

# Prediction of Submergence of Islands Due to Glacier Melting & Sea Level Rise using Deep Learning

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**Abstract** - Prediction of Submergence of Island Due to Glacier Melting & Sea Level Rise will have significant contribution in the field of Environmental Engineering. This research paper present comprehensive overview of development and implementation this project, which designed to predict the submergence of island especially Lakshadweep Islands which is union territory of India. Capitalizing technologies like LSTM for forecasting sea level rise over period of time and Linear Regression for forecasting glacier melting and python for model training. To enhance the user experience also making it easy to understand the prediction we integrated JavaScript via python ELL framework to show charts and outputs. This paper discusses about the technical innovations, methodology and result of the project. It also spotlights its potential to help people living in islands which are submerging to evacuate them before this threat. This project aims to develop system to migrate people living on island and saving thousands of lives.

**Key Words:** Submergence, LSTM, JavaScript, EEL, Model Training, Linear Regression, User Interface

## 1. INTRODUCTION

In coastal areas around the world, the possibility of island submergence brought on by glacier melting and sea level rise presents serious concerns. The Lakshadweep Islands, which lie far away in the Arabian Sea, are particularly prone to these environmental dangers.

Sea level rise is mainly caused by thermal expansion and glacier recession, accounting for around 75% of the rise in sea levels. Although there are roughly 123 glaciers that are continually monitored through direct field measurements, there are over 198,000 land glaciers in the world, making comprehensive and ongoing monitoring logistically and financially difficult. As a result, the effects of glacier melting and the ensuing rise in sea level are becoming more urgent problems, especially for island people.

Using modern technologies, this research initiative aims to tackle these issues, including Deep Learning techniques such as Long Short-Term Memory (LSTM) networks for forecasting sea level rise over time, and Linear Regression for predicting glacier melting. By harnessing the power of Python for model training and integration with JavaScript through the Python ELL framework, the project seeks to enhance user experience and facilitate the interpretation of predictions through visual aids such as charts and outputs. The main goal of this project is to develop how technology has the potential to help communities living on fragile islands.

## 2. OBJECTIVE

- Prediction of submergence of Islands in Arabian Sea (Lakshadweep).
- To utilize predictive methods, particularly deep learning models, to anticipate and forecast island submergence caused by sea level rise and glacier melting, in order to facilitate systematic and well-informed migration of vulnerable communities to secure locations.
- To enhance disaster preparedness and response strategies by employing predictive model.

## 3. SCOPE

- Utilize deep learning techniques for predicting the submergence of islands due to glacier melting and rising sea levels.
- Develop advanced predictive models to forecast the extent of environmental impact on island regions.
- Enable improved preparedness and planning strategies by providing accurate predictions of potential submergence.
- Evaluate the potential risks and vulnerabilities of specific island areas to prioritize mitigation efforts.

## 4. SURVEY OF EXISTING SYSTEM

A] M. V. Karamchedu, "Glacier Melting Risk: Predictive Model of Glacial Melting by Correlating Timeseries Analysis of Geoglacial Data with Fractal-Analysis of Remote-Sensed Images," IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, 2020

This paper highlights the significant role of glacial melting in contributing to observed sea level rise, emphasizing the challenges posed by the vast number of unmonitored glaciers worldwide. It underscores the importance of employing remote sensing techniques, such as multi-year satellite imaging, to gather comprehensive data for glacier surveillance. Unlike traditional methods that rely heavily on active field measurements, this study proposes the use of fractal analysis of Landsat images to predict glacial melt.

By examining annual changes in glacier surface geometry and correlating them with glacier mass balance and local temperatures, the study demonstrates the potential of fractal analysis as a predictive indicator of glacial melt. The results indicate a significant correlation between changes in fractal dimension and both glacier mass balance and mean temperatures. This suggests that readily available remote sensing techniques can be effectively utilized to continuously

monitor glaciers and identify regions undergoing critical melting. [1]

B] L. -h. Wang, A. -x. Lu, T. Yao and N. -l. Wang, "The study of typical glaciers and lakes fluctuations using remote sensing in Qinghai-Tibetan Plateau," 2007 IEEE International Geoscience and Remote Sensing Symposium, Barcelona, Spain, 2007, pp. 4526-4529

The findings reveal significant changes in lake area, strongly influenced by local climate patterns. Lakes in the middle Tibetan Plateau, particularly those around Selincuo Lake and Namucuo Lake, have expanded over the past three decades, accompanied by dramatic glacier retreat in surrounding areas. This expansion is attributed to increased precipitation, decreased potential evapotranspiration, and water runoff from glacier melting.

Conversely, lakes in the source region of the Yellow River on the Northeast Plateau have shrunk despite glacier retreat in the vicinity of Mt. A'nyêmaqên. Here, while precipitation trends have been positive, temperature increases have led to enhanced evapotranspiration, resulting in lake shrinkage. Additionally, human-induced ecosystem regression in the region is believed to have contributed to this phenomenon. [2]

C] K. M. A. Hassan, M. A. Haque and S. Ahmed, "Comparative Study of Forecasting Global Mean Sea Level Rising using Machine Learning," 2021 International Conference on Electronics, Communications and Information Technology (ICECIT), Khulna, Bangladesh, 2021

Climate change poses a significant challenge, with rising global temperatures leading to increased ocean and atmospheric warming and subsequent sea-level rise. This phenomenon has the potential to trigger catastrophic natural disasters worldwide. While current monitoring tools like tide stations and satellite radar altimeters track local and global sea-level changes, they lack the capability to predict future scenarios accurately. This paper aims to fill this gap by employing advanced machine learning models to forecast the most likely future global sea-level rise.

Drawing upon 28 years of sea-level rise data, the study trains various machine learning algorithms, including Linear Regression, Moving Average, Dense Neural Network (DNN), and Wave Net—a variant of Deep Convolutional Neural Network. By leveraging these models, the research seeks to provide insights into future sea-level rise trends, offering crucial information for policymakers, researchers, and stakeholders grappling with the complex challenges posed by climate change. [3]

## 5. IMPLEMENTATION

### A. Data Processing

Data processing means data is collected and translated into usable information. To get accurate result from predictive models the data which is collected should be in proper format so we process data. We used to datasets which are glacier melting dataset and sea level rise dataset. This dataset consists daily glacier melting extent and daily sea level rise which calculated through satellites. To calculate glacier melting extent we convert data into monthly mean average sea ice extent. For sea level rise to calculate sea ice extent we transformed data

into monthly average sea level rise suitable for both predictive models.

### B. Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) network is a recurrent neural network (RNN). The processed data is sequential which means it has particular pattern. LSTMs have internal memory blocks that can store information for extended periods, enabling them to learn from distant data points in the sequence and make accurate predictions. Time series data is typically divided into sequences of past values (inputs) and corresponding future values (targets). The LSTM network is trained on a portion of the data. It learns to map the input sequences to their corresponding future values by adjusting the weights of its internal connections. Once trained, the model can predict future values for unseen sequences by processing them through the LSTM blocks and generating an output. For this project LSTM is used for predicting sea level rise. Transformed dataset contains two columns one in date and second one is mean sea level rise. The layers of an RNN, also known as an LSTM network, are constructed using LSTM units. RNNs can retain inputs for extended periods of time because to LSTMs. This is thus because, like computer memory, LSTMs store information in a memory. Information can be read, written, and deleted from the LSTM's memory. This memory can be seen as a gated cell, where the gate denotes that the cell chooses, according to the value it places on the information, whether to keep it or not, or to open the gates. Weights are used to assign importance, and the algorithm also learns these. This essentially indicates that it gradually discovers what information is significant and what is not. Three gates are present in a long short-term memory cell: input, forget, and output. These gates control whether to allow data to enter the system (input gate), discard data that isn't needed (forget gate), or allow data to affect the output at the current time step (output gate).

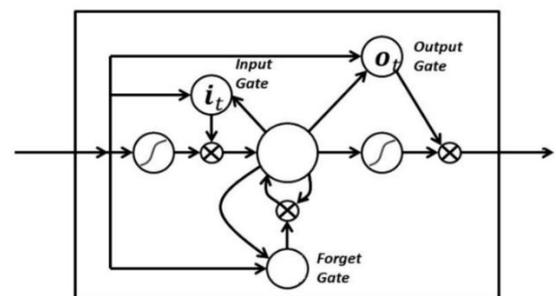


Fig 1. Long Short-Term Memory Model

An LSTM has analog gates that are sigmoid, or gates that range from zero to one. They can perform backpropagation since they are analog. LSTM solves the challenging problem of disappearing gradients because it

maintains sufficiently steep gradients, resulting in a quick training period and good accuracy.

In this project model considers pervious 12 inputs or data of past 12 months and then it predicts the next value by using these values by analyzing the trends. For next step the it considers previous values including the predicted value then predict next value. This process is continued until it predicts the all values.

C. Linear Regression Model

Linear regression is a statistical method used to model the relationship between one or more predictor variables and a continuous response variable. We are using a multiple linear regression model, which means we are predicting the response variable sea ice extent using two predictor variables year and sea ice extent. Linear regression assumes a linear relationship between the predictor variables and the response variable. It implies that the change in the response variable is linearly associated with changes in the predictor variables. The first step in linear regression is to fit the model to the data. This involves estimating the coefficients of the linear equation that best fits the observed data points. The coefficients represent the slopes of the lines that define the relationship between the predictor variables and the response variable. In the provided code, the linear regression model is fitted using the Ordinary Least Squares (OLS) method. OLS minimizes the sum of the squared differences between the observed and predicted values of the response variable. This method finds the line that best fits the data by adjusting the coefficients to minimize the errors between the predicted and observed values. Once the model is fitted, we can interpret the coefficients to understand the relationship between the predictor variables and the response variable. The coefficient for each predictor variable represents the average change in the response variable for a one-unit change in the predictor variable, holding other variables constant. After fitting the model, we evaluate its performance using various metrics such as Mean Squared Error (MSE) and R-squared. MSE measures the average squared difference between the predicted and observed values of the response variable. R-squared measures the proportion of the variance in the response variable that is explained by the predictor variables.

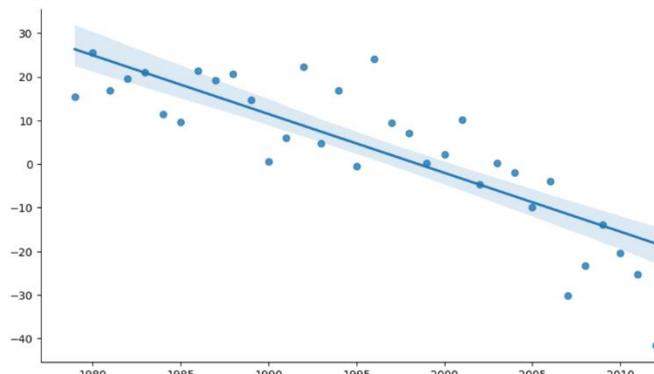


Fig 2. Sea Ice Extent Over Years

D. Python EEL

Python EEL (Embedding Python in HTML) is a powerful library that facilitates seamless communication between Python and HTML/JavaScript. It allows developers to build desktop GUI applications using web technologies such as HTML, CSS, and JavaScript, while leveraging the capabilities of Python in the backend. EEL simplifies the process of creating interactive user interfaces by providing a bridge between Python functions and frontend components. Developers can define Python functions and call them directly from JavaScript, enabling dynamic updates and interactions within the application. This library is particularly beneficial for Python developers looking to create cross-platform desktop applications with modern user interfaces, leveraging their existing Python skills alongside web development technologies. With its straightforward integration and extensive documentation, Python EEL empowers developers to build robust desktop applications efficiently.

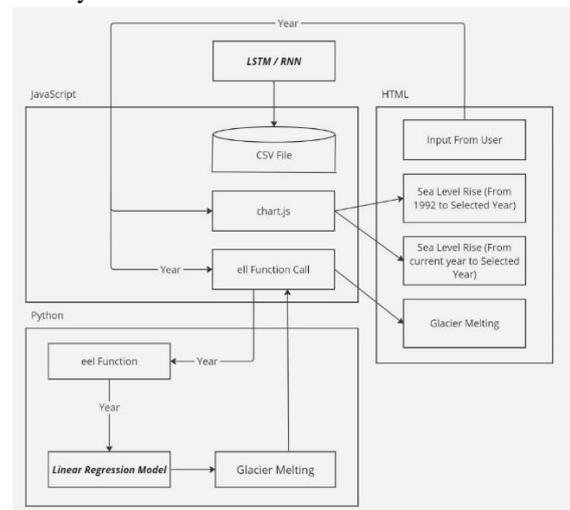


Fig 3. System Architecture

E. Chart.js

Chart.js is a versatile and lightweight JavaScript library that simplifies the process of creating interactive and visually appealing charts and graphs on web applications. It provides developers with a wide range of customizable chart types, including line charts, bar charts, pie charts, and more, allowing for the representation of complex data in a clear and concise manner. Chart.js offers a simple yet powerful API, making it easy to integrate dynamic data and customize various aspects of the charts, such as colors, labels, tooltips, and animations. Its responsive design ensures that charts adapt seamlessly to different screen sizes and devices, providing a consistent user experience across platforms. Here this is used to show the output of sea level rise till input year using chart.js it displays interactive line charts so that it is easy to

understand the seasonality in the data and better understanding.

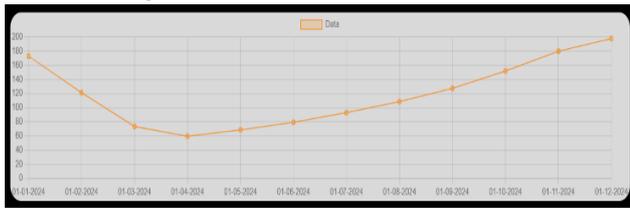


Fig 4. Line Plot of Predicted Sea Level Rise

6. RESULT

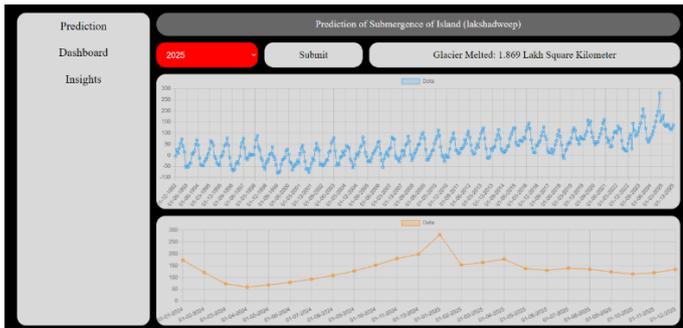


Fig 5. Prediction Web Pages

Model	Accuracy	F1-Score
ANN	1	0.01
Linear Regression	71	0.71

Fig 6. Performance Evaluation for Glacier Melting Model

Model	Loss (while training)	F1-Score
ANN	2113.65	0.01
LSTM	0.005	0.82

Fig 7. Performance Evaluation for Sea Level Rise

7. CONCLUSION

In conclusion, this project has endeavored to address the pressing environmental concerns surrounding island submergence in the face of glacier melting and rising sea levels. By integrating advanced machine learning models and leveraging valuable data insights. This endeavor not only enhances our understanding of the impending challenges but also provides a practical tool for mitigating potential damage. In addition, use of chart.js for plotting graphs to make it easier for individuals to understand the sea level rise over the years and get insights of project. And also, integration off python for creating model and training them also for interconnecting them with web page made it easy than other API's.

Moreover, during the development of this project there are some valuable insights. During march and April there is significant sea level rise than during September month. Sea level increasing every year and when data is plot there is seasonality in the data. During summer seasons as per Indian conditions which in month of march there is more sea level rise and during month of September Sea level rise is less as compared to march. Also, during month of march the glacier which melting is high as compared to in the month of September.

When combining both datasets in monthly basis we performed Pearson's coefficient of correction test to see if there is particular relation between both of them. The test result come out as both are moderately correlated. Which says both the values are increasing when one value increases or rises. In summary, there are multiple factors which are affecting the sea level rise like Thermal Expansion of Water, Changes in Land Water Storage, Ocean Circulation Changes, Tectonic Movements, Climate Variability and Natural Events, Oceanic Forcing. Through this project we get to understand the change in sea level rise which is affected by glacier melting.

8. REFERENCES

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