Monitoring Coastal Areas Using NDWI from Landsat Image Data From 1985 Based on Cloud Computation Google Earth Engine and Apps

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ABSTRACT:
The coastal area is an area that has a dense population with a lot of human activities that occur there. Due to environmental changes and human activities, changes often occur in coastal areas ranging from erosion and sedimentation. Changes must continuously be monitored to plan countermeasures due to the occurring phenomena. This study aims to create a website-based application to monitor coastal areas. This study will use Landsat data 5,7,8, and 9 to see changes in coastal areas. The analysis can be provided from 1985 until recent data by integrating four Landsat satellites. The NDWI index (Normalized Difference Wetness Index) analyzes changes occurring in coastal areas and differentiates between water and land area. The analysis is not only in the form of changes that occur in coastal areas but also in time series analysis, and trends that occur at a point can be analyzed using land trend analysis. The resulting website based on Cloud Computation in Google Earth Engine can be seen at the link https://bit.ly/MonitoringPesisir. This website can automatically update, and users can choose the location to monitor. This research is expected to be used by policymakers to monitor and plan the development and regulation of coastal areas.

1. INTRODUCTION

Coastal areas are densely populated areas. Many economic and tourism activities are developed in coastal areas. At this time, many changes in coastal areas can disrupt the activities of residents around the area. Changes in coastal areas occur due to various natural events such as wind, waves, and currents (Guerrera et al., 2021; Susanti et al., 2021). In addition, anthropogenic (human) effects are one of the causes of coastal changes (Goldberg et al. 2020; Ning et al. 2018). Monitoring changes in coastal areas must be carried out to manage coastal area use and protect the area (Elnabwy et al., 2020; Patel et al., 2021). Regular monitoring of changes in coastal areas is needed. Remote sensing technology is one alternative to regular coastal area monitoring because it can provide data within the scope of global, high-temporal observations and harmonious data collection (Anjar Dimara Sakti et al., 2023). Technological developments align with the increasing ease and cheapness of data to be obtained continuously (Anokwa et al., 2009; Zupan and Demsar, 2008). Knowing the development of spatially specific erosion and sedimentation rates can be used to see the implications and efforts to reduce them.

Several studies on changes in coastal areas have been conducted. Research by Elnabwy et al. (2020) mapping coastline changes using Landsat from 1985 to 2018 using the SVM machine learning classification method in Ezbet Elbong, Egypt, and mapping changes that occurred in coastal areas from 1985 to 2011 using the integration of Landsat and photogrammetry in False Bay, South Africa (Callaghan et al., 2015). In addition, mapping of coastline changes from 1978 – 2018 has been carried out using multi-temporal Landsat data in Gujarat. The study also predicted changes in the coastline by 2038 (Patel et al., 2021). Based on previous research, need to enhance monitoring of coastal change. This is important because the monitoring can be adjusted to the area of interest of each interested institution, and also by presenting the latest data can encourage better planning.

For continued monitoring, webgis can show change information (Nur Ihsan et al., 2021). The updating analysis can be informed quickly to the user data so they can identify the location of the change and plan to mitigate or manage it. The problem with webgis is that the data should be updated continuously to continue monitoring. It means that need to connect to the big database that continuously updates and automatically processes the data. Cloud computation is one of the ways to do continuous monitoring. Google Earth Engine is one platform that can continue monitoring natural phenomena(Tamiminia et al., 2020; Zhi et al., 2022). This is because the google earth engine is a big database that contains updated information from the data provider. This is an excellent opportunity to use the google earth engine to continue monitoring and periodically checking the coastal change. The monitoring using the google earth engine, besides the updated database, the monitoring location is also possible to do in large areas. This depends on the coverage area of data that will be used. So, it is made possible to monitor coastal change not only in a specific area but also in a global area.

This study aims to monitor coastal areas regularly using cloud processing applications google earth engine. Knowing the changes that occur in coastal areas, it is hoped that policymakers can use them in planning and overcoming problems that occur in coastal areas, especially in overcoming them. This research area is in the global area that Landsat Sattelite covers. In addition, this research is hoped to support SDGs 2030 point 14.2, which manages to protect marine and coastal ecosystems sustainably (UN, 2023).

2. METHODOLOGY

2.1 Data

This study will use Landsat data starting from Landsat 5, 7, 8, and 9. Using Landsat satellite integration will increase the possibility of Landsat data in the location you want to see. In addition, the processed data can be updated because it uses Landsat data that is still operating, but it can also analyze past events because it uses Landsat, available since 1984. Landsat data also covers the global area, meaning continuous monitoring will also work in covering the globe. The specification of the Landsat data used can be seen in Table 1.

No	Data	Product	Data Availability	Resolution	Source
1	Landsat 5 TM	USGS Landsat 5 TM Collection 1 Tier 1 TOA Reflectance	1984-2012	30 m	(USGS, 2022a)
2	Landsat 7	USGS Landsat 7 Collection 1 Tier 1 and Real-Time data TOA Reflectance	1999 - 2021	30 m	(USGS, 2022b)
3	Landsat 8	USGS Landsat 8 Collection 1 Tier 1 and Real-Time data TOA Reflectance	2013-Current	30 m	(USGS, 2022c)
4	Landsat 9	USGS Landsat 9 Collection 1 Tier 1 and Real-Time data TOA Reflectance	2021- Current	30 m	(USGS, 2022d)

Table 1. Data

2.2 Methods

In this study, there are several stages carried out. The first stage integrates Landsat data. Next, calculate each selected year's NDWI (Normalized Difference Wetness Index). The last step checks the changes that occur. In general, the method in this study can be seen in Figure 1.

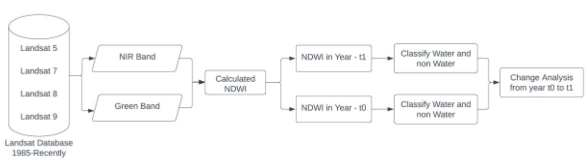

Figure 1. General Methodology

2.2.1 Integration Data Landsat

This research will integrate data from Landsat 5, 7, 8, and the recently launched Landsat 9. The data is integrated with a cloud processing process that first equalizes the band naming on each Landsat data in the google earth engine. After the band names have been equalized, all available imagery is unified on Landsat data 5, 7, 8, and 9. The image used is a level 2 Landsat image that has undergone geometric and radiometric correction. Radiometric correction is done because the data to be used in this study is surface reflectance data on each band.

2.2.2 NDWI Calculation and Change Scheme

Determining water and non-water bodies will use NDWI (Normalized Difference Water Index). The higher the NDWI value, the higher the humidity level (water body). NDWI is obtained from the processing of the green band and NIR band. NDWIs can be used in the identification of changes in water bodies in coastal areas (Alcaras et al., 2022; Wu et al., 2022). The NDWI formula can be seen in Equation 1. The NDWI value used is the average NDWI of each selected year. This is done to see the trend of water or non-water in coastal areas for one year. In this study, the classification of water bodies if they have an NDWI value of more than 0 while non-water bodies if the NDWI value is more than 0. The change identification scheme can be seen in Figure 2.

$$NDWI = \frac{Green - Nir}{Green + Nir} \tag{1}$$

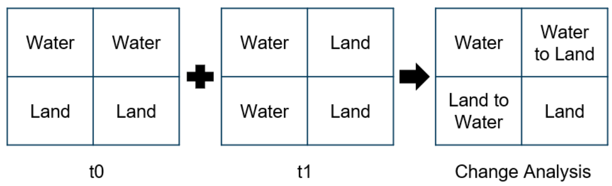

Figure 2. The Scheme of Change Identification in Coastal Area Skema

2.2.3 Time Series and Land Trend Analysis

Land trend analysis can determine the year of significant changes (loss and gain) at a particular point by employing spectral indices (Kennedy et al., 2010). This study will utilize the Normalized Difference Water Index (NDWI) as an indicator to identify the changes that occur at a specified point and observe the significant alterations. The research will employ land trend fitting to examine the changes in the generated NDWI data. By employing this analysis, significant patterns occurring at the selected point can be observed.

3. RESULT AND DISCUSSION

3.1 WebGIS Coastal Change Analysis App

This study has created a Website-based application that can be accessed via smartphones and desktops using a link https://bit.ly/MonitoringPesisir. The display and features available in the application can be seen in Figure 3, including location finder, data layer, initial year, late year, legend, NDWI chart time series, and digitization points for determining AOI. How the created application works can be seen in Figure 4. Generally, the work system can be divided into three parts: the user section, the website section, and the cloud processing section. Users can choose a location to process from the cloud system, and the chart and change detection will be shown. For change detection, the user can identify the t0 first and then choose the t1, and the map of change will automatically add to the layer manager. The user should turn on the layer to show the map in the main map. Users can use multi-time analysis to show this website. Time series data can be shown if the user chooses a location that will identify the time series of NDWI.

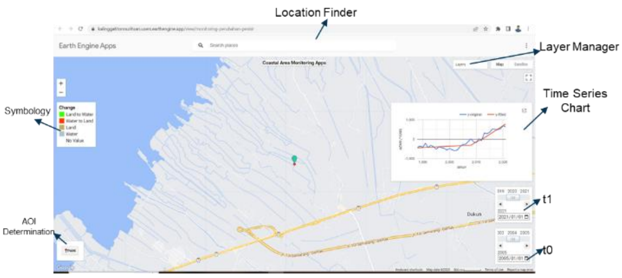

Figure 3. The WebGIS View for the User (User Interface)

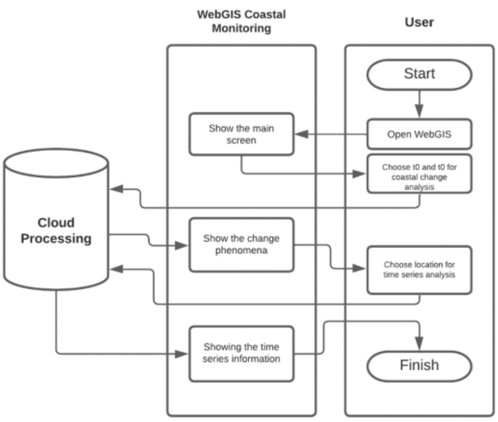

Figure 4. Coastal Monitoring Application Work System

3.2 Monitoring Coastal Change

Applications created can display changes that occur with a range according to the user's wishes and the desired region because it is global-based. Figure 5 is some examples of changes that occurred in the DKI Jakarta and Demak areas, where pictures A and B are examples of areas experiencing erosion, and figure C is an example of areas that are sedimentation (adding land). The period used for the example is that it changes every ten years. Pictures A and B show that water bodies in the area are advancing inland every ten years; this will be a problem because they will appear in settlements in coastal areas. Figure C shows the addition of land. In this case, reclamation in Jakarta can be identified with this application. When viewed properly, before undergoing reclamation, some areas in Jakarta experienced erosion.

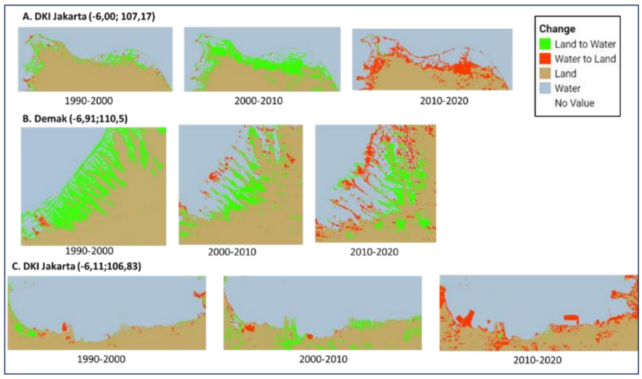

Figure 5. Some Examples of Coastal Changes That Happened

3.3 Time Series and Land Trend of NDWI

The application created can perform time series analysis with additional land trend analysis information, where the example made can be seen in Figure 6. Figure 6A shows that reclamation caused the area to become land previously a body of water based on NDWI values. Figure 6B shows that the location in 2005 and below was still land, but the NDWI value is increasing yearly, indicating that the area gradually became water.

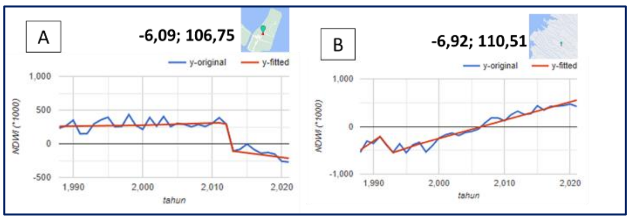

Figure 6. Some of NDWI Time Series and Land Trends for Change Time Identification

3.4 Prediction Change in Future

In this study, based on NDWI values from 1984 until now, changes from 2020 to 2050 will be analyzed, as shown in Figure 7. The projection technique used linear regression analysis to obtain the NDWI value 2050 (Gorelick et al. 2017). The projected changes obtained can be seen in Figure 7, where the erosion that occurs in the area will be higher so that the more advanced the waters to land. It should be underlined that this analysis assumes the same value addition every year; if later handling is carried out in the area, the projected results will undoubtedly change.

https://doi.org/10.5194/isprs-archives-XLVIII-M-3-2023-109-2023 |

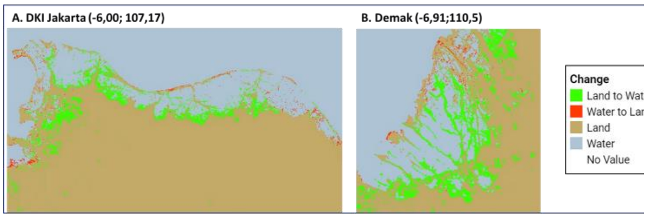

Figure 7. Prediction of Coastal Change in 2050

3.5 Limitation and Future Possible Study

This study has limitations as it only identifies land and water based on a single threshold value of 0 in this research. In this regard, satellite data may have inaccuracies due to location variations and environmental phenomena occurring in the area (Cressie and Kornak, 2003; Harris et al., 2010; Stock, 2022). This could result in suitable locations being limited to only a few, while other locations may not be suitable for analysis. Nevertheless, this change analysis can serve as an initial indication of coastal changes. In future research, these limitations can be addressed by not solely relying on NDWI-based land and water identification with a fixed threshold of 0. Other methods, such as machine learning and deep learning classification, can be employed for land and water delineation (Isikdogan et al., 2017; Talukdar et al., 2020; Zhang et al., 2019). Additionally, this study relies solely on NDWI averages and does not integrate tidal data to assess coastal changes. However, this research can serve as a reference for dynamic observations related to renewable energy potential (Bender et al., 2017; Ihsan et al., 2022, 2021; Sakti et al., 2022), air pollution (Pavani and Rao, 2017; A.D. Sakti et al., 2023), hazard (Das et al., 2006; Virtriana et al., 2023), and food security (Gommes et al., 2016; Virtriana et al., 2022) in a particular region.

4. CONCLUSION

In this study, a website-based application has been developed that can be used to monitor changes that occurred from 1984-present by integrating Landsat data 5, 7, 8, and 9. The webgis can identify where sedimentation occurred because of natural or anthropogenic phenomena using this method from indication change from water to land. On the other side, it can also identify the erosion phenomena that indicate change from land to water in a time range. Using analysis of time series and land trends also can show clearly the significance of time change from the time series data in a location. This research also tried to do future predictions using simple linear regression from NDWI data from 1985 until 2020 to predict the NDWI in 2050, which can be used to preliminary studies that indicate the change of a coastal location.

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