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Research Article

Decadal Monitoring of Upwelling Dynamics in Satonda Island Waters Using Landsat-8 and Machine Learning Regression

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ABSTRACT

Global warming and associated weather changes, notably the El Niño Southern Oscillation (ENSO), significantly impact marine ecosystems by altering water quality parameters such as *chlorophyll-a* (*Chl-a*) and sea surface temperature (SST). These changes are crucial in understanding the biogeochemical and ecological dynamics of marine environments, especially in regions affected by upwelling. This study aims to monitor upwelling events on Satonda Island, a volcanic island with unique central lake and status as a protected area using remote sensing. Utilizing Landsat-8 imagery and machine learning regression techniques—Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART)—this research evaluates the water quality in Satonda waters over a decade (2013–2023). The RF method emerged as the most accurate in estimating *Chl-a* and SST, indicating its efficacy in monitoring marine ecosystems with the result (RMSE = 0.309 and 0.274). The analysis reveals seasonal upwelling patterns, characterized by decreased SST and increased *Chl-a* concentration, with peaks varying annually between June and November. This study highlights the crucial role of remote sensing and machine learning in monitoring the effects of climate change on marine biodiversity. It provides valuable insights into the temporal dynamics of upwelling in the shallow waters of Indonesia.

Keywords: *Chlorophyll-A*; Sea Surface Temperature (SST); Landsat-8; Machine Learning Regression; Upweling

INTRODUCTION

The planet is currently undergoing global warming, which is causing weather changes. Weather variations can have an impact on water quality, which in turn has an impact on marine ecosystems (Henson et al., 2016). El Niño Southern Oscillation (ENSO) is a weather change phenomenon that has an impact on water quality. El Nino influences Upwelling in waters (Satar et al., 2023). Upwelling is the upward migration of nutrient-rich deep water with a low temperature to the surface (Umasangaji & Ramili, 2021). Wind-driven coastal upwelling is a major contributor to physical, biogeochemical, and biological variability in the vicinity of land-sea interactions (Jacox et al., 2018).

Upwelling has a significant impact on marine biogeochemistry, water quality dispersion, and climate change (Katlane et al., 2023). The relation between oceanographic conditions and climate change is determined using oceanographic parameters such as *chlorophyll-a* (*Chl-a*) and sea surface temperature (SST) (Antoni et al., 2019). *Chlorophyll-a* is a sign of water fertility because it contains a lot of phytoplankton, which helps with photosynthesis in water (Sari et al., 2021). Phytoplankton are vital to the ocean carbon cycle and ecological change. *Chl-a* is highly susceptible to climate change at many scales. At the same time, sea surface temperature (SST) is critical for tracking and comprehending numerous marine and atmospheric phenomena across space and time (Jang & Park, 2019). When the upwelling conditions occur, sea surface temperatures fall, dissolved oxygen falls, and nutrients rise, resulting in an abundance of phytoplankton. As a result, *Chl-a* and water temperature must be monitored.

Remote sensing technologies, like those mentioned by Lakshmi et al. (2023); Mohebzadeh et al., (2020), help monitor water more efficiently and cost-effectively. They allow us to use *Chl-a* remote sensing to assess ecological impacts over specific periods (Free et al., 2021). However, satellite detection of *Chl-a* concentration estimates surface levels but cannot accurately measure primary (Manzar Abbas et al., 2019; Rahman et al., 2019). Temperature variations also affect aquatic life due to atmospheric processes and land proximity, causing surface temperatures to change significantly over time (Kniebusch et al., 2019). Despite advances in remote sensing and machine learning for monitoring marine ecosystems, predicting climate impacts such as El Niño's effect on upwelling and marine life remains challenging. Remote sensing helps estimate ocean *Chl-a*, but it only provides a partial view of marine ecosystems, and limited data availability can affect prediction accuracy (Efriana et al., 2024; Hedley et al., 2016). The ocean's complexity, influenced by weather and chemical processes, makes modeling even more complex. Moreover, the variability in upwelling events across different marine areas adds another layer of difficulty (Dabuleviciene et al., 2020). Addressing these issues requires cooperation to improve remote sensing techniques and ensure we have reliable data for model validation and refinement.

Several studies by Ampou et al. (2020); Katlane et al. (2023); Welliken et al. (2018) which utilized MODIS imagery and the Google Earth Engine for monitoring waters, identified significant seasonal variations in *Chl-a* concentrations, with notable peaks during periods of lower sea surface temperatures between May and September. This observation underscores the critical relationship between oceanic temperature variations and marine productivity, as influenced by climatic and environmental conditions. However, due to the current spatial resolution of 250 m × 250 m, there are limitations in accurately capturing fine-scale variations and features within the landscape. This lower resolution may result in losing crucial details, especially in areas with complex land cover patterns or dynamic environmental processes. However, In general, it is not as critical in the study of oceans to have much detailed land cover data about areas where there are uniform cover conditions compared to places where the cover types are pretty diverse and changing frequently compared with terrestrial environments or coastal regions characterized by varying types of coverage tend to be heterogeneous, possessing remarkable characteristics. Homogeneous water bodies may require less detailed data when considering lower spatial resolutions (Schourup-Kristensen et al., 2021). Specifically, in marine science research, the accuracy of analysis or findings is less likely to be affected by the sacrifice of details in such areas, such as reduced maximum spatial resolution (Radoux et al., 2020). In contrast, coastal regions have complex interactions between sea/ocean and land, requiring high resolution for studying marine ecosystems, pollution effects on those ecosystems, and other things happening within them.

Building upon the insights from previous research, this study aims to further explore and refine the monitoring of marine ecosystems through advanced remote sensing and machine learning techniques, including address detail gaps by priotizing the use of Landsat 8 over MODIS, Although Landsat data is available every 16 days, with research locations that focus on shallow water, it is better to use more detailed imagery, which allows for more detailed observations of land features and environmental parameters. By utilizing Landsat-8 more extensively, the study seeks to capture finer nuances in the water quality around Satonda Island, particularly during upwelling events. These events can be spatially localized and may have significant impacts on local marine ecosystems, but their finer-scale effects might be missed or underestimated when using lower-resolution imagery like MODIS. Therefore, by leveraging Landsat-8's superior spatial resolution, the study aims to fill these spatial detail gaps and provide more precise assessments of water quality dynamics in the study area.

METHODS

Study Area and Data

Indonesia is known for its large archipelagic landscape. The country has one of the richest marine habitats in the world. Satonda Island is the exclusive feature of many islands, like a volcanic island in the center of the Flores Sea (Figure 1). One of its characteristic geological features is a striking lake, which lies at its central position and has developed into a major tourist site. This is further accentuated by the fact that Satonda Island is a National Park, which only goes on to depict a nation's dedication in protecting the nation's natural heritage (Decree of the Minister of Environment and Forestry of the Republic of Indonesia, 2022)

The fact that a large percentage of the waters of Satonda Island fall within a protected area makes it of great significance to monitor the waters of Satonda Island. This is so because the quality of the waters plays a great role in determining the health and diversity of the biota that lives underwater and is near Satonda Island. The guarantee is that the quality of water should be considered paramount for maintaining an ecological balance, which is, in turn, a platform that supports and sustains the rich marine life in these waters. This goes a long way in the conservation of natural biodiversity and also in ensuring the island remains a source of attraction to visiting eco-tourists.

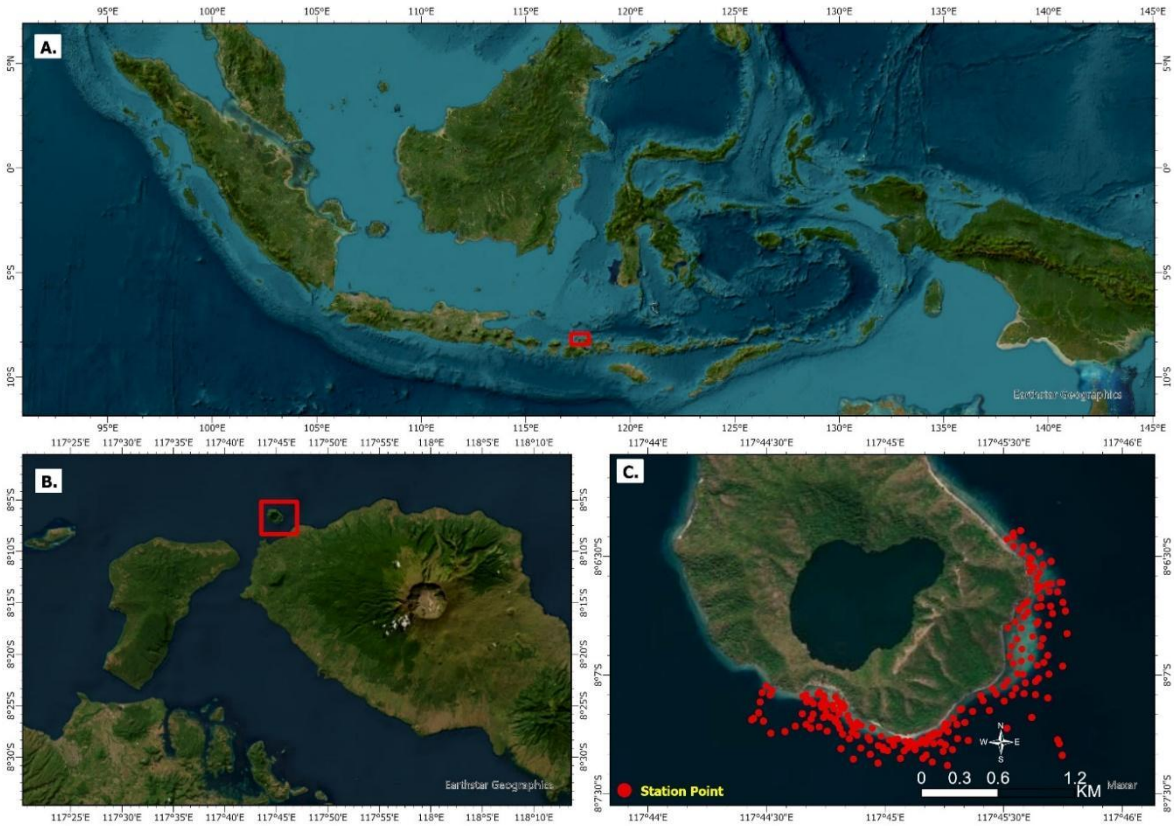

Figure 1. Study site: (a) Indonesia; (b) Dompu, West Nusa Tenggara; and (c) Satonda Island

This study used 190 stations of in situ data to validate the use of algorithms on Landsat 8 imagery that launched on February 11, 2013. This satellite consis of two sensors, namely the Operational Land Imager (OLI) sensor and the Thermal Infrared Sensor (TIRS), with a spatial resolution of 30 meters (visible, NIR, SWIR), 100 meters (thermal), and 15 meters (panchromatic)

(USGS, 2014). Then use image data from 2013–2023 to see the upwelling that occurs in Satonda waters.

Classification and Accuracy Test

Data processing carried out on Google Earth Engine (GEE) (Gorelick et al., 2017) with two data types: in situ data in the form of *Chl-a* concentration values and sea surface temperature at 190 station points. Data was collected on Satonda Island from April 29, 2023, to April 2, 2023, using the AAQ-RINKO instrument. In situ data is divided into Training (70%) and Validation (30%). Training data were used to determine the algorithm's performance, while validation data were used to test its performance. Then there is secondary data, Using Landsat-8 OLI satellite imagery to estimate *Chl-a* concentrations; the Landsat-8 data used is already level 2, so there is no need for radiometric correction and calibration, while for water surface temperature and using Landsat-8 satellite imagery TIRS, calibration, and radiance correction are needed. The image processing process also carried out fog and sunscreen filtering, however the cloud removal process cannot be carried out, so several parts of the water in the Landsat 8 image were recorded by clouds. The Landsat data used is from 2013–2023.

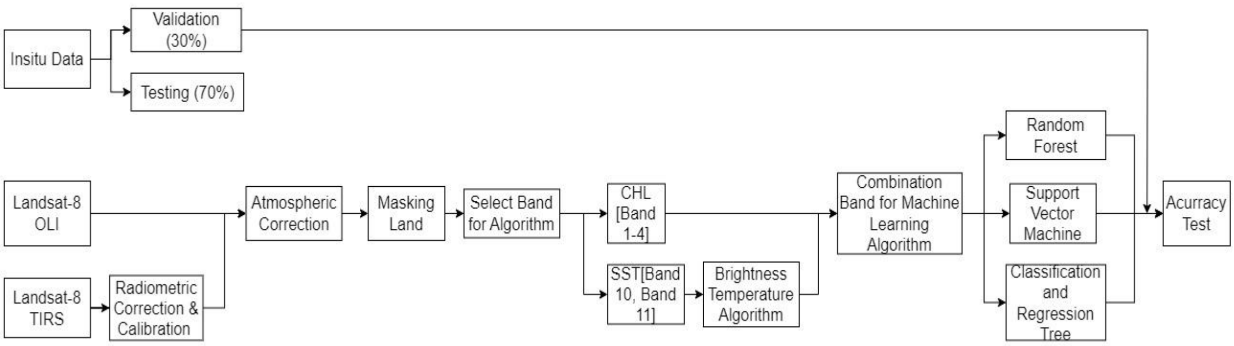

Figure 2. Research Framework

The estimation for the *Chl-a* parameter uses the algorithm (Ha et al., 2017), there was the band combination formula = [Band 1/Band 4]. Meanwhile, sea surface temperature estimation uses an algorithm, specifically the band combination formula = [Band 10, Band 11]. After determining the band combination, perform machine learning regression with data that has been divided into training data. We tested three machine learning regressions, namely Random Forest, Support Vector Machine, and Classification and Regression Tree. Then accuracy was tested with in situ data which has been divided into testing data. The best machine-learning results was used to estimate *Chl-a* and temperature. *Chl-a* and temperature data were processed for 10 years so that the condition of the waters can be known when upwelling occurs in Satonda waters.

Machine Learning Regression

Random Forest (RF)

The random forest algorithm was developed in 2001, which has been used particularly for classification and regression. This algorithm showed exceptional performance, indicated by the number of variables which significantly higher than the number of observations, and it can handle large data dimensionality and multicolinearity while remaining quick and immune to overfitting. It is, however, affected by the sample design (Belgiu & Drăguţ, 2016).

Support Vector Machine (SVM)

Simulations of several parameter combinations were carried out to test the accuracy of the SVM, where the SVM also looked for the maximum marginal Hyperplane to determine separate data classes (Mountrakis et al., 2011). Furthermore, characteristic of SVM is increasing numbers of classes can reduce the level of accuracy.

Classification and Regression Tree (CART)

The CART was employed to classified response variables consisting nominal, ordinal, or continuous. This algorithm determines variables and thresholds in classifying data. The classification tree is formed by the CART algorithm if it has a categorical scale on the response variable. Meanwhile, a regression tree is produced if the response variable is continuous data (Zacharis, 2018).

Data Analysis

This study's data analysis is descriptive, taking into consideration both spatial and temporal elements. Then, using in-situ data, statistical analysis is used to validate the algorithm. R-square and Root Mean Error Square (RMSE) were utilized in this investigation (Zhang et al., 2020).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Xesti,i - Xmeas,i)^2}{N}} \quad (1)$$

$$R^2 = \frac{1}{2}\sum_{i=1}^{N}(X_{esti,i} - X_{meas,i})^2 \quad (2)$$

Explanations,
N: number of data
Xmeas: value from in situ data,
Xesti: the value of the data obtained from the estimation by the image

The connection between observed and expected values is measured by R squared (R^2). R-square helps us know how well the overall regression model explains variations in the data. The formula for calculating R^2 is given below as equation (1). R-square values vary from 0 to 1. The closer the value is to one, the more precise the data collected. On the other hand, RMSE helps find out how accurate the model estimates are in predicting actual values in the same data units. The RMSE value, is closer to one; the larger it is, the more erroneous the data. The best results are obtained when the value is close to zero.

RESULTS AND DISCUSSION

Chl-a and SST derived maps based on Machine Learning

Chlorophyll (*Chl-a*) concentrations and Surface Temperature (SST) during upwelling periods can vary depending on water depth, wind speed, and nutrients available in those waters (Suhermat et al., 2021; Wirasatriya et al., 2018). Upwelling is a process in which water masses in the ocean are more profound, but what happens in the sea will undoubtedly affect the surroundings, including shallow waters. This phenomenon is usually rich in nutrients, such as nitrates and phosphates, rising to the surface (McDowell & Hamilton, 2013; Katlane et al., 2023). The rising water mass brings these nutrients to the sea surface, which can then support phytoplankton growth, including algae containing *Chl-a*. Meanwhile, sea surface temperatures are cooler than in the surrounding area.

The *Chl-a* and sst parameters require an algorithm to figure out their concentration value when monitoring water quality via remote sensing. Monitoring carried out using remote sensing of course depends on the image quality. As a consequence, the accuracy of the algorithm and satellite photos must be tested. *Chl-a* is used as a marine fertility indicator to assess the concentration of phytoplankton in a body of water. This study used *the chl* algorithm from Ha et al. (2017). This machine learning algorithm was employed through its paces using three machine learning regressions: random forest, support vector machine, and classification and regression trees. On Satonda Island, the best accuracy test results were utilized to estimate *Chl-a*.

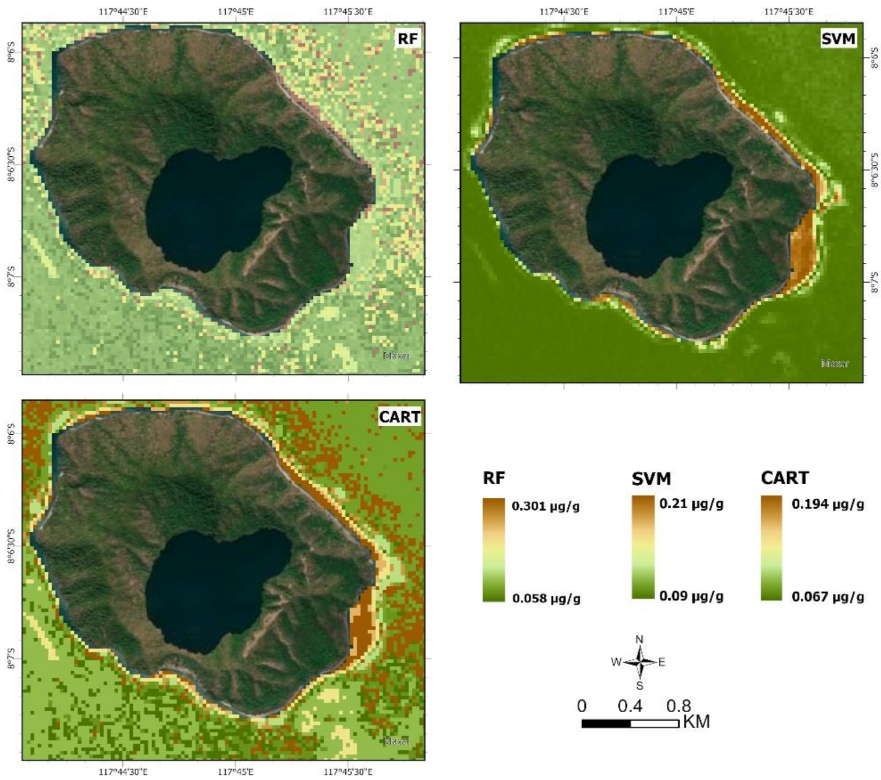

Figure 3. *Chl-a* derived maps based on Machine Learning: a) Random Forest b) SVM c) CART

Based on the results of three accuracy tests conducted on machine learning regression using the *Chl-a* algorithm, Random Forest demonstrates superior performance to other machine learning algorithms. The Random Forest method exhibits a broader range when juxtaposed with the outcomes obtained from alternative machine learning algorithms (Figure 3). In Satonda waters, the *Chl-a* concentration ranges from a minimum value of 0.058 to a maximum of 0.301. Analysis of the random forest accuracy tests using in-situ training data yields an R-square value of 0.365 and an RMSE value of 0.124. In contrast, employing data validation division indicates an R-square of 0.137 and an RMSE of 0.309. These findings suggest that the RF machine learning approach outperforms other methods (Table 1). The R-Square value is indeed moderate. However, the accuracy of this result shows that this method can use the data. This finding is in line with previous studies by Karimi et al. (2022) that found *chl-a* concentration is R= 0,32 in Western Coast of South Sulawesi-Indonesia during the Rainy Season and RMSE = 1.12 in a shallow freshwater Chitgar lake, northwest of Tehran city.

The outcomes obtained from alternative machine learning techniques reveal that the Classification and Regression Trees (CART) method achieved accuracy test scores on the training dataset of R-square 0.093 and RMSE 0.142, and on the testing dataset of R-square 0.019 and RMSE 0.321. Conversely, the Support Vector Machine (SVM) method displayed the least favorable performance, with accuracy test scores on the training dataset of R-square 0.043 and RMSE 0.324, and on the testing dataset of R-square 0.017 and RMSE 0.152. Between these two methods. When analyzing data variations across the spectrum, CART shows more significant variability compared to SVM, indicating the CART method is better than SVM. The results of this research can be used as a reference method for estimating chlorophyll in Indonesia's shallow water areas. This is because the data built on the model uses direct field data surveys.

Table 1. *Chl-a* accuracy test results with a machine learning algorithm on Landsat-8 OLI.

Machine Learning Algorithm	**Training**		**Testing**	
	RMSE	**R-Square**	**RMSE**	**R-Square**
Random Forest	0.124	0.365	0.309	0.137
Support Vector Machine	0.324	0.043	0.152	0.017
Classification and Regression	0.142	0.093	0.321	0.019

On the other hand, the sea surface temperature parameter functions as an indicator that plays an important role in the growth conditions of marine biota (Androulidakis & Krestenitis, 2022; Sari et al., 2021). Machine learning regression random forest, support vector machine, and classification and regression tree methods are all included in the algorithm used to predict the temperature in Satonda waters. The precision was assessed using in-situ data on sea surface temperature in Satonda coastal.

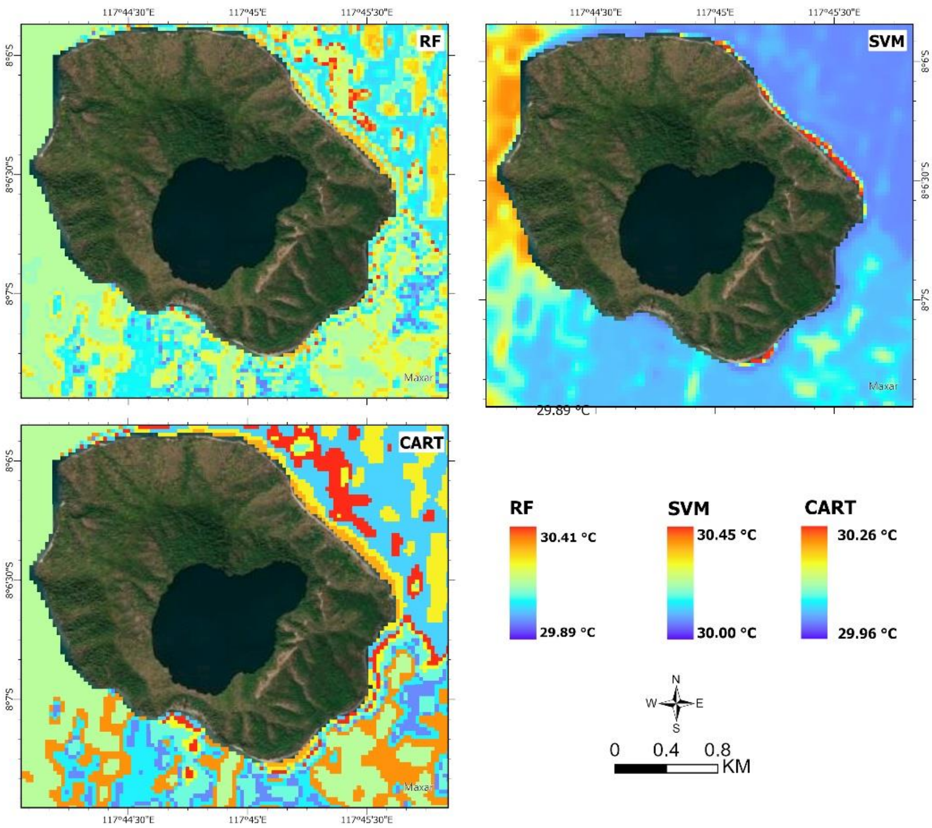

Figure 4. SST derived maps based on Machine Learning: a) Random Forest b) SVM c) CART

The findings from three machine learning regression analyses conducted on sea surface temperature (SST) characteristics indicate that Random Forest emerges as the most effective technique. Random Forest exhibits a broader range of SST estimation results than other methods (Figure 4). Specifically, the data reveal a detected temperature range with a minimum value of 29.89 and a maximum value of 30.41 using the Machine Learning RF method. Detailed comparisons in Table 2 demonstrate RF's superior performance over SVM and CART, with a Training R-square value of 0.411 and an RMSE of 0.180. The testing dataset corroborates these findings, revealing an R-Square testing result value of 0.30 and an RMSE of 0.27. These results affirm the effectiveness of the Random Forest machine learning approach in SST estimation on

Satonda Island. This finding is in line with previous studies by Liu et al. (2021) and Dyba et al. (2022) that found estimation of SST is (RMSE= 1.85 and R-Square = 0.95) in Arid Northwest China Using Landsat Satellite Images and also in lakes in north Poland with the result (RMSE = 1.66 and R-Square = 0.95).

The comparative analysis reveals notable disparities in the results obtained from SVM and CART methods. The performance metrics of CART demonstrate similarities to those of the RF method, with R-square values of 0.169 and 0.034 and RMSE values of 0.206 and 0.270, respectively, on the training and testing datasets. In contrast, SVM exhibits relatively poorer performance on the training and testing datasets, as evidenced by R-square values of 0.031 and -0.000004 and RMSE values of 0.226 and 0.287, respectively. These findings underscore CART's superior performance following RF while highlighting SVM's comparatively inferior performance.

Table 2. SST accuracy test results with machine learning algorithm on Landsat-8 TIRS

Machine Learning Algorithm	Training		Testing	
	RMSE	R-Square	RMSE	R-Square
Random Forest	0.180	0.411	0.274	0.030
Support Vector Machine	0.226	0.031	0.287	-0.000004
Classification and Regression	0.206	0.169	0.270	0.034

Upwelling on Satonda Coastal From 2013 to 2023

Upwelling occurs when deeper ocean water ascends to the surface, typically cooler and nutrient-rich (Rutledge et al., 2024). This phenomenon is driven by forces such as wind, the Earth's crust, and the Coriolis effect, which push deeper water towards the surface. While upwelling primarily manifests in the deep sea, its effects extend to surrounding areas, including shallow waters (Bakun et al., 2015). Upwelling change affects the life of marine biota. From the accuracy results of the three machine learning algorithms tested, it was found that the best algorithm was a random forest (Table 2) . Thus, the Random Forest algorithm was used to estimate water quality parameters *Chl-a* and Sea Surface Temperature (SST) on Satonda Island from 2013 to 2023 (Figure 5).

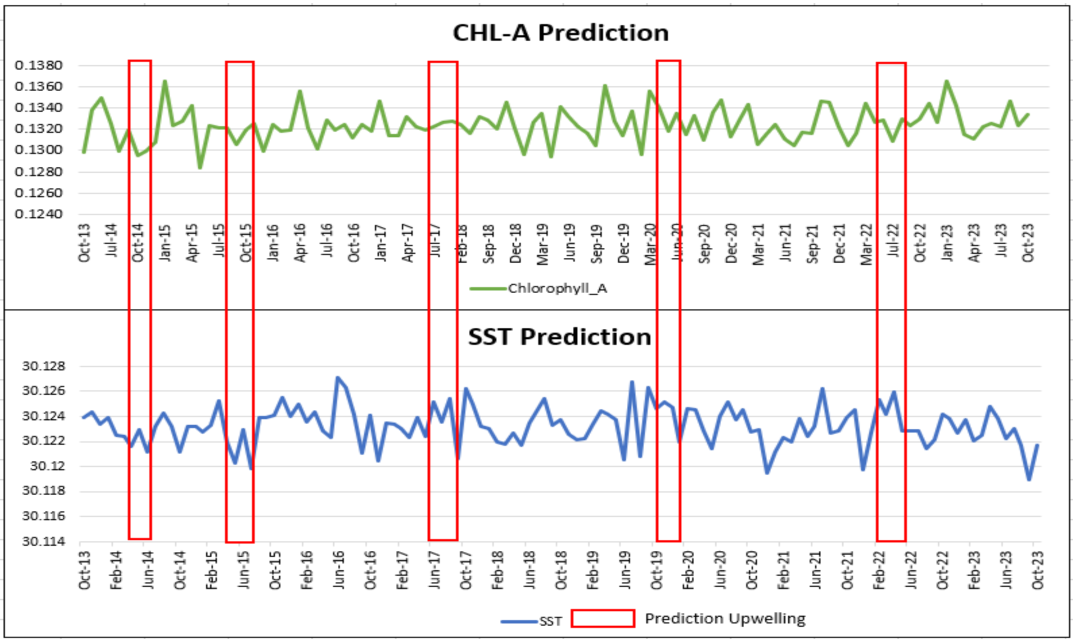

Figure 5. Timeseries *Chlorophyll-a* and Sea Surface Temperature (SST) from 2013 to 2023

There is no definitive answer on how much increase in *chlorophyll-a* and sea surface temperature occurs during upwelling, as this can vary greatly depending on location, time of day and local environmental conditions. Stronger upwelling may increase *chlorophyll-a* and more significant changes in sea surface temperature than weak upwelling. The upwelling phenomenon in Satonda Island can see the results of *Chl-a* and SST in the last 10 years. From the graphic results (Figure 5), it can be seen that the peak of upwelling in Satonda Coastal is different every year. However, from ten years of data, upwelling occurs in Satonda waters between June and November. In 2014, the peak of upwelling occurred in June; in 2015, it occurred in July. Then, in 2017, the peak of upwelling occurred in September. In 2019, it occurred from November to February 2020. Next, there was a peak of upwelling in August 2022, and in 2023, there was a peak of upwelling in September, starting until October 2023.

In the last ten years, the average value of chlorophyll concentration was 1.32 mg/m^{-3} with the lowest value reaching 1.28 mg/m^{-3} around May - June, and the highest value for chlorophyll concentration was 1.36 mg/m^{-3} around December - March. Meanwhile, the average value of SST concentration is 30.12°C with the lowest value reaching 30.118 °C around October – January, and the highest value for SST concentration is 30.128°C round June – August. This finding is in line with previous study by Simanjuntak & Lin (2022) that found chlorophyll concentrations can reach more than 1.5 mg/m^{-3}, occurring in August, while the minimum SST, lower than 25 °C, also appears in August along the South Coast near the Indian Ocean. The chlorophyll concentration results were similar to the research results but occurred in different months due to regional differences and the influence of seasonal winds. Meanwhile, research by Sari et al. (2022) found different responses from surface chlorophyll and peak SST in western Sumatra following wind speed patterns. The chlorophyll concentration and SST values in the southern part of Sumatra Island experienced upwelling in June, July, and August, while in the central part of Sumatra Island, this occurred in September, October, and November. The northern part of Sumatra Island strongly correlates with January, February, and March. Several factors, including location, wind direction and speed, and depth of topography, influence upwelling.

CONCLUSION

In this decade-long study on Satonda Island, imagery from Landsat-8 and machine-learning techniquees were used to monitor changes in water quality indicators of the island, such as chlorophyll-a (*Chl-a*) and sea surface temperature (SST). This is characteristic of an upwelling phenomenon, in which conditions occur under which cool, nutrient-rich water is lifted to the surface in marine environments. Among these algorithms, Random Forest (RF) was the best performer, with improved accuracy shown from an R-square of 0.448 and an RMSE of 0.169 for estimating the level of *Chl-a*. This study has revealed a marked seasonal upwelling at Satonda Island, particularly from June to November every year. It was marked with a drop in SST and an increase in *Chl-a* concentration of water, and the phenomenon was observed for these months, suggesting enhanced marine productivity. The peaks of the upwelling were subject to annual variations, but the variations showed the continuity of ecological rhythm attached to the fluctuating climatic and oceanographic conditions. The precise performance of the RF algorithm in capturing these variations points to its robustness in monitoring the environment. Such results clearly emphasize the critical utilization of cutting-edge technologies in environmental surveillance and marine conservation, such as remote sensing and machine learning. More advanced research and analysis will help general research show more comprehensive spatial scales and environmental factors related to variations. Our summarized work, on the one hand, shows that satellite data combined with machine learning is adequate in the study of marine conditions and, on the other hand, underscores predictability patterns in upwelling and implications on aquatic biodiversity and productivity. The success of the RF algorithm in estimating key water quality parameters over a considerable period opens the way for marine health preservation, together with the possible understanding of the impacts of climate change on ocean dynamics.

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DECLARATIONS

Conflict of Interest

We declare no conflict of interest, financial or otherwise.

Ethical Approval

On behalf of all authors, the corresponding author states that the paper satisfies Ethical Standards conditions, no human participants, or animals are involved in the research.

Informed Consent

On behalf of all authors, the corresponding author states that no human participants are involved in the research and, therefore, informed consent is not required by them.

DATA AVAILABILITY

Data used to support the findings of this study are available from the corresponding author upon request.

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