

# DEVELOPMENT OF GOOGLE EARTH ENGINE APPLICATION FOR SPATIOTEMPORAL ANALYSIS OF TURBIDITY IN BATAN ESTUARY, AKLAN THROUGH THE HARMONIZATION OF LANDSAT AND SENTINEL-2 IMAGERY

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## ABSTRACT:

Water turbidity poses a threat to marine life and the economy. To address this, regular monitoring is crucial. Field methods are commonly employed, but they can be costly and challenging to perform consistently and historically. Luckily, remote sensing satellites offer a viable solution by collecting image data from space for Earth observation. Researchers have utilized these satellite images to develop indices for analyzing water turbidity and chlorophyll-a content. Leveraging the Google Earth Engine geospatial data computing platform, an application has been created to facilitate water quality monitoring. The app harmonizes Landsat and Sentinel-2 Imagery to improve temporal resolution and increase historical data availability. These images are then subjected to indices, namely the Normalized Difference Turbidity Index (NDTI) and the Normalized Difference Chlorophyll Index (NDCI), to estimate water turbidity and chlorophyll-a content, respectively. To evaluate the effectiveness of the app, the Batan Estuary in Aklan was selected as a test site. Annual mean water turbidity data from 2000 to 2021 were processed and downloaded through the app and subsequently imported into ArcGIS Pro for further analysis. Raster statistics revealed that turbidity and chlorophyll-a content have consistently decreased since 2000, with already low levels observed. Although the river section exhibited the highest turbidity relative to the estuary, it can still be deemed nonpolluted based on US EPA standards. Moreover, ArcGIS's emerging hotspot analysis indicated that the estuary predominantly featured cold spots, indicating minimal areas with clusters of turbid water over time.

## 1. INTRODUCTION

Turbidity is a parameter of water quality that measures the murkiness of the water. This is caused by the matter dissolved in water, which scatters light. Such matter may be clay, silt, organic matter, plankton, etc. (ASTM International, 2000). Water turbidity poses significant risks to various aspects of the environment and the economy, which the Minnesota Pollution Control Agency (2008) listed. First, it can harm marine life by impacting food sources, disrupting spawning beds, and impairing gill function. Furthermore, turbidity diminishes the aesthetic appeal of water bodies, negatively affecting recreational activities and tourism. Lastly, it increases the costs associated with producing drinking water and food processing.

The conventional method of measuring water turbidity typically involves physically collecting water samples, which can be a time-consuming and labor-intensive process. However, advancements in technology have presented a more efficient alternative. Remote sensing satellites, such as Sentinel-2, now offer the capability to estimate water turbidity without the need for physical presence. By utilizing optical imaging sensors mounted on satellites, researchers have developed indices that can effectively assess water quality. Furthermore, the availability of cloud-based archives for satellite images enables spatiotemporal analysis of water quality.

While the Sentinel-2 satellite system began operations only in 2015 and has a revisit time of five days (Spoto et al., 2012), there are certain limitations to consider. As an optical sensor, it is susceptible to cloud cover, leading to occasional data obfuscation. Nevertheless, Nguyen et al. (2020) have proposed a solution to address these challenges by harmonizing Sentinel-2 data with other optical satellite image providers like Landsat-7 and Landsat-8. The availability of Landsat-7 data since 1999

allows for the creation of historical datasets, while the harmonization process ensures near-daily image data for continuous monitoring purposes.

However, it is worth noting that the solution proposed by Nguyen et al. (2020) relies on Google Earth Engine (GEE) script-based programming, requiring researchers to possess knowledge of GEE scripting. Consequently, this study aims to develop a user-friendly application that enables researchers to easily download water turbidity and chlorophyll-a content data, along with their corresponding trends over time. By leveraging indices on harmonized satellite imagery, this application facilitates continuous monitoring of water quality. To validate its effectiveness, the app was tested in the Batan Estuary, advocating for the implementation of water quality management policies based on the findings.

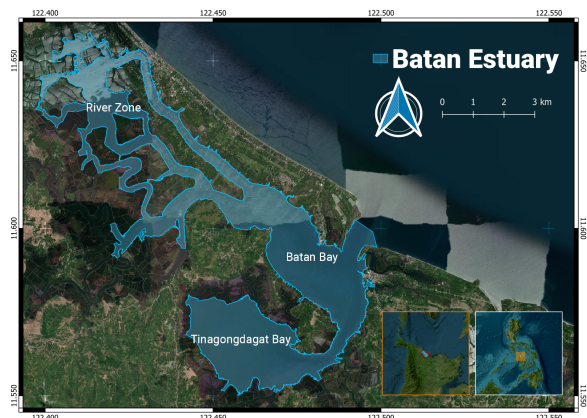
### 1.1 Study Area

On the coasts of Aklan, fishing is the basic livelihood. One of the coastal areas is Batan Estuary (containing Batan Bay). According to the 2012 municipal fisheries profile, the total population of the three municipalities enclosing Batan Estuary (i.e., New Washington, Batan, and Altavas) was 101,382 where 80% of that lived on or near the coasts. Furthermore, 5,369 people worked in the fishing industry (as cited in Kamiyama et al., 2015). Thus, fishing is an active industry in Batan Estuary with much of its population relying on it.

However, Altamirano and Kurokura (2006) studied the worsening fishing industry in Batan Estuary (containing Batan Bay). They found that the second-most and third-most perceived problem fishers have that could have impacted the industry is water pollution and shoaling of rivers and lagoons, which are

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directly related to water turbidity (Altamirano & Kurokura, 2010). Thus, water quality monitoring in this area is necessary and was chosen as the pilot study area for this research (Figure 1).



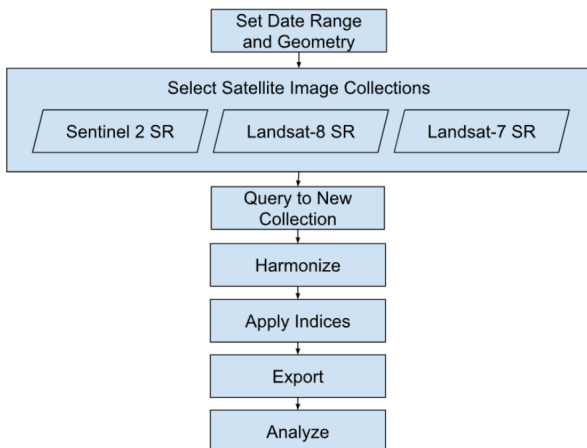
**Figure 1.** Batan Estuary Boundary based from Philippine Statistic Authority overlaid on ESRI Image.

## 2. DATA AND METHODS

### 2.1 Data

Water turbidity can be measured from remotely sensed images. 43 Sentinel-2 (with less than 30% cloud cover) from 2017 to 2021, 337 Landsat 7, and 353 Tier 1 surface reflectance images of Batan Estuary from 2000 to 2021 were used in this study.

### 2.2 Methodology



**Figure 2.** Methodological workflow of this study. SR = Surface Reflectance.

Figure 2 shows the workflow of this study. In most of the parts, Google Earth Engine (GEE) Javascript Application Programming Interface (API) was used. GEE is a cloud-based platform for the geospatial processing of large datasets (Gorelick et al., 2017). It provides functionality to query the required datasets, do geospatial processing capabilities, and develop a web application for the public's use. The study utilized these features to achieve its objectives.

The application developed queries images within the geometry of choice and will undergo the following processing steps: reprojection to WGS 84, resampling to 10m, band adjustment to

make the different sensors' bands compatible (Nguyen et al., 2020), and computation of water turbidity indices.

GEE is not a panacea among geospatial data processing technologies. Other Geographic Information System (GIS) programs have features that it does not have. However, GEE provides an export data function, which allows users to further analyze the data in different applications. In this study, the exported water turbidity data were imported into ArcGIS Pro and underwent emerging hot spot analysis to see spatiotemporal clusters of turbid waters in Batan Estuary.

### 2.2.1 Water Turbidity Indices

This study made use of two (2) indices to measure, in a relative manner, water turbidity: Normalized Difference Turbidity Index (NDTI) by Lacaux (2007) and the Normalized Difference Chlorophyll Index (NDCI) by Mishra and Mishra (2012). NDCI is not a turbidity index but it measures chlorophyll-a in water bodies that may indicate the number of algae growing in it (US Environmental Protection Agency, 2022), which contributes to water turbidity. Table 1 shows how to compute these indices from various satellite images.

Index	Landsat-8	Landsat-7	Sentinel-2
NDTI	$(B4 - B3)/(B4 + B3)$	$(B3 - B2)/(B3 + B2)$	$(B4 - B3)/(B4 + B3)$
NDCI	$(B5 - B4)/(B5 + B4)$	$(B4 - B3)/(B4 + B3)$	$(B5 - B4)/(B5 + B4)$

**Table 1.** The water turbidity indices and band combinations for each satellite in this study. Bi = Reflectance in Band i.

Mishra and Mishra (2012) used the red edge band reflectance of MERIS originally for NDCI, instead of NIR. However, Landsat does not have this band, unlike Sentinel-2. The NDCI formula for the Landsat images in Table 1 was adopted from Buma and Lee (2020), which found that replacing the red edge band with NIR (B5 for Landsat-8 and B4 for Landsat-7) will still produce accurate chlorophyll-a estimation results.

Elhag et al. (2019) collected field water quality data daily for two years and tested it to remotely sensed water quality parameters such as the NDTI in a dam lake of Wadi Baysh, Saudi Arabia. Ground truth water turbidity scored a high correlation with NDTI with  $R^2$  of 0.94. Similarly high correlation with  $R^2$  of 0.84 and 0.97 and was found at Borabey Lake, Turkey (Kaplan et al., 2020) and Ukai Reservoir, India (Pompapathi et al., 2022), respectively.

On the other hand, Kislik et al. (2022) showed that NDCI strongly identifies with chlorophyll-a data from two northern California reservoirs between October 2015 and November 2020, scoring an  $R^2$  of 0.84. Lobo et al. (2021) and Kirtiloğlu and Karabörk (2022) agree with this as they got  $R^2$  of 0.86 and 0.726 in select reservoirs in Latin America with field data from August 2015 to November 2020 and Lake Bafa, Turkey with field data on July 2018 and September 2019, respectively. While the NDCI in Conopio et al. (2019) correlated relatively lower ( $r$  of 0.56) with in situ data taken on December 2018 at Laguna de Bay, Philippines compared to the other two studies, NDCI still scored the highest among other indices in that time.

Overall, there is a good amount of studies across the globe that support NDTI and NDCI as valid estimators of turbidity and chlorophyll-a content even if they use remotely sensed data. Thus, answers the reason why they are used in the development of this app as an alternative (or a supplement) to taking field measurements.

### 2.2.2 Harmonization of Sentinel-2 and Landsat Imagery

Band	Landsat-8		Landsat-7	
	Slope	Intercept	Slope	Intercept
Blue	1.0946	-0.0107	-0.0139	1.1060
Green	1.0043	0.0026	0.0041	0.9909
Red	1.0524	-0.0015	-0.0024	1.0568
NIR-8	0.8954	0.0033	-0.0076	1.0045
NIR-8a	1.0283	-0.0021	-0.0140	1.1515
SWIR1	1.0049	0.0065	0.0041	1.0361
SWIR2	1.0002	0.0046	0.0086	1.0401

**Table 2.** Landsat transformation coefficients to harmonize with Sentinel-2 imagery

While Sentinel and Landsat calibration teams are ensuring the compatibility of their data with each other, some adjustment is still necessary for their harmonized use (Barsi et al., 2017). Nguyen et al. (2020) provided a GEE script with the transformation coefficients for band adjustment of Landsat imagery to harmonize with Sentinel-2. Table 2 shows the slopes and intercepts that are to be multiplied and added to the band reflectances, respectively

### 2.2.3 Emerging Hot Spot Analysis

The emerging hot spot analysis of ArcGIS Pro can detect hot spot and cold spot patterns (Esri, 2022). The yearly NDCI and NDTI

raster of Batan Estuary were converted to point data and aggregated to produce a space-time cube dataset. The space-time cube was then imported into the emerging hotspot analysis tool. The classes (or patterns) produced by this tool are listed in Table 3.

Pattern	Definition
No Pattern Detected	Not a hot spot nor a cold spot.
New Hot Spot	Recently became a hot spot.
Consecutive Hot Spot	Recent hot spot for a while.
Intensifying Hot Spot	A long-time hot spot that is intensifying.
Persistent Hot Spot	A long-time hot spot.
Diminishing Hot Spot	A long-time hot spot that is toning down.
Sporadic Hot Spot	On-and-off hot spot.
Oscillating Hot Spot	Sometimes a hot spot, sometimes a cold spot.
Historical Hot Spot	A hot spot for a long time except recently.
New Cold Spot	Recently became a cold spot.
Consecutive Cold Spot	Recent cold spot for a while.
Intensifying Cold Spot	A long-time cold spot that is intensifying.
Persistent Cold Spot	A long-time cold spot.
Diminishing Cold Spot	A long-time hot spot that is toning down.
Sporadic Cold Spot	On-and-off cold spot.
Oscillating Cold Spot	Sometimes a hot spot, sometimes a cold spot.
Historical Cold Spot	A cold spot for a long time except recently.

**Table 3.** ArcGIS Pro's Emerging Hot Spot Analysis Patterns

### Water Turbidity Explorer

This app provides visualization of Water Turbidity from harmonizing Landsat 8, Landsat 7, and Sentinel-2.

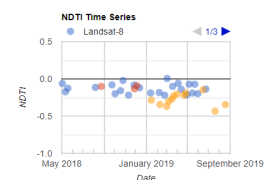
by Cristian Dave C. Zablan

#### Indices Used:

NDTI = Normalized Difference Turbidity Index = (Red-Green)/(Red+Green)

NDCI\_Sentinel-2 = Normalized Difference Chlorophyll Index = (Red Edge-Red)/(Red Edge+Red)

NDCI\_Landsat = Normalized Difference Chlorophyll Index = (NIR-Red)/(NIR+Red)



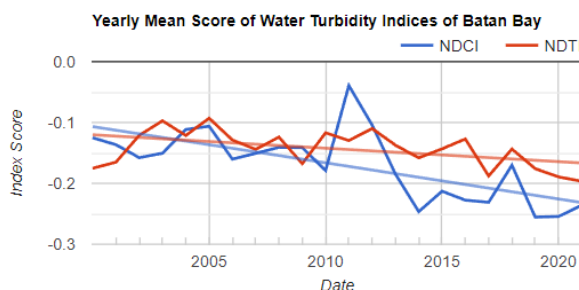
**Figure 3.** GEE Water Turbidity Explorer App User Interface showing the NDTI of Batan Bay of Batan Estuary.

## 3. RESULTS AND DISCUSSION

The developed application provides the capability for users to create geometry and set a date range to compute, visualize, and export the mean NDTI and NDCI and their time series in that area (Figure 3).

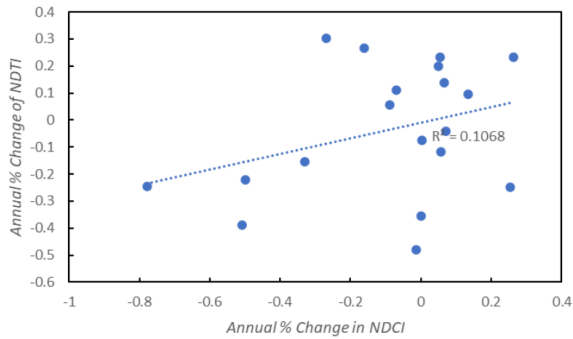
Figure 4 shows the annual mean score of the selected water turbidity indices of Batan Estuary in this study. Both NDCI and NDTI are found to have a downward trend. However, in 2011, it can be observed that there is a spike in NDCI. Mishra and Mishra (2012) estimate that a value within that range (-0.1 to 0) has an estimated chlorophyll-a content of 7.5-16 mg/m<sup>3</sup>, which is still relatively low. Ogawa et al. (2021) found that the organic matter "pollution" is not caused by aquaculture pond operations but more by mangrove litter (that has stored carbon) that remained even after massive deforestation several decades ago. Thus, the

reduced turbidity must be from other matter that does not have any benefits, unlike mangrove litter.



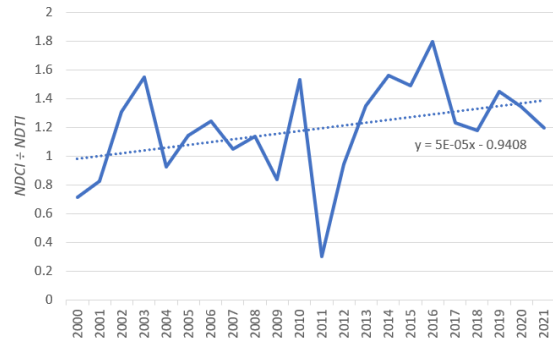
**Figure 4.** Yearly Mean Score of NDCI and NDTI in Batan Estuary

Figure 5 shows the scatter plot of the annual percentage change in NDTI and NDCI. The computed correlation coefficient is 0.3268, which implies that the linear relationship between chlorophyll-a present in Batan Estuary and turbidity is weak but positive.

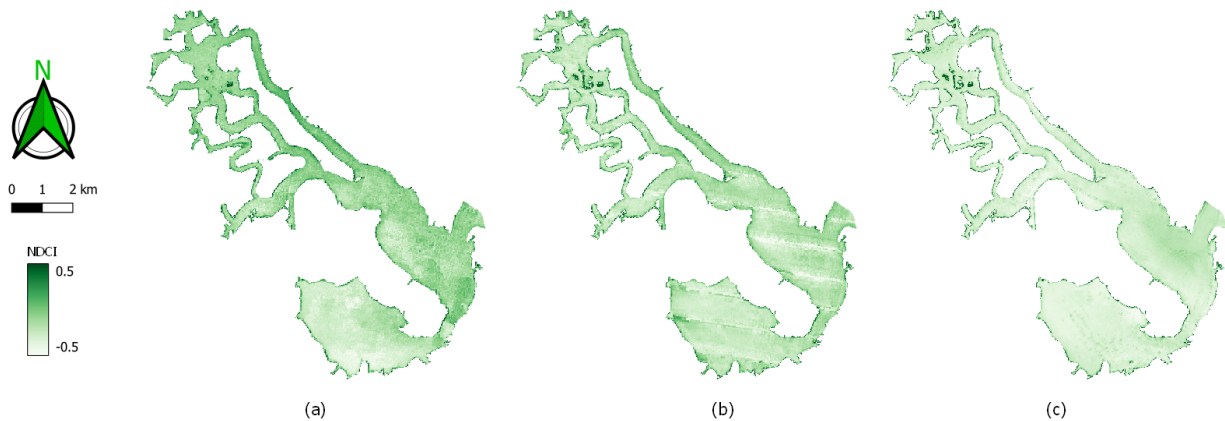


**Figure 5.** Correlation between the annual mean time series of NDCI and NDTI.

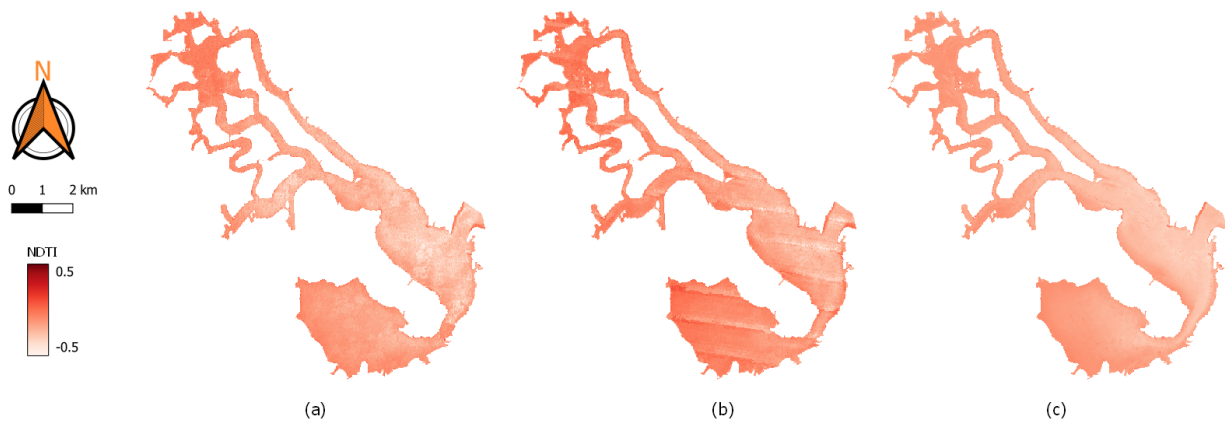
Figure 6 displays the ratio of NDCI values over NDTI in a time series. The ratio has an upward trend implying that chlorophyll-a's contribution to turbidity is increasing over time. Figures 2 and 4 mean that chlorophyll-a is not a strong cause for turbidity in Batan Estuary but is gradually becoming a bigger part of it through time.



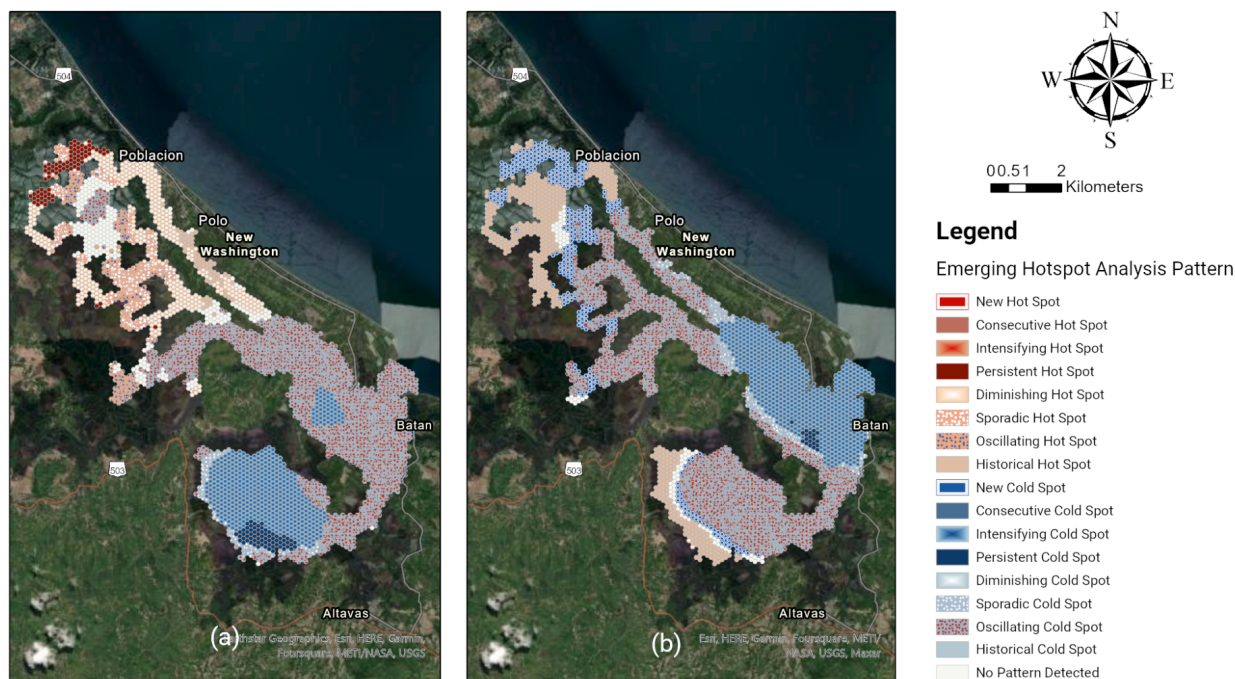
**Figure 6.** Ratio between NDCI and NDTI through time



**Figure 7.** Decadal mean NDCI for years (a) 2000, (b) 2010, (c) 2020. Relatively higher NDCI zones can be found in the Tinagong Dagat (channel) and in portions of Batan Bay.



**Figure 8.** Decadal mean NDTI for years (a) 2000, (b) 2010, (c) 2020. Tinagongdagat Bay and the northernmost river zone generally have higher NDTI compared to other parts of the Batan Bay Estuary.



**Figure 9.** Emerging Hot Spot Analysis of (a) NDCI and (b) NDTI from 2000-2021 in Batan Estuary.

Figure 7 shows how NDCI has changed throughout time in Batan Estuary. It can be noticed that the NDCI was strong in Batan Bay and the river zone in 2000 but generally becomes lower (in agreement with Figure 4) and more homogenous throughout time. On the other hand, turbidity was higher in the Tinagongdagat Bay and river zone in the 2000s (Figure 8) and remained so until 2020, but overall became lower and slightly more homogenous as well. This is consistent with Ogawa et al. (2021) as both the Tinagongdagat Bay and river zone are found to accumulate mangrove litter and microphytobenthos (a type of microalgae). Nevertheless, albeit having relatively higher turbidity in 2020, the river area is considered non-polluted by US Environmental Protection Agency's (US EPA) standard (Nillos et al., 2020).

The researchers performed the emerging hot spot analysis of NDCI and NDTI scores in Batan Estuary from 2000-2020 (Figure 9). In Tinagongdagat Bay, the area predominantly became new cold spots in terms of chlorophyll-a content. Meanwhile, its turbidity has oscillating intensity yet is still low. Except for Tinagongdagat Bay's edges as it is historically turbid. Around the same part has a history of being a hot spot for NDCI, which implies that its turbidity may be caused by chlorophyll-a.

Moving to the Bay zone, we can see that turbidity has consistently gone down in the area as denoted by the New Cold Spot pattern dominating its body. The bay's chlorophyll-a content is also low but oscillates to hot spots at certain times, denoted by the oscillating cold spot patterns. Overall, the Bay Zone does not show much turbidity and algal bloom problems throughout the two decades.

Lastly, the River Zone is dominated by hot spots in terms of NDCI and NDTI with notable historical and persistent hot spot patterns. However, there are areas whose chlorophyll-a is decreasing based on the detected diminishing hot spot pattern, but the turbidity in these areas remains as historical hot spots. Thus, this implies that a certain percentage of the river area's chlorophyll-a content contributes less and less to its turbidity.

#### 4. CONCLUSION

Turbidity in water is caused by matter dissolved and the presence of algal and non-algal particles in it. In bodies of water where marine life exists, water turbidity can pose a problem to their lives that may cause reduced food production. Thus, it is necessary to regularly monitor the quality of these areas. A method to do so is by taking water samples and running them through the chemistry lab. The problem with this methodology is that it can be time and labor expensive. Fortunately, there are satellites that take images from outer space for Earth's observation and monitoring, including its water bodies. While different satellite image sources provide different image quality altogether, they can be harmonized through a model (Nguyen et al., 2020). Researchers then created indices to estimate water quality from the image datasets. Moreover, the availability of older satellite imagery from several years ago makes spatiotemporal analyses possible. Thus, the researchers took advantage of remote sensing technology to develop an application that will help other researchers and stakeholders to monitor the turbidity of water bodies all around the world at any time (beyond the year 2000).

To develop the app, the researchers utilized Google Earth Engine (GEE), a cloud computing platform for geospatial datasets that also offers functions for app development. The platform was used to query free satellite images from Sentinel-2, Landsat-8, and Landsat-7 missions. The images then underwent processing including harmonization and index computation. The indices to measure the water turbidity in this app are the Normalized Difference Turbidity Index (NDTI) by Lacaux (2007) and Normalized Difference Chlorophyll Index (NDCI) by Mishra and Mishra (2012). The latter is not a water turbidity index but was included to provide insights into how it contributes to turbidity. The developed app provides a function to download the produced index datasets for further analysis. The researchers selected Batan Estuary, Aklan as a study site to test the app. The produced NDCI and NDTI yearly rasters from 2000 to 2021 covering Batan

Estuary were downloaded and underwent raster statistics and Emerging Hotspot Analysis in ArcGIS Pro to see the spatiotemporal patterns and changes of its water turbidity.

It was found in this research that turbidity and chlorophyll-a are generally decreasing in Batan Estuary. While there is a weak but positive correlation between NDCI and NDTI for this estuary, it was also found that chlorophyll-a is contributing more to turbidity throughout time. Overall, Batan Estuary does not have a big water turbidity problem as most of the area is filled with cold spots in terms of turbidity and chlorophyll-a presence. However, the river area is found to be more turbid relatively and should be monitored.

## RECOMMENDATIONS

The app's product is not validated by field methods. The proponents recommend testing its results and correlating them with turbidity and chlorophyll-a measured in situ using a multi-parameter water quality sensor.

Google Earth Engine has limited analytical tools and UI capabilities. However, for those who are also planning to develop apps within GEE, it is recommended to explore how GEE can be imported as a module to a different base platform instead of using it as the base platform for this research project.

Future research could also explore other analyses and other indices for more insights into the water turbidity of Batan Estuary or other study sites.

## ACKNOWLEDGMENT

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## APPENDIX

Link to Water Turbidity Explorer - Google Earth Engine App:  
<https://cczablan1.users.earthengine.app/view/water-turbidity>