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Impact of Global Warming on water height using XGBOOST & MLP algorithms †

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Abstract: Over the past few years, the effects of global warming have become more pronounced, particularly with the melting of the polar ice caps. This has led to an increase in sea levels, which poses a threat of flooding to coastal cities and islands. Furthermore, monitoring and analyzing changes in water levels has proven effective in predicting natural disasters caused by rising sea levels. One vital factor in understanding the impact of global warming is sea surface height (SSH). Measuring SSH can provide valuable information about changes in ocean levels. This study used data from the Jason 2 altimetry radar satellite, which provided 36 cycle periods per year, to investigate water heights around the Hawaiian Islands in 2019. To accurately evaluate water height variations, a specific area near the Pacific Ocean close to the Hawaiian Islands was selected. By analyzing the collected satellite data, a chart of water heights was generated, which showed an overall increase in height over one year. This analysis provided evidence of changing ocean levels in the region, highlighting the urgency of addressing potential threats faced by coastal communities. The study also explored several factors that contribute to water height variations, such as sea surface temperature, precipitation, and sea surface pressure in the Google Earth engine cloud-based platform. Algorithms, including MLP and XGBOOST, were used to model water height within the specified range. The results showed that the XGBOOST algorithm was superior in accurately predicting water height, with an impressive R-squared value of 0.95. In comparison, the MLP algorithm achieved an R-squared value of 0.92. This study shows that advanced machine learning techniques are effective in understanding and modeling the complex changes in water height due to climate change. This information can help policymakers and local authorities make informed decisions and create strategies to protect coastal cities and islands from the growing threats of rising sea levels. Taking proactive measures is crucial in reducing the risks posed by more frequent and severe natural disasters caused by global warming.

Keywords: global warming; ocean; water height; XGBOOST; MLP; Google Earth Engine

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1. Introduction

Anthropogenic climate change has a significant impact on the planet, particularly through rising sea levels. However, the rate of sea level rise (SLR) is not consistent across oceans and varies over time due to a complex interplay of ocean dynamics, heat absorption, and surface forcing [1]. Radar satellite altimetry is a crucial technique for collecting precise global data on sea level and monitoring various geophysical characteristics of water bodies. Over the past four decades, satellite altimetry has revolutionized geosciences, particularly oceanography, geophysics, and geodesy. This method has been instrumental in Earth shape modeling, studying gravity acceleration, seabed relief mapping, monitoring coastal vertical displacements, and observing climate phenomena and long-term changes [2]. Human activities are impacting Earth's climate and shaping the planet. Global warming, caused by humans, is making the oceans warmer and causing ice to melt, resulting in rising sea levels. This is changing the physical shape of our planet. Satellites like TOPEX-Poseidon, Jason-1, Jason-2, and Jason-3 have been crucial in tracking these changes since the 1990s. These satellites measure sea-level changes and have improved our understanding of how heat is stored and distributed in the oceans. They show us how fast our climate is changing [3]. Using satellite altimetry data to track changes in average sea level is an important way to monitor climate change [4]. Currently, the assessments show a clear rise in sea level, increasing by around 3.1 ± 0.4 millimeters per year [5]. Using remote sensing data [6] is crucial for (CC), natural hazards (NH) [7,8], and environmental science [9], On the other side GEE cloud-based platform [10] has had an important role in monitoring Earth. Satellite data [11,12] and machine learning algorithms [13,14] are employed to predict and model every NH & CC. In recent years precipitation has affected water level [15], sea surface temperature can change the amount of precipitation [16] and additionally, sea surface pressure can be examined for indicating water level [17]. Water level forecasting is crucial for flood prevention and disaster readiness. Over the years, there have been advancements in water level prediction models [18]. Xin et al. conducted research on water height in Indonesia. They focused on the Indonesian Throughflow (ITF), which connects the tropical Pacific and Indian Oceans and plays a critical role in both regional and global climate systems. Through the use of a CNN model, they were able to improve the accuracy of predictions and found that the model could validly predict ITF transport with a lead time of 7 months. This discovery suggests that deep-learning approaches using SSH data can effectively predict ITF transport [19].

2. Material and methods

In the table below, the missions used in this paper are indicated.

Table 1. The following table displays the materials that were used in this paper.

Mission	*Band*	*Year*
ECMWF/ERA5/MONTHLY	surface_pressure	2019
OpenLandMap Precipitation Monthly	Jan Precipitation monthly,…	
GCOM-C/SGLI L3 Sea Surface Temperature (V1)	SST_AVE	
Jason-2/OSTM	C-band	

This table was created to present the data used in this study.

2.1. Case study

The Hawaiian archipelago is located in the central Pacific Ocean and is the southeastern part of the Hawaiian-Emperor chain. These islands were formed by a stationary hotspot that created volcanic islands on the Pacific plate, which moves toward the northwest [20]. The Big Island of Hawaii (21°N, 156°W) is the youngest and farthest southeast island in the Hawaiian archipelago. Over millions of years, the archipelago has sunk due to the weight of volcanic activity associated with this hotspot [21].

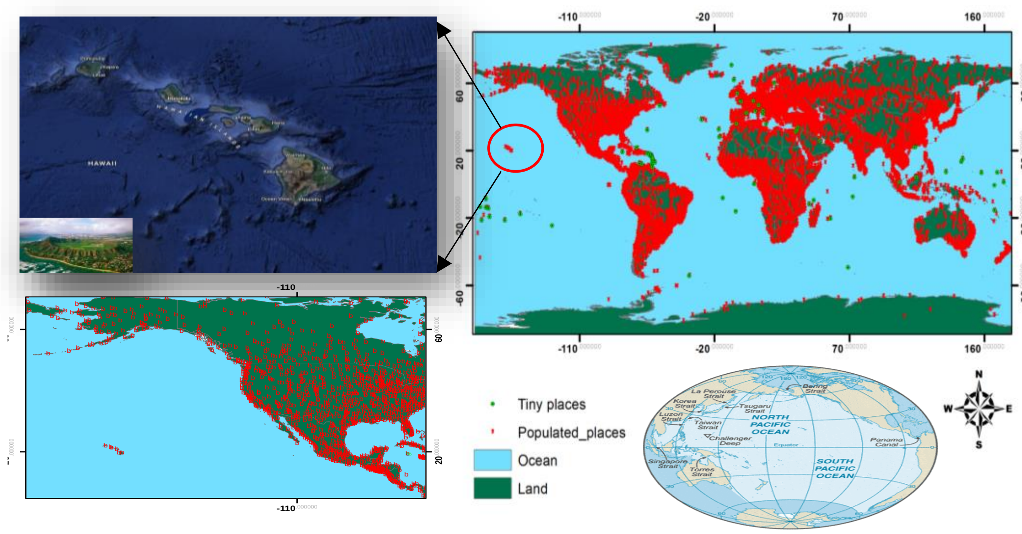

Figure 1. Location of the study area.

2.2. Methods

The sea surface height (SSH) data obtained from Jason-2 were sourced from the Archiving Validation and Interpolation of the Satellite Oceanographic Data Center (AVISO). The along-track SSH data have a spatial resolution of approximately 6-7 km, with the satellite ground track repeating every 10 days. [22], through the use of BRAT software [23] The 36 J-2 data in 2019 were processed. Also, the SSH for a region near Hawaiian island was extracted & and showed a trend of rising. We utilized Sea Surface Temperature (SST), Sea Surface Moisture (SSM), and Sea Surface Precipitation (SSP) which were created by using the GEE cloud-based platform, as inputs, while the target variable for prediction was the sea surface height (SSH). Inverse Distance Weighting (IDW) [24] in ArcMap software interpolation was used to estimate the SSH values between available data points. To model and predict SSH, we employed XGBOOST [25] and MLP [26] algorithms. Below, you can find more information about the architecture of both algorithms.

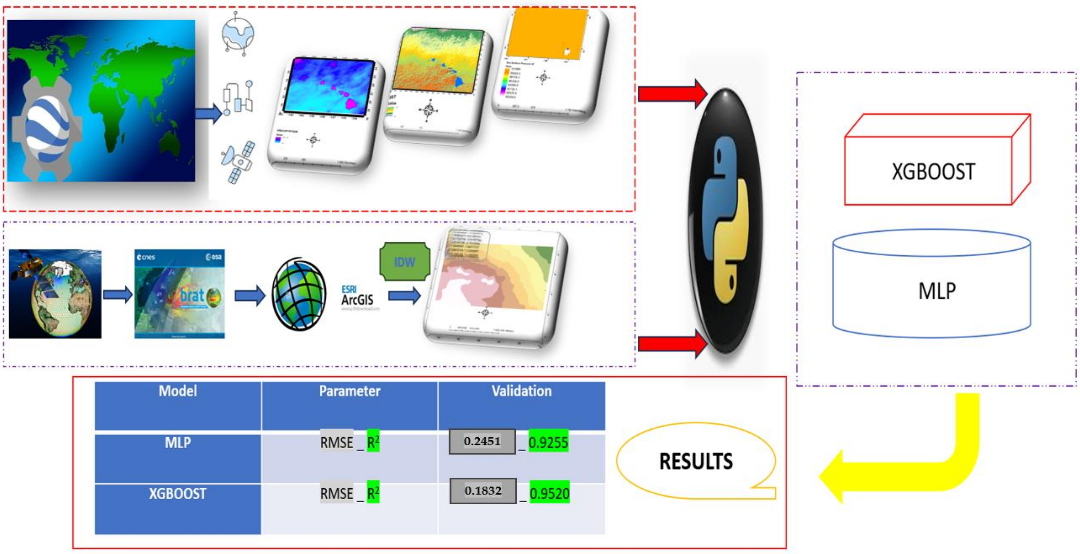

Figure 2. The process of study.

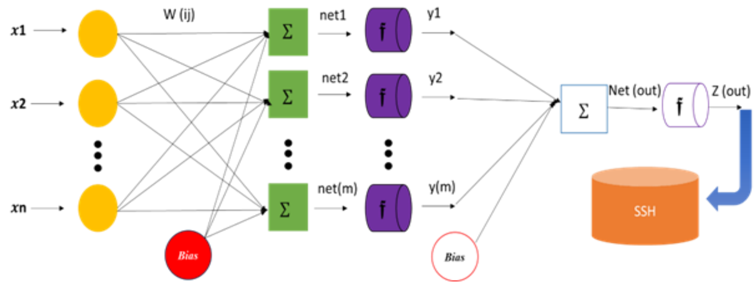

Figure 3. The architecture of the multi-layer perceptron (MLP) model.

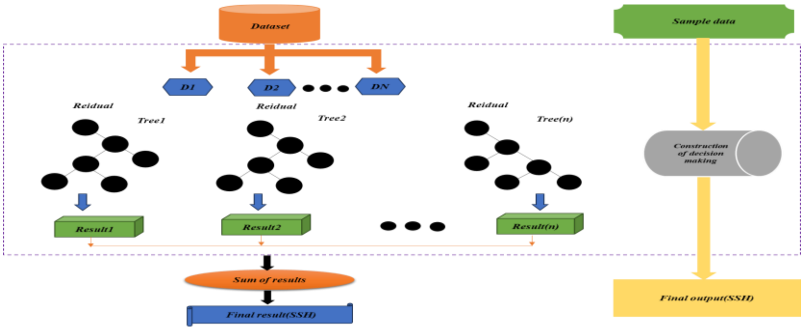

Figure 4. The architecture of the Extreme Gradient Boosting (XGBOOST) model.

Here is the architecture of the algorithm used to emphasize its performance in this study.

3. Results

Utilizing algorithms, a prediction map was generated. To assess the accuracy of the models, comparisons were made between the performances on the test, train, and overall datasets for both XGBOOST and MLP algorithms. Additionally, a chart was created to visualize the water level based on the SSH (Sea Surface Height) data points.

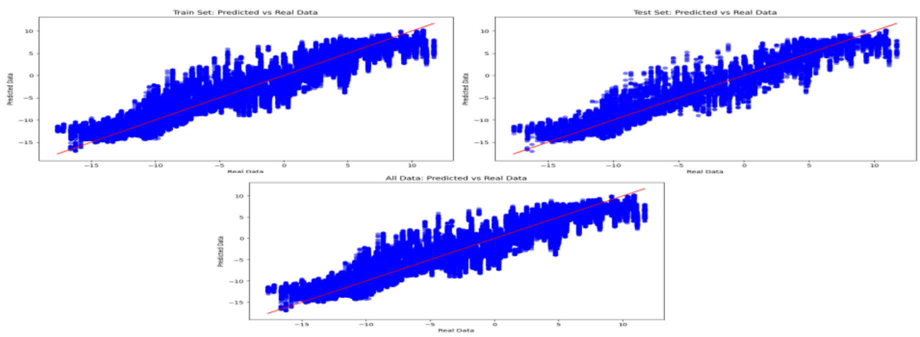

Figure 5. Compatibility between testing & training in MLP.

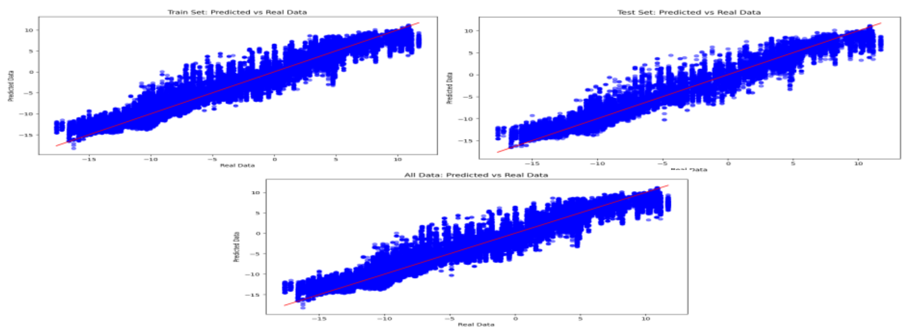

Figure 6. Compatibility between test & train in XGBOOST.

After using XGBOOST and MLP, Figure 5 and Figure 6 show a comparison between the predicted and real data. Based on this comparison, it is clear that the model performed well.

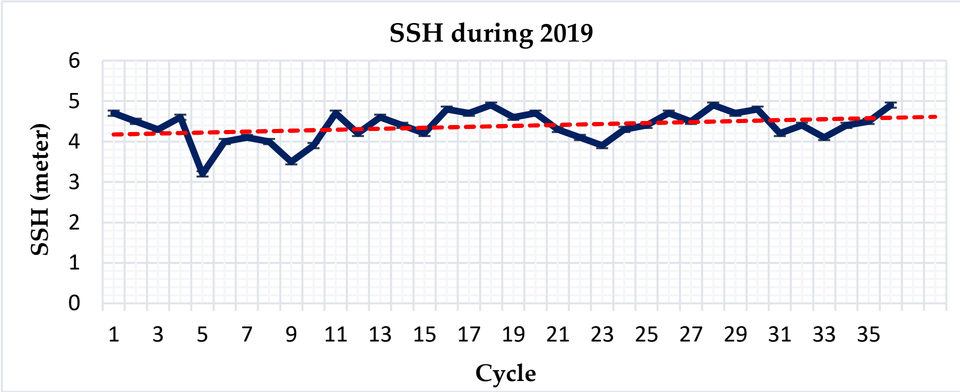

Figure 7. The trend of SSH (Y) during 36 cycles (X).

This chart shows the amount of water raised during 36 cycles in 2019 for the mentioned case study.

4. Validation

In evaluating the efficacy of our models, we employed R-squared and RMSE. R-squared offers an estimation of the correlation between the movements of a dependent variable and those of an independent variable. While it signifies potential biases in the data and predictions, it does not conclusively determine the quality of the selected model. A higher R-squared value suggests a more optimal fit, indicating a stronger correlation between the variables. [27]

$$\mathbf{R\_squared} = \mathbf{1} - \frac{\sum_{i=1}(\,(\boldsymbol{y}\,\boldsymbol{i} - \boldsymbol{y}\,\boldsymbol{i}\,\hat{}\,)^{2}}{\sum_{i=1}^{n}(\boldsymbol{y}\,\boldsymbol{i} - \boldsymbol{y}\,\boldsymbol{i})^{2}}$$

Lower values indicate better fit for the model [28].

$$\mathbf{RMSE} = \frac{\mathbf{1}}{\boldsymbol{n}} = \sum_{i=1}^{n}(\boldsymbol{y}\,\boldsymbol{i} - \boldsymbol{y}\,\boldsymbol{i}\,\hat{}\,)^{2}$$

Table 2. Validation.

Model	Parameter	Validation
MLP	RMSE _ R^2	0.2451_ 0.9255
XGBOOST	RMSE _ R^2	0.1832 _ 0.9520

We used 36 Jason-2 datasets corrected and processed with BRAT software. We assigned 20% for training and 80% for testing. Our goal was to see if different algorithms could help predict future outcomes.

5. Discussion

It's unfortunate, but the impact of global warming on places like the Hawaiian Islands is worse. This study used algorithms such as XGBOOST and MLP to forecast rising sea levels (SSH) in the region. The research emphasizes the urgency of addressing climate change and indicates the important role of data in protecting coastal communities from the risk of higher sea levels. The study opted for XGBOOST and MLP algorithms due to their efficacy in decoding complex patterns within the rising sea level data. XGBOOST is particularly skilled at capturing simple relationships, while MLP, functioning as a sophisticated neural network, proves adept at handling complex connections.

6. Conclusion

Global warming has hurt the planet, causing climate change and rising sea levels. To study the sea surface height (SSH) over the term of a year, we analyzed Jason-2 radar altimetry data from 2019 in the North Pacific Ocean around the Hawaiian Islands. The findings indicate that water levels in this area increased by approximately 20 centimeters in 2019. Two algorithms, Extreme Gradient Boosting and Multi-layer Perceptron, were employed to model and predict the SSH. The results revealed that the XGBOOST algorithm outperformed the MLP algorithms, with an R-squared value of 0.9520 compared to 0.9255. The SSH trend chart clearly showed evidence of increasing water levels near the Hawaiian islands where a considerable number of people live there. It is crucial to monitor these areas to protect them from the threat of rising water levels.

Author Contributions: Nilufar Makky: Conceptualization, Methodology, Software Data curation, Writing-Original draft preparation, Software, Validation. Dr. Khalil Valizadeh Kamran & Dr. Sadra Karimzadeh: Visualization, Investigation, Writing-Reviewing and Editing.

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