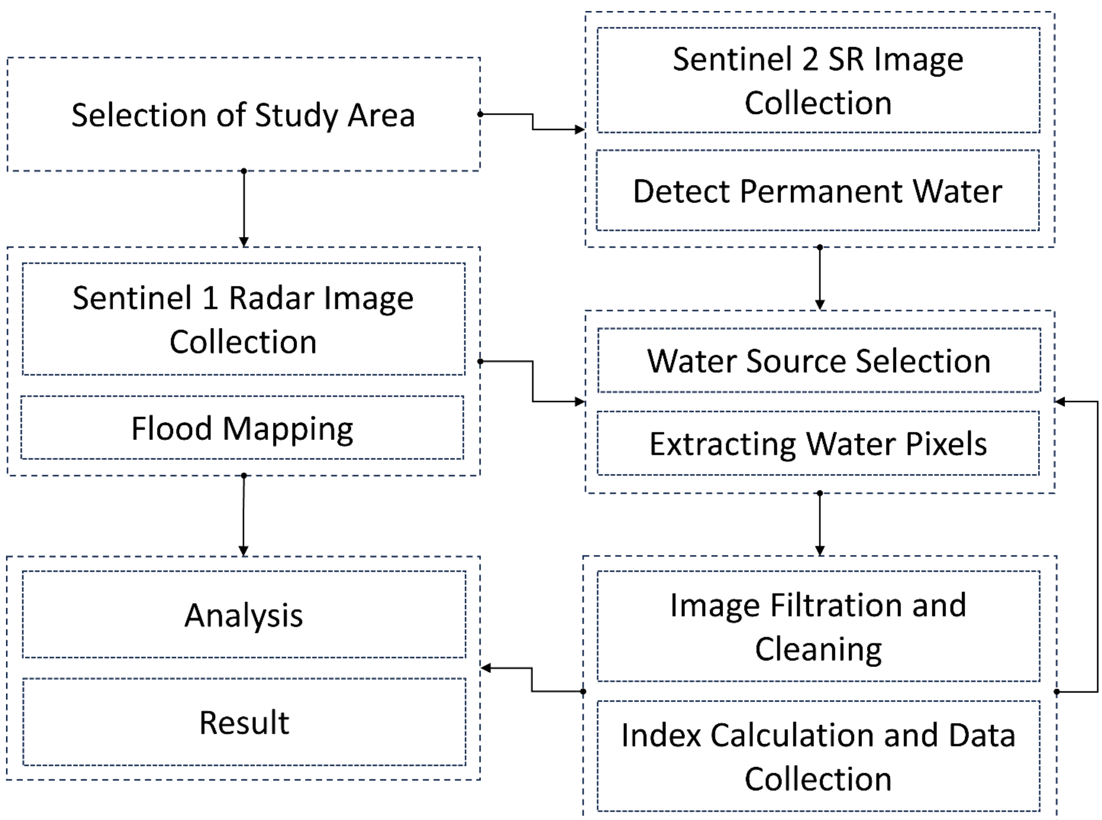

Figure 1: Methodology

3.2 Selection of Region of Interest

To conduct this study, the Feni district of southern Bangladesh, which was affected by a out of the blue flash flood in August 2024 in it's history of hundred years that crippled life for the people of the region. To select the region, the second level administrative boundary dataset of Global Administrative Unit Layers by Food and Agriculture Organization of United Nations (FAO GAUL 2015) was collected and filtered to define the region of interest for this study. **A1** shows the required Earth Engine code to carry out this operation. The dataset was collected under the variable name 'admin' from the Googles Database and then filtered for it's property 'ADM2_NAME' to select the region of interest 'Feni' and stored under the variable name 'roi'.

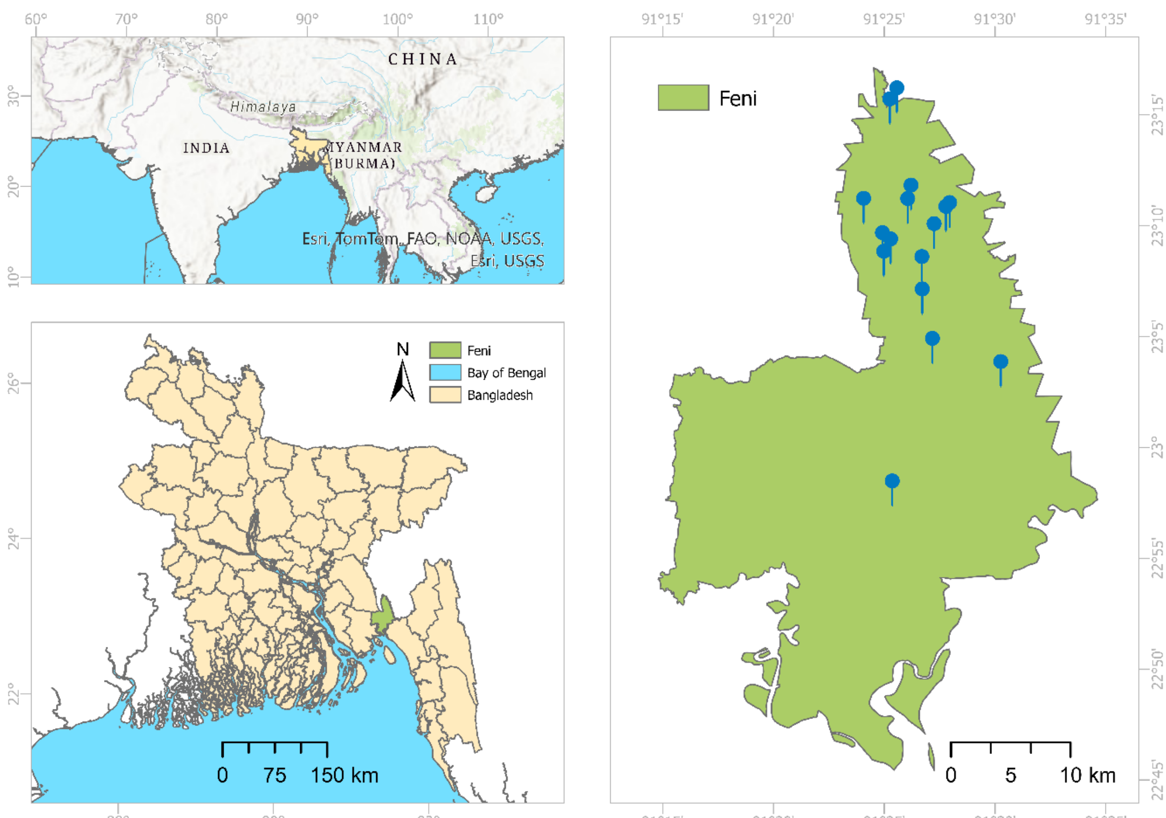

Figure 2: Study Region

3.3 Flood Mapping

To identify the areas affected by flood, three consecutive flood mapping was done for the region selected for the study. One visualizing the condition of the region before the flood, one while the flood affected the area and one after one week of the flood event. **A2** shows the required Earth Engine code for the flood mapping. The Flood Mapping was done using the Sentinel-1 SAR GRD radar image dataset which is available in the earth engine repository. The period for the before flood, during flood, and after flood were selected based on flood update in local news portals. The satellite image was collected and filtered for the region and required band 'VV' was selected to conduct the flood mapping. Then the collected images were composed using the mosaic function, smoothened for false pixels and exported using earth engine.

3.4 Detection of Permanent Water

The permanent surface water sources were detected and mapped using the AWEI equation. The equation for AWEI is used is: [4 * (GREEN - SWIR2) - (0.25 * NIR + 2.75 * SWIR1)]. **A3** shows the required code for this action. It was done using the Sentinel 2A Surface Reflectance Harmonized dataset which is available in earth engine repository. The dataset is collected and filtered for the study region, one year time period and minimum cloud coverage of 10%. The filtered images were compiled next using 'median' operation and the AWEI function was run on the image to detect permanent water bodies. Then it is masked using self-masking option to clean out the non-water portion from the map.

3.5 Selection of Water Source for the Study

By comparing the flood mappings and detected permanent water bodies, the water source that possibly affected by the flood is marked out using the geometry marking tools in the earth engine.

Then the permanent water portion was cleaned for false pixels and converted to vector file for further use in the study. **A5** shows the required code for this operation.

3.6 Image Collection, Filtration and Cleaning

The collected Sentinel 2A Harmonized Surface Reflectance dataset is filtered further for our observation period, that is taken from May of 2024 to October of 2024, and for the selected study source using the vector file and the available images were collected under 'filtered' variable. The image collection was cleaned, using the script shown in **A4**, to remove any clouds in order to avoid the error in analysis due to cloud interference with the data. Standard Cloud masking procedure 'Cloud Score Plus' proposed by the Earth Engine developers is used for this operation.

3.7 Check for Data Availability and Index Calculation and Visualization

The calculation of the indices 'NDTI' and 'NDCI' were done using the standard normalized difference formula derived for these indices. The function script shown in **A6** was run on the filtered and cleaned image collection and the calculated value of the indices was added as bands 'ndti' and 'ndci' to the images. Appendix B shows the earth engine code for this operation. These values of the indices were visualized in a combined line graph, projecting the month in horizontal axis and index values in vertical axis. This operation was conducted over the possibly affected surface water bodies and checked for the availability of data before and after the flood. At the end the graphs and the data table was collected from the earth engine.

3.8 Data Collection and Analysis

Standard earth engine export function shown in **A7** is used to export the calculated data and then analyzed to draw conclusion on the change behavior of Turbidity and Chlorophyll of water after getting affected by flood.

Chapter 4: Result & Discussion

4.1 Flood Mapping

The flood extent mapping using sentinel 1 satellite radar imagery in Google Earth Engine revealed significant spatial changes in surface water distribution in Feni, Bangladesh. Water extent increased sharply during the flood compared to pre-flood conditions, indicating widespread inundation across low-lying and agricultural areas. The flood maps show that the eastern region of Feni was the most affected, experiencing the highest extent of flooding during and after the flood event shown in **Figure 4** and **Figure 5**. The eastern region remained waterlogged even one week after the peak flood event, confirming that drainage was slow and surface water did not recede immediately. This pattern is evident from the classified water masks for the three time periods—before, during, and after the flood—which clearly illustrate the persistence of standing water.

Figure 3: Map of the Region Before Flood

Figure 4: Map of the Region During Flood

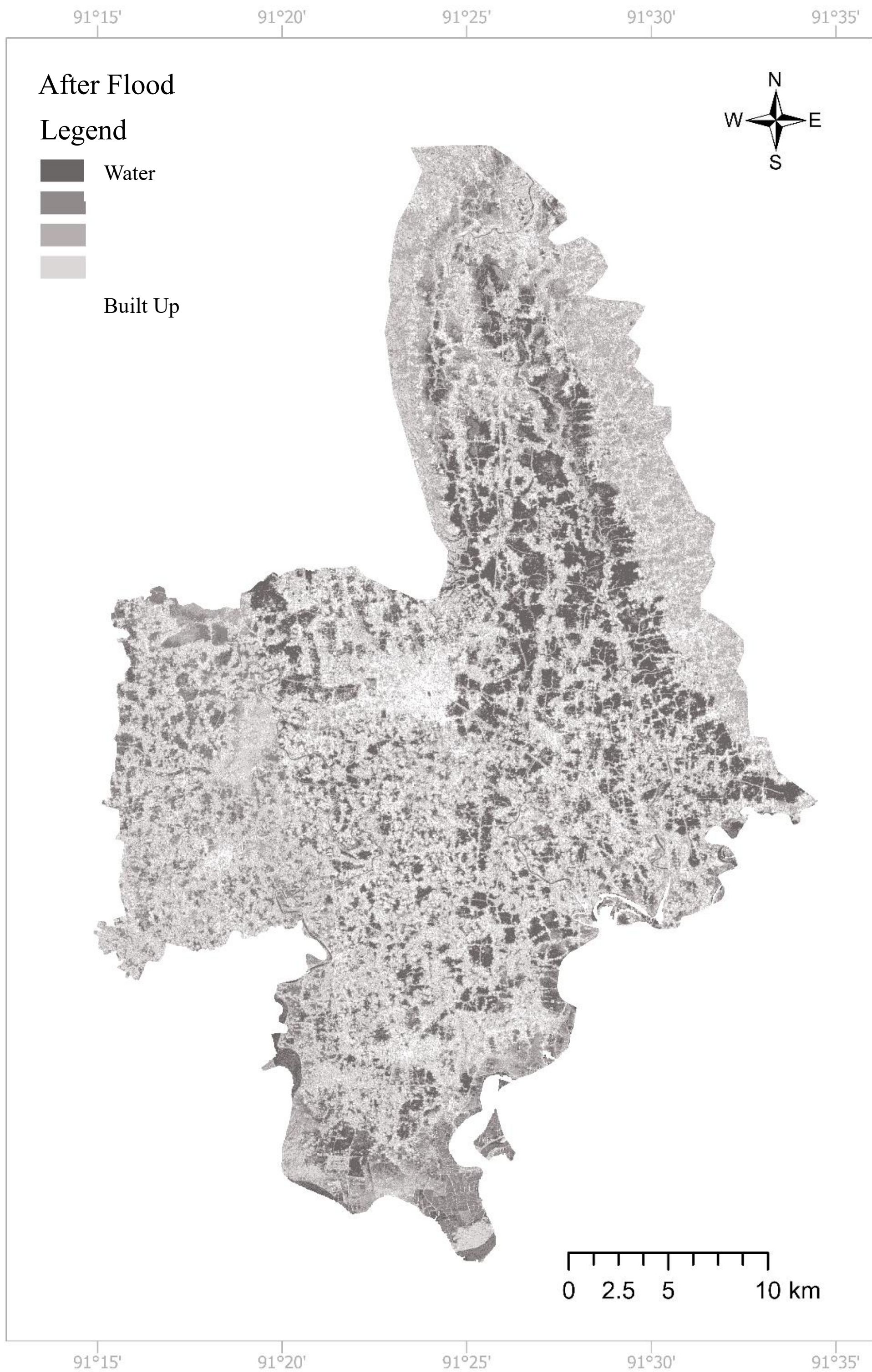

Figure 5: Map of the Region After Flood

4.2 Change Behavior of Quality Parameters

The data for the values of the indices before and after the flood was taken from individual dataset of the sources and compiled into a comprehensive dataset, as shown in **Table 1** and **Table 2**, also visualized in **Figure 6** and **Figure 7**, to better understand how Turbidity and Chlorophyll concentration of water changed with flood. Along with that, individual graphs for each monitored water source shown in Appendix C, consistently shows that NDTI values increased following the flood. This suggests an overall rise in water turbidity, likely due to increased sediment runoff and suspended particles introduced during and after the flood. In contrast, the Normalized Difference Chlorophyll Index (NDCI) decreased following the flood. This drop may be due to the dilution of nutrient concentrations or disturbance of aquatic ecosystems that temporarily reduced chlorophyll levels. Together, these trends indicate that the flood had a measurable impact on surface water quality, increasing turbidity while reducing chlorophyll concentration.

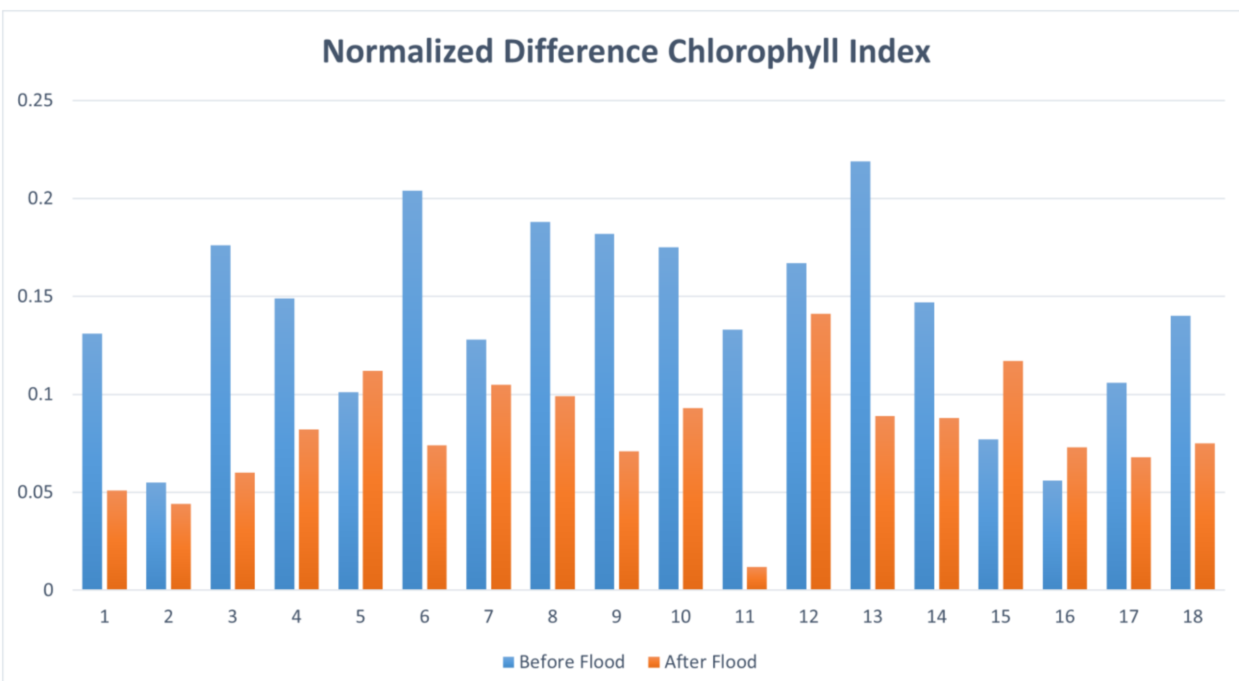

Figure 6: Before and After Flood Value of NDCI

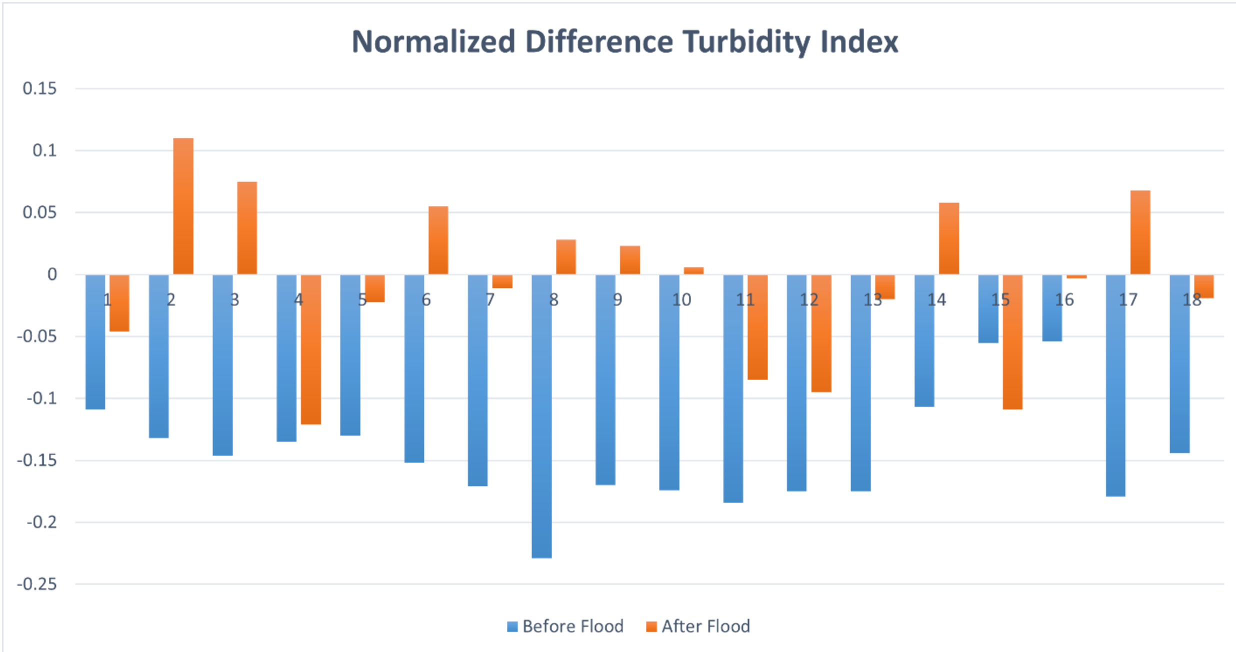

Figure 7: Before and After Flood Value of NDTI

These findings are consistent with flood-related disturbances reported in similar low-lying and riverine environments, where erosion, sediment input, and hydrological changes can significantly alter water quality parameters. The opposing behavior of NDTI and NDCI also highlights the complexity of flood impacts, where increased sediment can suppress light penetration and phytoplankton growth despite possible nutrient inputs. Analyzing the values of NDTI and NDCI post flood it was observed that, in most cases, as the floodwater decreases and stabilizes the turbidity decreases and chlorophyll-a concentration in the water increases, also found in the past studies shown in **Table 3.** Though in some cases the chlorophyll concentration increases with increase of turbidity for various reasons. These results suggest that remote sensing indices such as NDTI and NDCI can serve as reliable tools for rapid post-flood water quality assessments, especially in data-scarce regions.

Chapter 5: Conclusion

This study used Google Earth Engine to analyze the environmental impacts of flooding in Feni, Bangladesh, focusing on both flood extent and surface water quality. The flood mapping results revealed a sharp increase in water coverage during the flood, with large areas—especially in the eastern region—remaining inundated even one week after the peak event. This indicates slow drainage and prolonged waterlogging in vulnerable zones.

The analysis of water quality using remote sensing indices further showed that flood events significantly altered surface water conditions. NDTI values increased after the flood, reflecting higher turbidity due to sediment and runoff. In contrast, NDCI values decreased, suggesting reduced chlorophyll concentration, possibly due to ecosystem disturbance or dilution effects. These combined results indicate a clear degradation in water quality following the flood.

While the study effectively demonstrates the power of satellite-based indices and cloud computing tools in flood impact assessment, some limitations must be noted. One of the main challenges encountered was the difficulty in obtaining cloud-free satellite images, which can obscure flood mapping and water quality analysis, especially during the rainy season. Additionally, satellite images cannot be used non-optically active parameters, such as dissolved organic matter or specific pollutants, which may also be crucial for a comprehensive understanding of water quality.

Overall, the findings highlight the usefulness of remote sensing for large-scale, timely flood monitoring and water quality analysis, particularly in regions with limited ground-based data. However, complementary methods, such as in-situ measurements and advanced sensor technologies, would be necessary for more accurate and comprehensive assessments. The results emphasize the need for continued monitoring and targeted recovery strategies, particularly in flood-prone areas like eastern Feni.

Chapter 6: Future Prospect

Though this study demonstrates the value of remote sensing in monitoring optically active parameters such as turbidity and chlorophyll-a during flood events, it is limited in its ability to capture optically non-active water quality parameters, such as dissolved oxygen (DO), biochemical oxygen demand (BOD), pH, heavy metals, and other pollutants that play a significant role in water quality assessment. These parameters cannot be detected directly using satellite-based optical indices like NDTI and NDCI, which are sensitive to visible and near-infrared light reflected by suspended particles and chlorophyll.

To address this limitation, future research should focus on integrating in-situ measurements with remote sensing data to establish robust relationships between optically active and non-active parameters. In-situ data collection during flood events, such as sampling for chemical contaminants, could be used to validate and calibrate remote sensing models, enabling more comprehensive water quality assessments. By correlating satellite-derived indices with ground-based measurements, it will be possible to expand the scope of remote sensing to include a broader range of water quality indicators. Additionally, combining the strengths of remote sensing and in-situ data will enhance flood management strategies by providing real-time insights into both physical (turbidity, suspended sediments) and chemical (nutrient concentrations, heavy metals) water quality parameters. This will allow for a more accurate assessment of flood-induced contamination and its effects on aquatic ecosystems and public health.

Future work should also explore the development of advanced sensor technologies, such as portable water quality sensors or autonomous sampling systems, to complement satellite data. These technologies could offer continuous, localized measurements of non-optical parameters, which could be integrated into larger remote sensing datasets for more precise monitoring.

Appendix

Appendix A: GEE Scripts

```
var admin = ee.FeatureCollection("FAO/GAUL/2015/level2")
var roi = admin.filter(ee.Filter.eq('ADM2_NAME', 'Feni'))
```

A1: Script to select region of interest

```
var s1 = ee.ImageCollection("COPERNICUS/S1_GRD")
var filtered = s1
.filter(ee.Filter.eq('instrumentMode', 'IW'))
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VV'))
.filter(ee.Filter.listContains('transmitterReceiverPolarisation', 'VH'))
.filter(ee.Filter.eq('orbitProperties_pass', 'ASCENDING'))
.filter(ee.Filter.bounds(roi))
.select('VV')
var before_start = '2024-04-01'
var before_end = '2024-05-01'
var during_start = '2024-08-20'
var during_end = '2024-08-25'
var after_start = '2024-08-26'
var after_end = '2024-08-31'
var beforeCollection = filtered.filter(ee.Filter.date(before_start, before_end))
var duringCollection = filtered.filter(ee.Filter.date(during_start, during_end))
var afterCollection = filtered.filter(ee.Filter.date(after_start, after_end))
var beforeImage = beforeCollection.mosaic().clip(roi)
var duringImage = duringCollection.mosaic().clip(roi)
var afterImage = afterCollection.mosaic().clip(roi)
var beforeSmoothen = beforeImage.focal_median(10,'circle', 'meters')
var duringSmoothen = duringImage.focal_median(10,'circle', 'meters')
var afterSmoothen = afterImage.focal_median(10,'circle', 'meters')
```

A2: Script for flood mapping

```
var s2 = ee.ImageCollection("COPERNICUS/S2_SR_HARMONIZED")
var filteredImage = s2
  .filter(ee.Filter.date('2023-04-01','2024-05-01'))
  .filter(ee.Filter.bounds(roi))
  .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE' , 30));
var compositeImage = filteredImage.median();
var awei = compositeImage.expression(
  '4 * (GREEN - SWIR2) - (0.25 * NIR + 2.75 * SWIR1)', {
    'GREEN': compositeImage.select('B3').multiply(0.0001),
    'SWIR2': compositeImage.select('B12').multiply(0.0001),
    'NIR': compositeImage.select('B8').multiply(0.0001),
    'SWIR1': compositeImage.select('B11').multiply(0.0001)
  }).rename(['awei1']);
var waterBody = awei.gt(0);
```

A3: Script to detect permanent water

```
var csPlus =
ee.ImageCollection('GOOGLE/CLOUD_SCORE_PLUS/V1/S2_HARMONIZED
');
var csPlusBands = csPlus.first().bandNames();
var filteredS2WithCs = filtered.linkCollection(csPlus, csPlusBands);
function maskLowQA(image) {
  var qaBand = 'cs';
  var clearThreshold = 0.5;
  var mask = image.select(qaBand).gte(clearThreshold);
  return image.updateMask(mask);
}
var filteredMasked = filteredS2WithCs.map(maskLowQA);
```

A4: Script for cloud masking to remove cloud

```
var studyArea = geometry1
var water = waterBody.clip(studyArea)
var kernel = ee.Kernel.circle({radius: 1});
var cleaned = water
  .focal_max({kernel: kernel, iterations: 1})
  .focal_min({kernel: kernel, iterations: 1});
var waterSource = cleaned.selfMask().reduceToVectors({
  geometryType: 'polygon',
  reducer: ee.Reducer.countEvery(),
  scale: 10, // Set scale to match Sentinel-2 resolution
  geometry: studyArea, // Specify the region to vectorize
  maxPixels: 1e13});
```

A5: Script to extract water body

```
function addNDTI(image) {
  var ndti = image.normalizedDifference(['B4', 'B3']).rename('NDTI');
  return image.addBands(ndti);
}
var withNdti = filteredMasked.map(addNDTI);


function addNDCI(image) {
var ndci = image.normalizedDifference(['B5', 'B4']).rename(['NDCI']);
  return image.addBands(ndci);
}
var withBands = withNdti.map(addNDCI);
```

A6: Script for NDCI and NDTI calculation

```
var chart = ui.Chart.image.series({
 imageCollection: withBands.select(['NDTI', 'NDCI']),
 region: waterSource,
 reducer: ee.Reducer.mean(),
 scale: 10})
.setOptions({
    lineWidth: 2,
    pointSize: 3,
    title: ‘NDTI and NDCI Graph',
    interpolateNulls: true,
    vAxis: {title: 'Indices'},
    hAxis: {title: '', format: 'MMM-YY'},
    series:{
      0: {color: 'green'},
      1: {color: 'blue'}
    }});
print(chart);
```

A7: Script to generate NDCI and NDTI graph

Appendix B: Tables

Source ID	Before Flood	After Flood
1	0.131	0.051
2	0.055	0.044
3	0.176	0.06
4	0.149	0.082
5	0.101	0.112
6	0.204	0.074
7	0.128	0.105
8	0.188	0.099
9	0.182	0.071
10	0.175	0.093
11	0.133	0.012
12	0.167	0.141
13	0.219	0.089
14	0.147	0.088
15	0.077	0.117
16	0.056	0.073
17	0.106	0.068
18	0.14	0.075

Table 1: Variation of NDCI

Source ID	Before Flood	After Flood
1	-0.109	-0.046
2	-0.132	0.11
3	-0.146	0.075
4	-0.135	-0.121
5	-0.13	-0.022
6	-0.152	0.055
7	-0.171	-0.011
8	-0.229	0.028
9	-0.17	0.023
10	-0.174	0.006
11	-0.184	-0.085
12	-0.175	-0.095
13	-0.175	-0.02
14	-0.107	0.058
15	-0.055	-0.109
16	-0.054	-0.003
17	-0.179	0.068
18	-0.144	-0.019

Table 2: Variation of NDTI

Study	Findings
(Yuan et al., 2022)	- Turbidity and pH were the most important predictors for Chl-a variability (turbidity importance: 52.86%). - High turbidity reduced light availability, leading to lower Chl-a concentration due to inhibited algal productivity
(Salem & Mageed, 2021)	- Turbidity increased significantly after flood: from 1.70–10.10 NTU (before flood) to 1.99–23.00 NTU (after flood). - Chl-a increased in most locations after flood (except lake entrance), indicating that moderate post-flood turbidity did not inhibit algal growth significantly in this context. - However, high turbidity in some southern stations negatively impacted crustaceans, suggesting localized light limitation effects.

Table 3: Findings from previous studies

Appendix C: Individual Graphs of the Water Sources

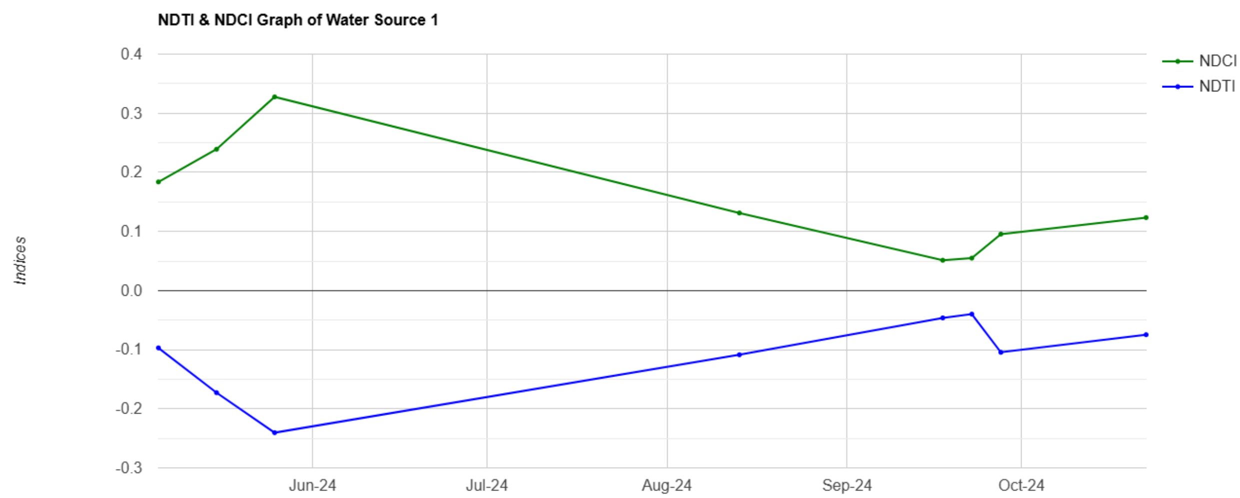

Figure 8: NDCI and NDTI Graph of source 1

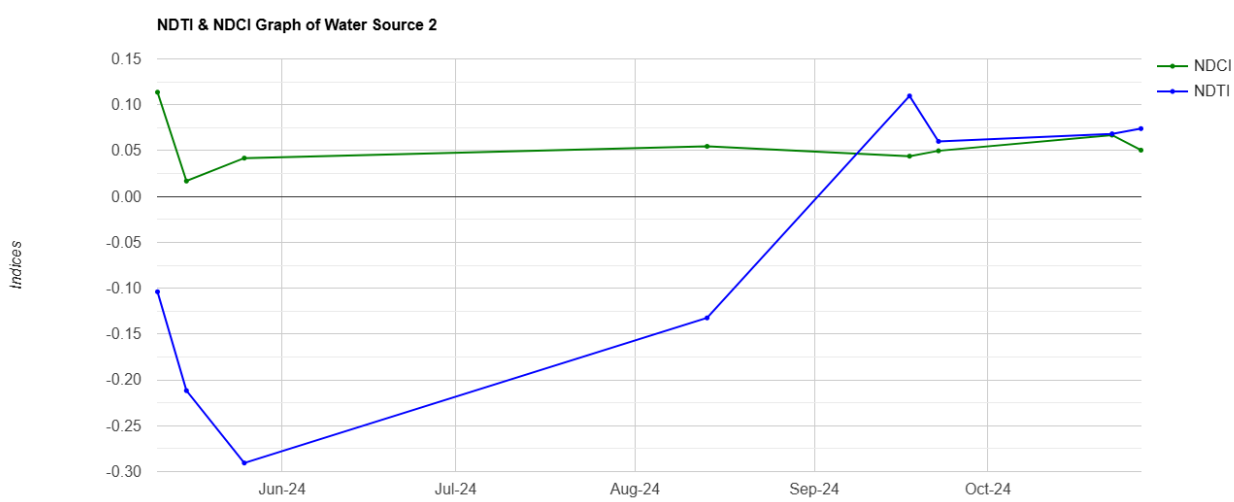

Figure 9: NDCI and NDTI Graph of source 2

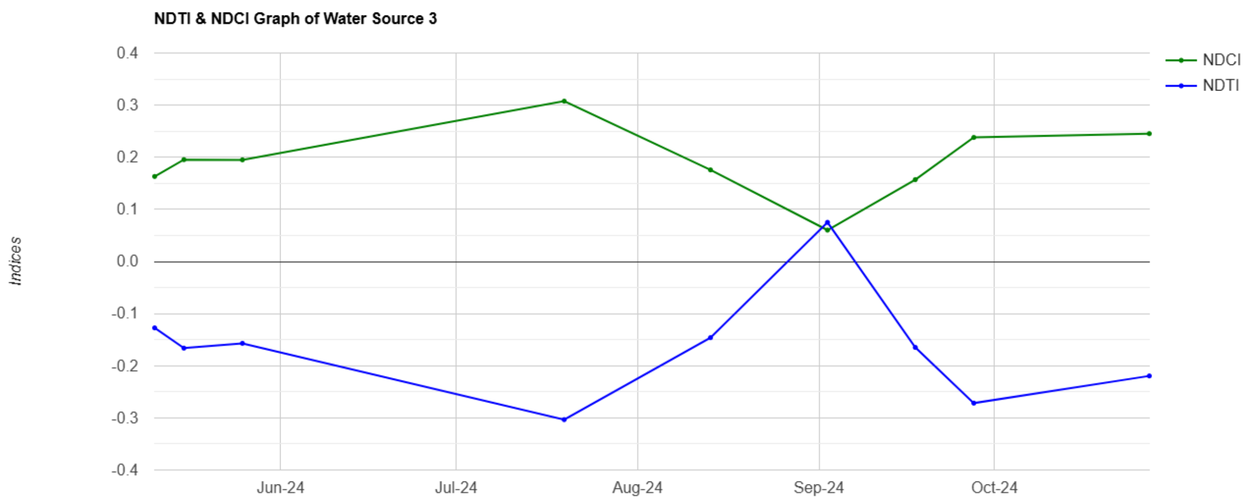

Figure 10**:** NDCI and NDTI Graph of source 3

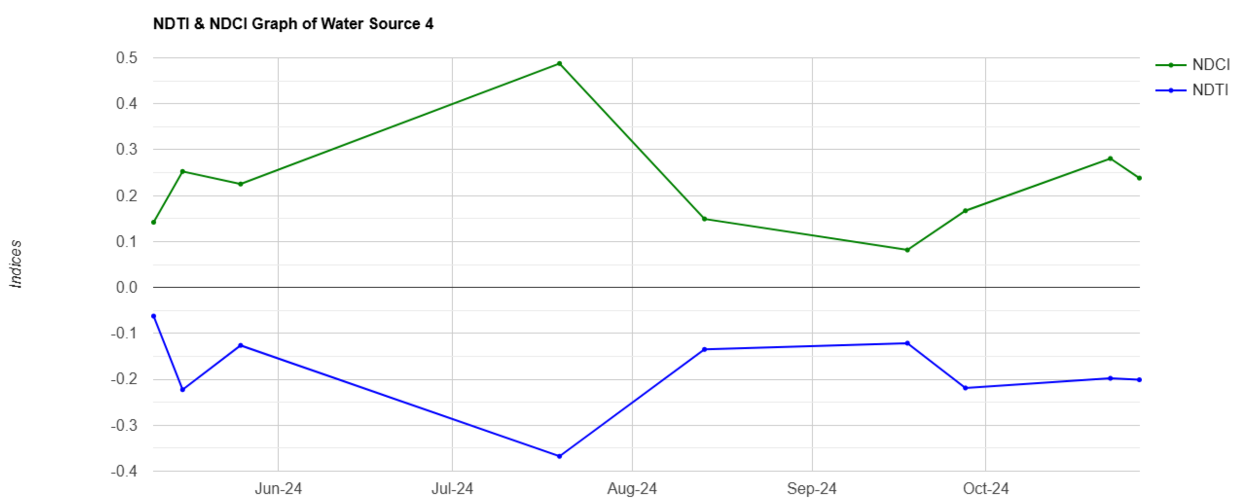

Figure 11: NDCI and NDTI Graph of source 4

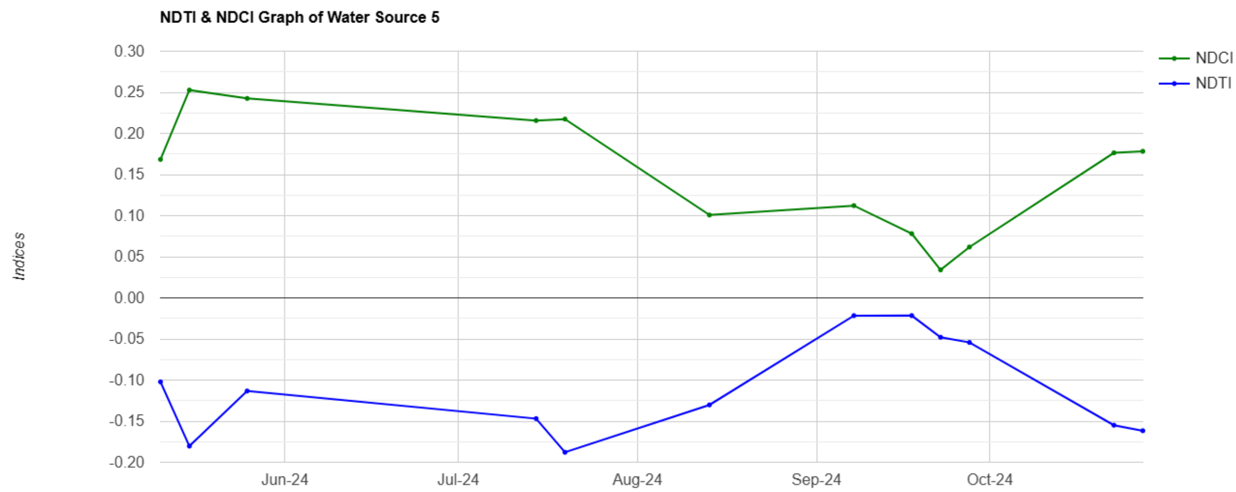

Figure 12: NDCI and NDTI Graph of source 5

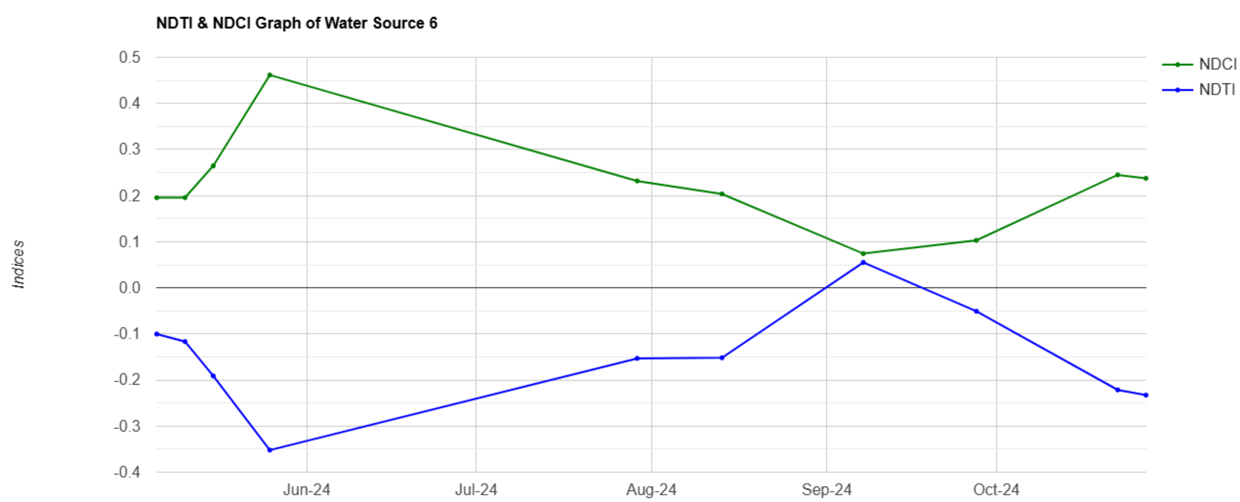

Figure 13: NDCI and NDTI Graph of source 6

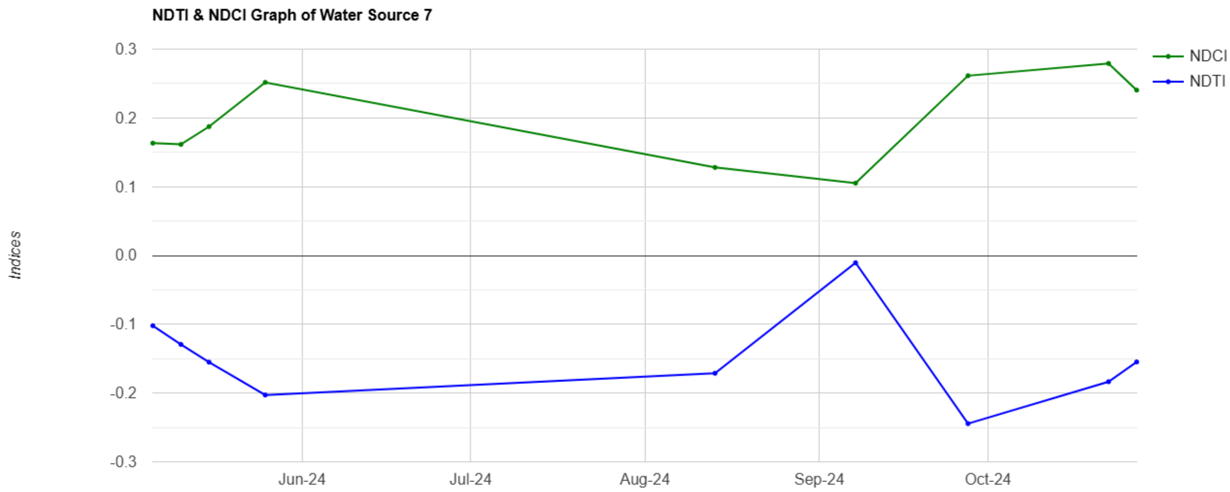

Figure 14: NDCI and NDTI Graph of source 7

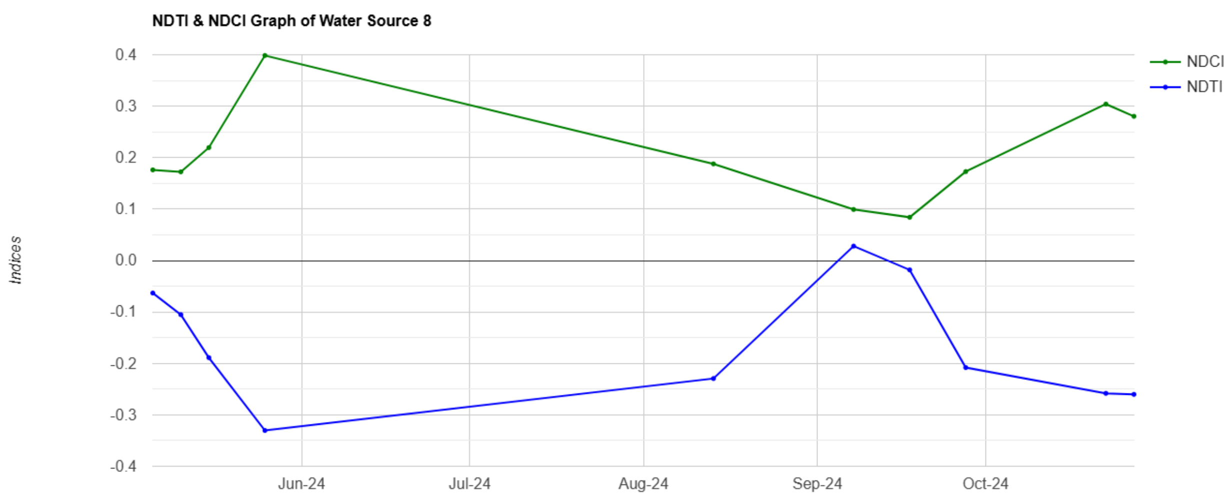

Figure 15: NDCI and NDTI Graph of source 8

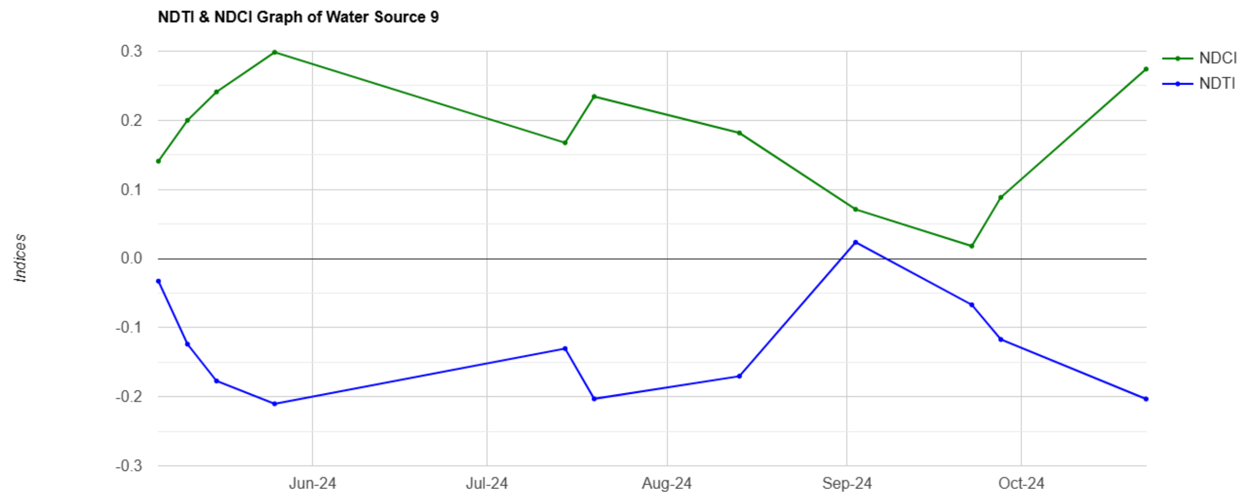

Figure 16: NDCI and NDTI Graph of source 9

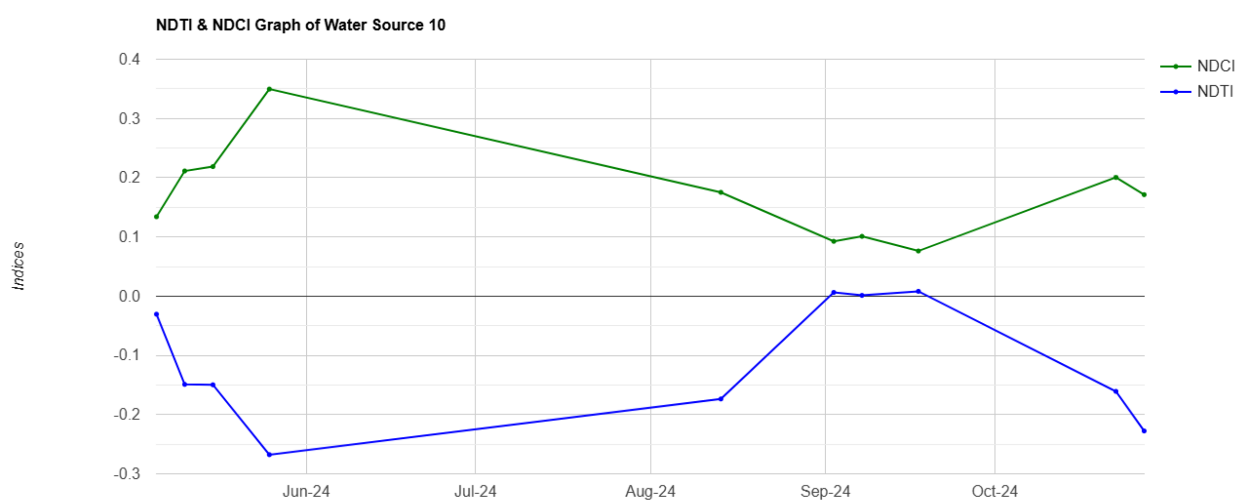

Figure 17: NDCI and NDTI Graph of source 10

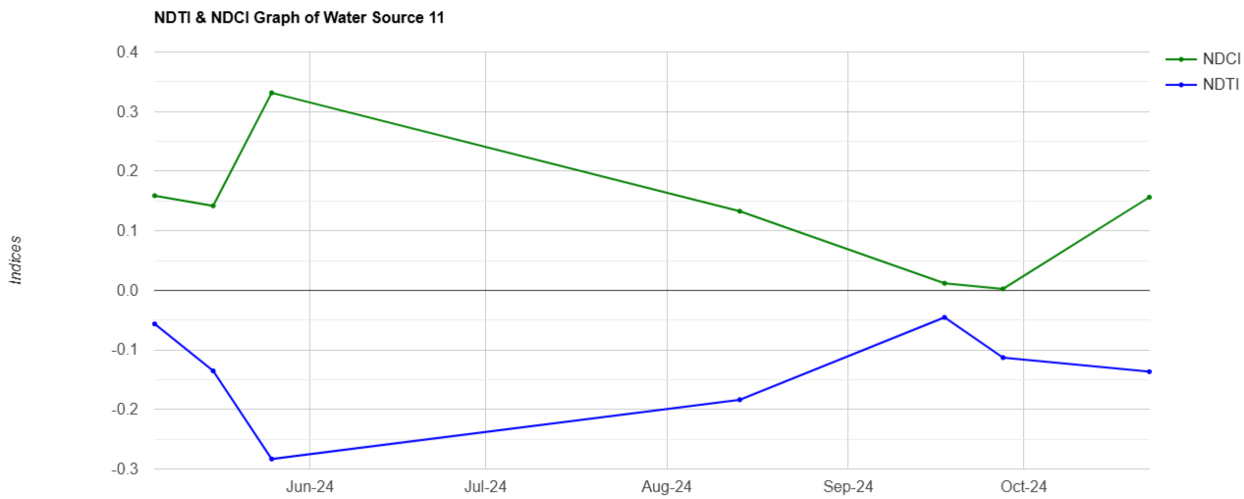

Figure 18: NDCI and NDTI Graph of source 11

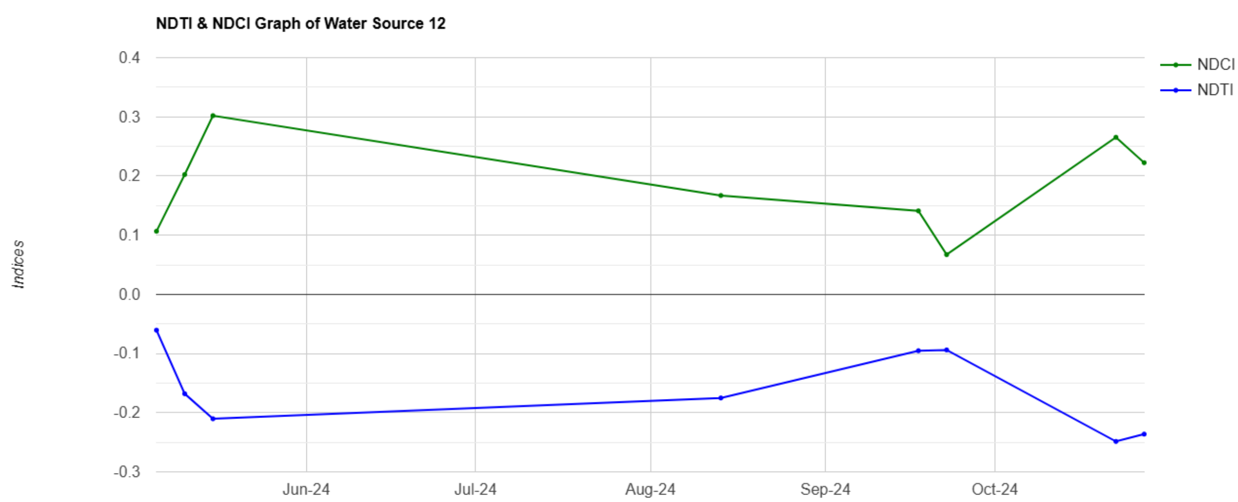

Figure 19: NDCI and NDTI Graph of source 12

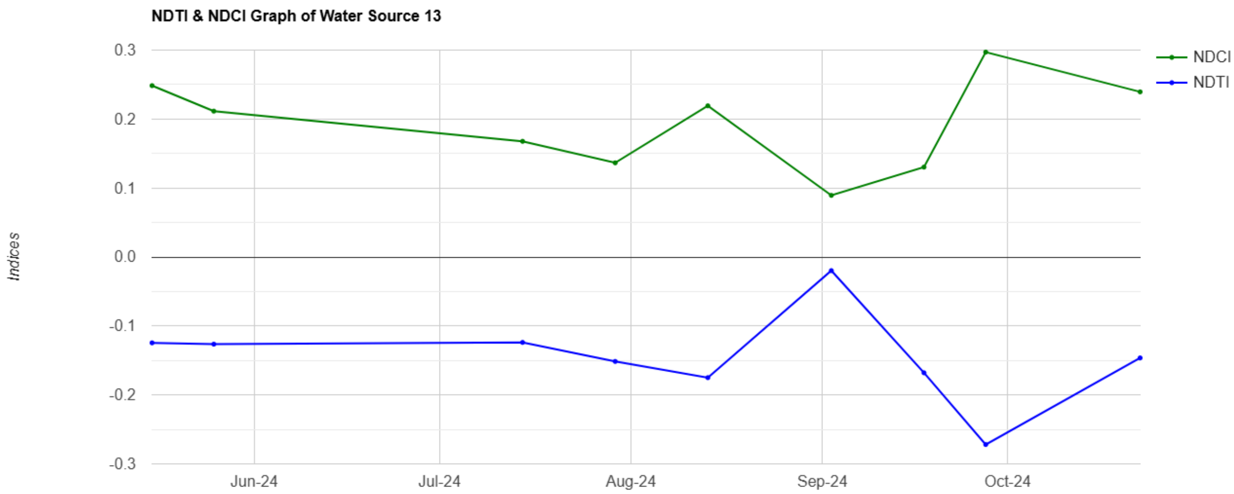

Figure 20: NDCI and NDTI Graph of source 13

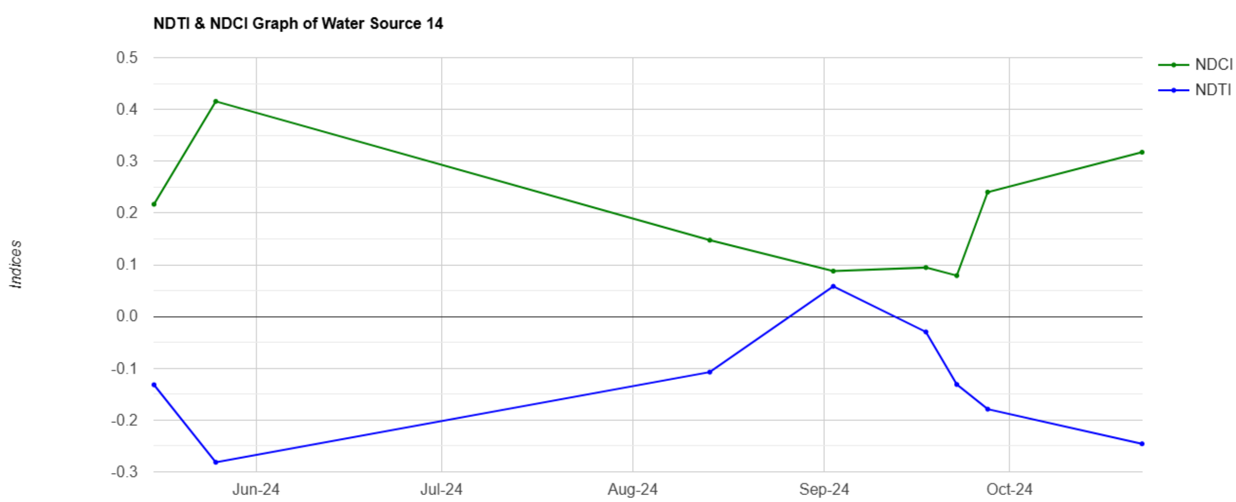

Figure 21: NDCI and NDTI Graph of source 14

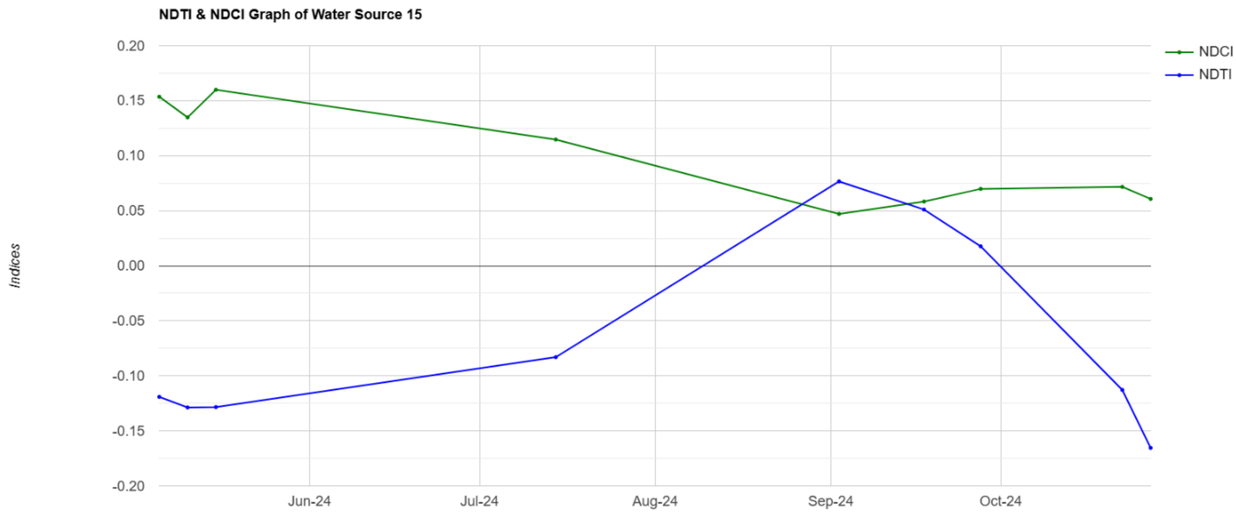

Figure 22: NDCI and NDTI Graph of source 15

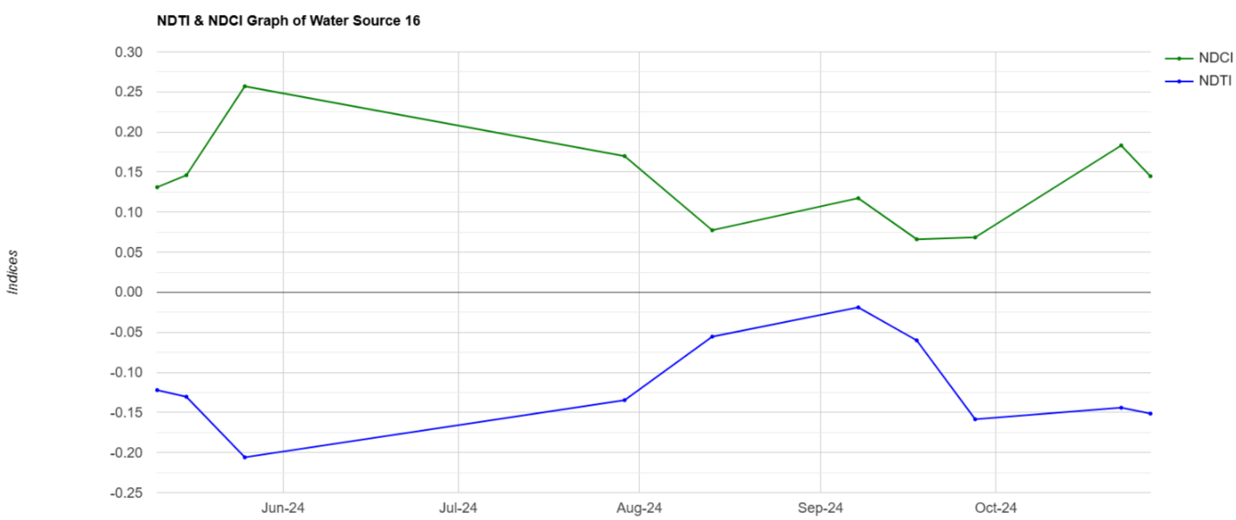

Figure 23: NDCI and NDTI Graph of source 16

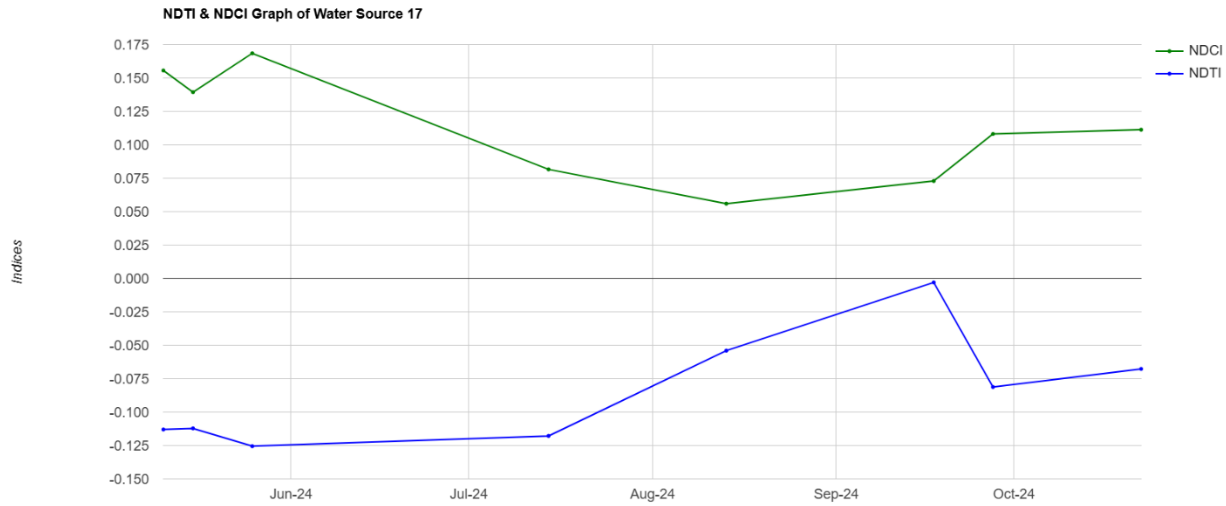

Figure 24: NDCI and NDTI Graph of source 17

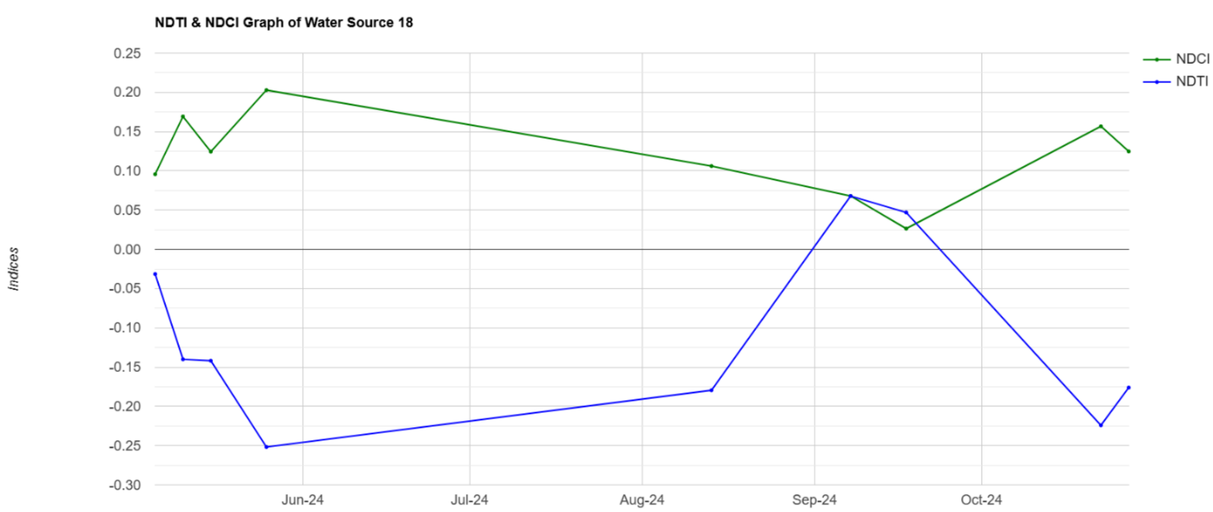

Figure 25: NDCI and NDTI Graph of source 18

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