Improving Coastal Adaptation: Climate Change Impact Modelling for Resilient Communities

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ABSTRACT

Continuous change in climate highlights the vulnerability of coastal communities, there will be a lot of worries among the coastal communities with the risk of rising sea levels, storm surges, and extreme weather conditions, This study helps in identifying the risk of flood using two machine learning algorithms Random Forest and Support Vector Machine for predicting flood-prone areas. The experiment was performed on the Permanent Service for Mean Sea Level (PSMSL) dataset. The random forest algorithm accuracy of calculating Flood situation is 78%, and that of the Support Vector Machine it is 71%, also random forest shows high precision around 74% which is greater than the Support vector machine which is 71%, the comparison of recall is about 86% for random forest and that for Support vector machine it is 71%. The study concludes by emphasizing the crucial role of ML-driven predictive models in climate resilience planning, particularly in improving flood risk assessments and disaster mitigation.

Keywords

Climate Change, Coastal Resilience, Machine Learning, Geospatial Analysis, Disaster Mitigation, Cultural Heritage Preservation, Coastal Vulnerability.

INTRODUCTION

Sea level rise is making coastal communities around the world more vulnerable to climate change and global warming. Rising sea levels have put infrastructure, ecosystems, and livelihoods at risk, resulting in more frequent flooding, land loss, and unstable economies. The intricate relationships between oceanic, atmospheric, and terrestrial elements make it difficult to estimate sea level rise with great precision, even with major advances in climate modelling. The accuracy required for localised adaptation techniques is frequently lacking in traditional models. By using machine learning approaches to improve the accuracy of sea level rise projections, our study fills this knowledge vacuum and offers useful information that policymakers and urban planners may use to create more resilient coastal infrastructure.

The adverse effects of climate change are increasing the vulnerability of coastal communities worldwide. Rising sea levels intensified storm surges, and extreme weather events are putting infrastructure and natural ecosystems in danger. Environmental changes have a significant impact on low-lying coastal regions, as the interaction between land use changes and climate variability increases their vulnerability to floods. Urban expansion, deforestation, and climate-driven hydrological shifts, along with climate change, have been shown to increase flood risks, leading to the vulnerability of the coastal region of Tamil Nadu. Flood susceptibility mapping is a tool that can help predict high-risk zones and mitigate disaster impacts through machine learning (ML) and geospatial tools. The machine learning algorithms in climate modeling help to understand how to improve flood forecasting and help us in predicting disasters to develop better strategies to reduce environmental risk Abijith, D et. al. (2025).

The adaptive resilience technique will be utilized to prevent the deterioration of historic structures as a result of climate change threatening cultural heritage monuments and the environment. According to recent studies, Machine learning algorithms-based predictive models are used in the preservation of heritage sites that are at risk Hegazi, Y. S et. al.(2022). The involvement of local communities in planning can reduce climate risk, also with the help of recent technologies like cloud computing, real-time data analytics is essential for enhancing climate resilience and improving risk assessment, which will help in early warning about climate risk Levin, E., Beisekenov et. al. (2023).

The protection of coastal communities involves changing the current coastline infrastructure so that they can resist wave and storm surges. Researchers have demonstrated physical modeling techniques to demonstrate how nature-based solutions can enhance coastal defenses against climate threats Liu, N et. al. (2022). The climate-related risk is increasing day by day. Multidisciplinary approaches like data analytics, and computational intelligence, and involving local communities can help in creating strong strategies for adapting to climate change Sumardjo et. al. (2023).

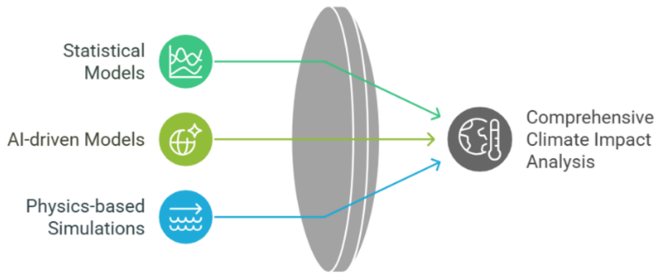

Figure 1: Integration of Model Approach

Figure 1 shows the techniques to assess the impact of climate change on coastal communities. This study also focuses on using a multidisciplinary approach to solve climate-related problems. The machine learning algorithm will be the pioneer in predicting the climate risk. This study focuses on geospatial datasets, the ML model to ensure the stability of climate risk in coastal communities Fahrudin et al (2024).

Related Work

In this section, the literature studied is on two aspects the first Category examines climate change's impact on coastal communities like sea level rise, flood risk, extreme weather conditions, and its impact on their lives and infrastructure, and the second shows how machine learning techniques are used in climate change assessment the effect of climate change. Here, the focus is on how machine learning techniques can be used in the accurate prediction of climate change, weather forecasting, and data-driven plans for environmental sustainability.
The following sections cover the details of these categories

1. Change Impact Assessment on Coastal Communities and 2. Machine Learning Techniques for Climate Adaptation and Mitigation

Climate Change Impact Assessment on Coastal Communities

The impact of climate change on coastal regions and the strategies used to adapt can be understood by analyzing significant studies presented in Table 1. In 2023, Laino & Iglesias et.al. (2023) conducted a thorough global study of the effects of climate change on coastal areas, which included information from 97 countries and highlighted the deficiency of research in developing nations. Berman, et al. (2019) look into the impact of climate change on ecosystem services and discuss the methods used by coastal communities to maintain their livelihoods. Arabadzhyan et al. (2010) examined how climate change impacted coastal destinations and the financial effects it had on the tourism industry.
Carvalho et al. (2023) studied how cultural and gender roles affect the coastal communities. They also talk about how the strong coastal infrastructure is facing challenges. Camera and Lane (2015) discuss how to adapt to climate change. This can be done using a protective structure and planning various strategies.
The objective of this study is to comprehend the impact of climate change on coastal communities and the diverse strategies required to tackle these obstacles.

Table 1: Change Impact Assessment on Coastal Communities

Sr. No.	Author(s)	Title	Journal/Source	Key Contribution
1	Laino & Iglesias 2023	Climate Change Impacts on Coastal Zones: A Global Review	Environmental Research	Highlights the impact of climate change on 97 countries, emphasizing the lack of research from developing nations.
2	Berman et al. 2019	Ecosystem Services and Coastal Livelihoods: Adaptation Strategies	Marine Policy	Talks about the effects of climate change on coastal ecosystem services and community adaptation.
3	Arabadzhyan et al. 2020	Tourism and Climate Change: The Case of Coastal Destinations	Tourism Management	Analyzes how climate change affects tourism in coastal regions.
4	Carvalho et al. 2023	Climate Change, Coastal Communities, and Cultural Practices	Sustainability Science	Explores how cultural practices and gender perspectives impact climate adaptation in coastal zones.
5	Camare & Lane 2015	Adaptation Pathways for Coastal Infrastructure Under Climate Change	Environmental Science & Policy	Discusses protective measures such as breakwaters and multi-scale adaptation approaches.
6	Serrao-Neumann et al. 2013	Cross-Sectoral Adaptation Strategies for Coastal Communities	Climate Policy	Evaluates comprehensive adaptation strategies involving multiple sectors.
7	Bolsen et al. 2018	Communicating Climate Change: The Role of Visual Tools	Public Understanding of Science	Examines how animated maps influence the public's perception of climate change risks.

Machine Learning Techniques for Climate Adaptation and Mitigation

Table 2 shows how AI, policy analysis will help us in reducing the climate risk. This study shows that AI policy and climate science work together to tackle environmental challenges.

Table 2: Machine Learning Techniques for Climate Adaptation and Mitigation

No.	Author(s)	Year	Title	Sector	Journal / Conference
1	Milojevic-Dupont, N., & Creutzig, F.	2020	Machine learning for geographically differentiated climate change mitigation in urban areas	Urban Planning	*Sustainable Cities and Society*
2	Srivastava, A., & Maity, R.	2023	A regional approach to AI-driven climate adaptation strategies	Climate Adaptation	*Environmental Research Letters*
3	Eitan, Y.	2021	Renewable Energy and Climate Change Adaptation: A Policy Discourse Analysis	Renewable Energy Policy	*Energy Policy*
4	Coelho, A., Mendes, T., & Silva, R.	2023	Integrating Machine Learning with Physical Climate Models for Long-Term Forecasting	Climate Modelling	*Climate Change Modelling and Adaptation Conference (CCMAC 2023)*

RESEARCH METHODOLOGY

In this study, the Permanent Service for Mean Sea Level (PSMSL) dataset is used, which is widely used for sea level measurements. Machine learning technology is used to predict the risk of sea level rise, using the following algorithms.

1) Random Forest
2) Support vector machine

The PSMSL dataset has been trained with the above algorithms to improve the accuracy of predicting the sea level for the early alert system. Figure 2 shows the climate resistance strategy framework. The implementation of the Resilience strategy includes an early warning system, policy recommendations, infrastructure development, and adaptation, AI policy also makes a difference in considering climate risk, which includes allowing AI in decision-making. The data plays an important role in developing this model. PSMSL is one such dataset that is used in this study. The above-prescribed machine learning algorithms have been applied to it to classify risk, early prediction alert.

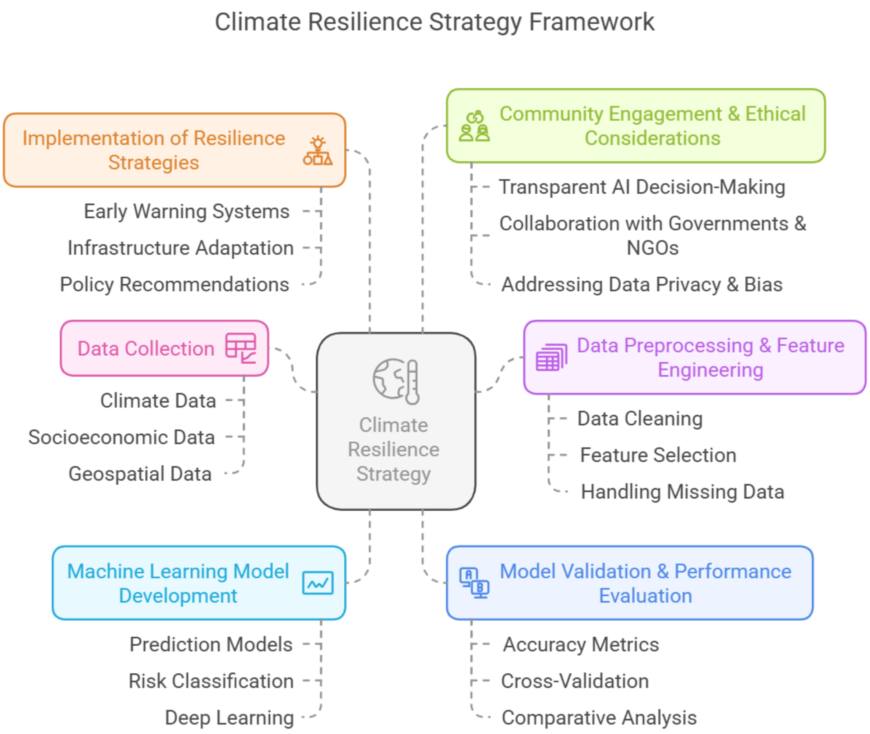

Figure 2: Methodology used in this experiment

DATASET INTEGRATION AND PREPROCESSING FOR COASTAL RESILIENCE MODELLING

Data Acquisition

PSMSL's Permanent Service for Mean Sea Level (PSMSL) provided the dataset for this study, which contains long-term sea-level observations recorded by tide gauges worldwide. Analyzing trends in sea-level variability is an important aspect of climate research using this dataset.

Data Source and Features

- Source: PSMSL sea-level dataset
- Period: 1900–2024

Key Features:

- The time dimension of observations is represented by the year as a temporal feature.
- The primary target variable is the observed sea-level height, which is measured relative to a fixed reference point.
- The identifier for the tide gauge location is provided as station information.
- Data consistency is ensured by using metadata such as distance and solution dates.

Data Preprocessing

Preprocessing steps were applied before training machine learning models to ensure high data quality and reliability.

Handling Missing Values

Linear interpolation was utilized to deal with missing values, which is a popular technique for time-series data. This technique relies on a linear trend between neighbouring points to estimate missing values, which ensures temporal continuity and prevents data gaps.

Outlier Detection and Removal

The Z-score method was employed to identify outliers in the dataset, which measures the deviation from the mean in standard deviations. Any data point with |Z| > 3 was considered an outlier and removed. The equation for Z-score detection:

$Z = \frac{X-\mu}{\sigma}$--- eq 1

- X = data point
- μ = mean of the dataset
- σ = standard deviation

Feature Scaling

To ensure that machine learning models perform better with normalized inputs, Min-Max scaling was implemented to ensure that all features are in the same range of [0,1]. Different scales make it impossible for one feature to dominate the learning process through this transformation.
The Min-Max normalization formula:

$$X_{scaled} = \frac{X - X_{min}}{X_{min} - X_{max}}$$

By using normalized data, models like Random Forest and Support Vector Machines can achieve faster convergence and more stable predictions.

MACHINE LEARNING MODEL SELECTION

In this study, **two different models** were applied for predicting sea-level rise:

1. **Random Forest Regression** (Ensemble-based non-parametric model)
2. **Support Vector Machine**

Random Forest Regression Model

Random Forest is an ensemble learning method using multiple decision trees. It performs better for non-linear relationships.
The equation for Random Forest prediction:

$\hat{Y} = \frac{1}{N}\sum_{i=1}^{n} f_i(x)$-- eq 2

Where:

- N = number of trees
- fi(x) = prediction from the i^{th} tree

```
• from sklearn.ensemble import RandomForestRegressor
• # Train the model
• rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
• rf_model.fit(X_train, y_train)
• # Predict
• y_pred_rf = rf_model.predict(X_test)
```

Support Vector Machine (SVM) for Regression (SVR)

A supervised learning system called Support Vector Machine (SVM) determines the best hyperplane for tasks involving regression or classification. In regression, a kernel function is used to map data into a higher-dimensional space, and a hyperplane that fits the data as closely as possible within a given margin is fitted.

Equation for SVM Regression (SVR)

The goal of SVR is to find a function f(x) f(x) that has at most ε\varepsilon deviated from the actual target yy, while keeping the model complexity low:

$\text{Min}\frac{1}{2}||w||^2$ --- eq 3

Where:

- ww = weight vector
- xix_i = input features
- bb = bias term
- ε\varepsilon = margin of tolerance

Python Code for SVR Implementation:

```
from sklearn.svm import SVR
# Train the model
```

```
svr_model = SVR(kernel='rbf', C=1.0, epsilon=0.1)
svr_model.fit(X_train, y_train)
# Predict
y_pred_svr = svr_model.predict(X_test)
```

In this implementation:

- The **'rbf' kernel** (Radial Basis Function) is used for non-linear regression.
- The **C parameter** controls the trade-off between model complexity and error.
- The **epsilon parameter** defines a margin where predictions are not penalized.

SVR works well when dealing with high-dimensional data and small data sets, but it may struggle with very large datasets due to computational complexity.

RESULT AND DISCUSSION

Height vs. Station Analysis

Figure 3 shows how the height (m) is compared to the station across various computational solutions (GT3, JPL14, NGL14, ULR6b, ULR7a), and it shows significant variations in elevation. The oscillations of the ULR7a solution (green) are more pronounced, but the transitions of JPL14 (orange) are easier to understand. These differences may be caused by differences in data sources, computational methodologies, or resolution. The presence of peaks and dips is a sign of rapid terrain changes, observational noise, or estimation inconsistencies. The close alignment of certain models indicates that there is agreement in certain regions, while deviations point out potential discrepancies that require further investigation.

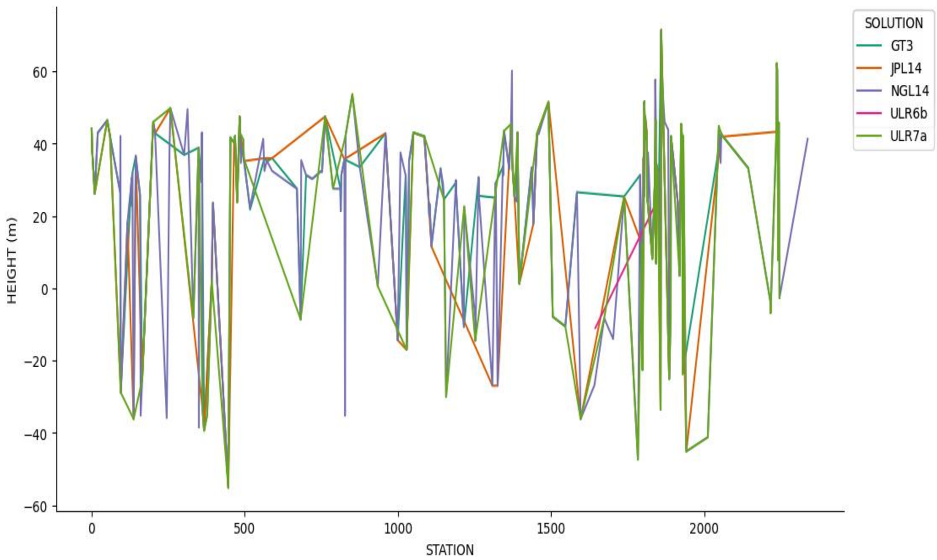

Figure 3: Dataset features analysis (Height vs. Station Analysis)

Rate vs. Data Points Analysis

Figure 4 displays a graph showing the Rate (mm/yr) vs. Data Points, which indicates that most values fluctuate around zero, indicating minor differences in measured rate changes. Two sharp spikes at around data point 200 are exceeding 40 mm/yr, which suggests significant anomalies. It's possible that these could be connected to extreme events, measurement errors, or rapid environmental changes like tectonic activity or subsidence. To determine whether these peaks are genuine trends or artefacts from data collection, more analysis is needed.

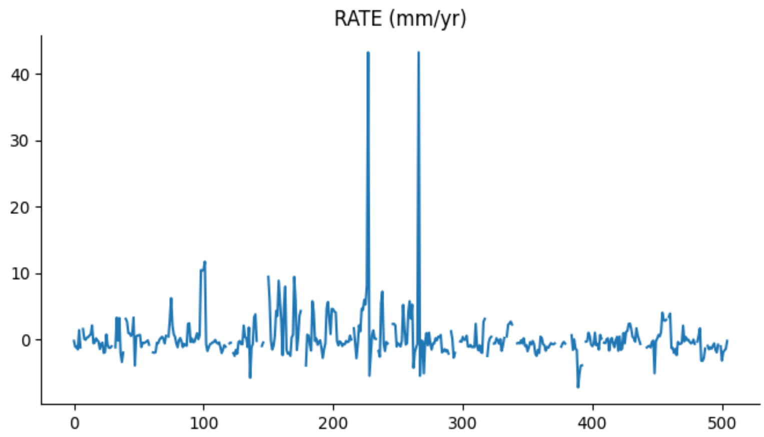

Figure 4: Dataset features analysis: Rate vs. Data Points Analysis

Random Forest Model Performance

Actual vs. Predicted Scatter Plot

Figure 5 illustrates the scatter plot that compares actual values with predicted values for the Random Forest regression model, showing that there is a deviation from the ideal 45-degree diagonal line. The clustering at lower values indicates that the model is struggling to accurately predict higher values. Hence, R^2 score, RMSE, and MAE were used for additional evaluation to provide additional insights

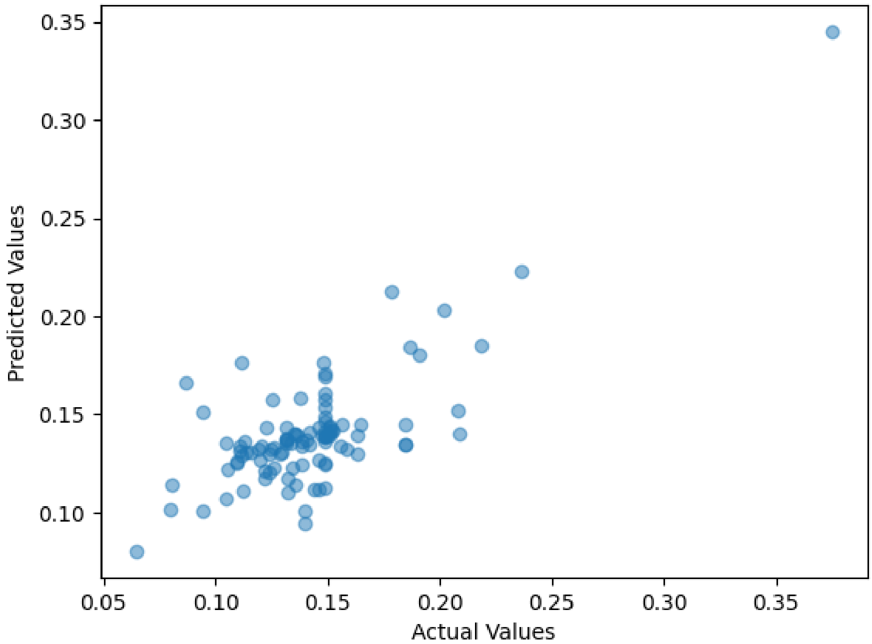

Figure 5: Actual/ Predicted plot

Feature Importance Analysis

- The Random Forest model's bar chart shows the importance of features:
- Height (m) holds the most significant importance (importance score > 0.7).
- The Station's contribution is not as significant.
- The impact of height uncertainty (m) on predictions is minimal.

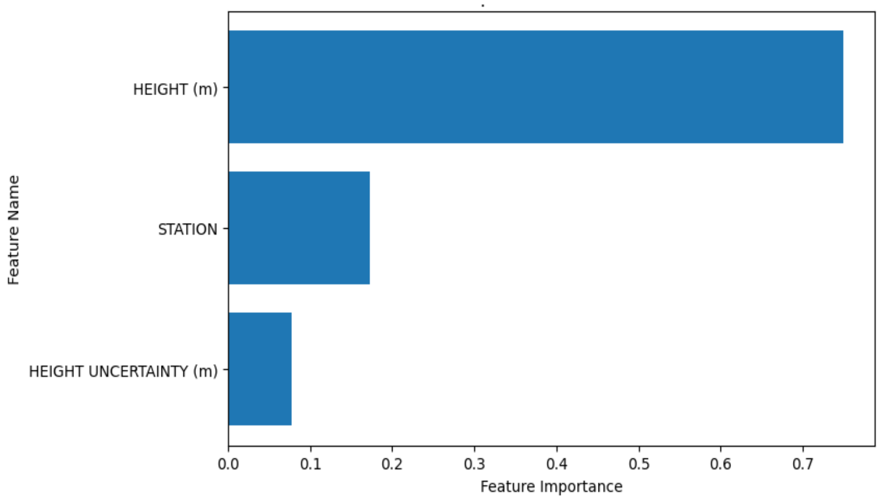

Figure 6: Feature importance in random forest

Residual Analysis

- Figure 7 shows the histogram of residuals, indicating that there is a normal error distribution with a mean near zero, which indicates that predictions are unbiased.
- The symmetric distribution of residuals in the box plot is indicative of some extreme mispredictions.

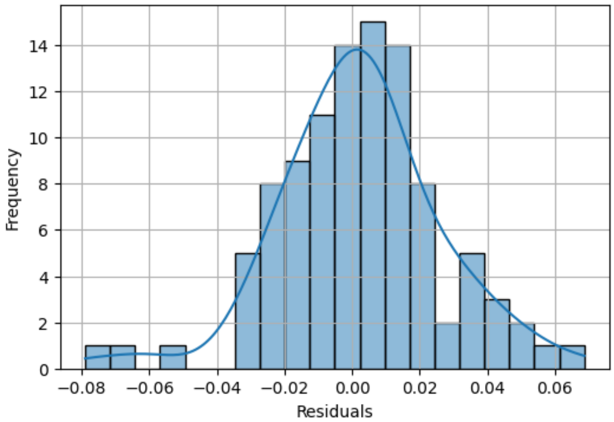

Figure 7: Residual plot in random forest

Learning Curve Analysis

Figure 8 shows that the training score (blue line) is steadily increasing, reaching 1.0, which indicates that the training set is well-fitted. The validation score (orange line) starts with a low score but improves, although the gap remains, which suggests possible overfitting. As estimators go beyond 100, the Mean Squared Error (MSE) drops considerably, with the lowest MSE around 200 estimators.

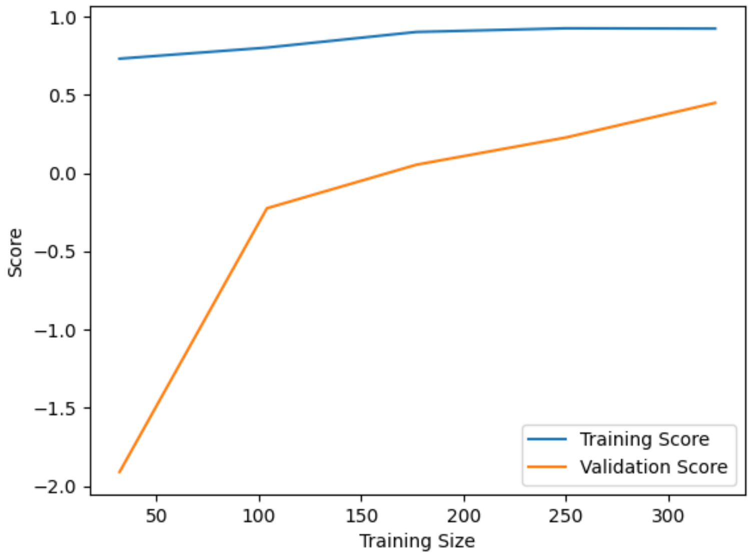

Figure 8: Learning Curve in random forest

Diagonal Values = 1: Each variable is perfectly correlated with itself.
Low to Moderate Correlations:

- In figure 9, most feature correlations are close to zero, indicating weak relationships.
- Height (m) and Distance (-0.26) show a weak negative correlation.
- Epoch and End Date (0.37) have the strongest positive correlation.

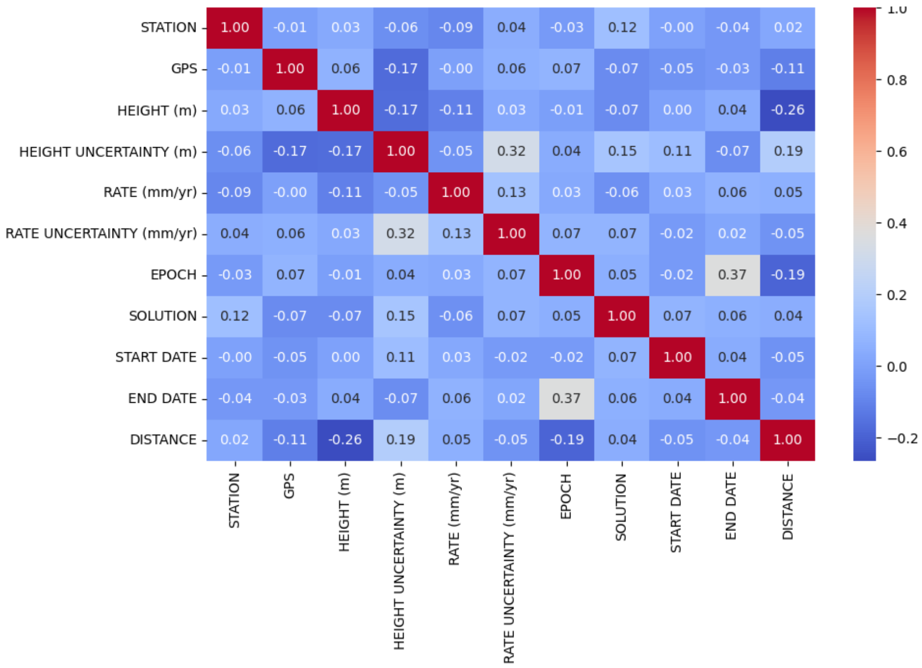

Figure 9: Heatmap in random forest

Support Vector Machine (SVM) Model Performance

Correlation Analysis

- Rate Uncertainty (mm/yr) and Height Uncertainty (m) show the strongest positive correlation (0.31).
- Height (m) and Distance exhibit a negative correlation (-0.26), implying lower heights are associated with greater distances.
- Most other feature correlations are weak (<0.2).

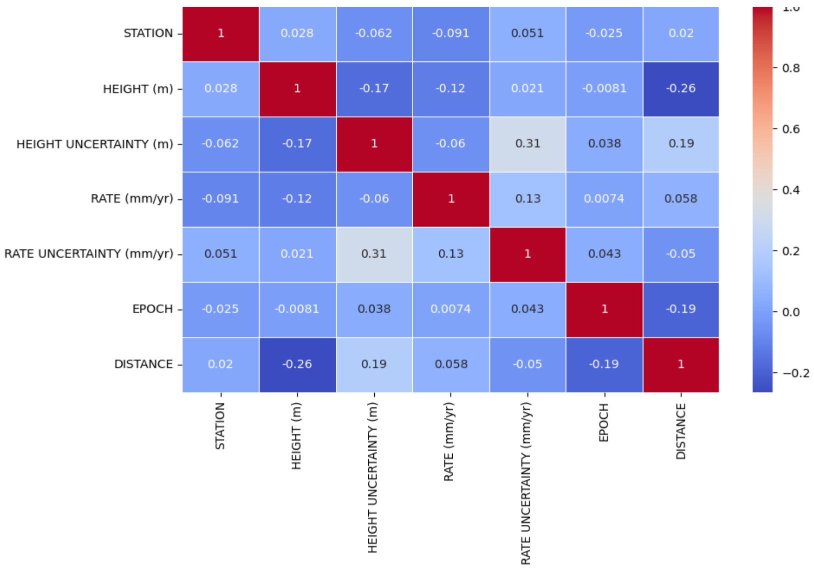

Figure 10: Heatmap in SVM

Model Learning Behaviour

Figure 10 shows the model of Learning Behaviour

- Training score starts low (~0.04–0.05) and gradually improves, indicating learning but no overfitting.
- Validation score starts negative but improves slightly, still suggesting underfitting.

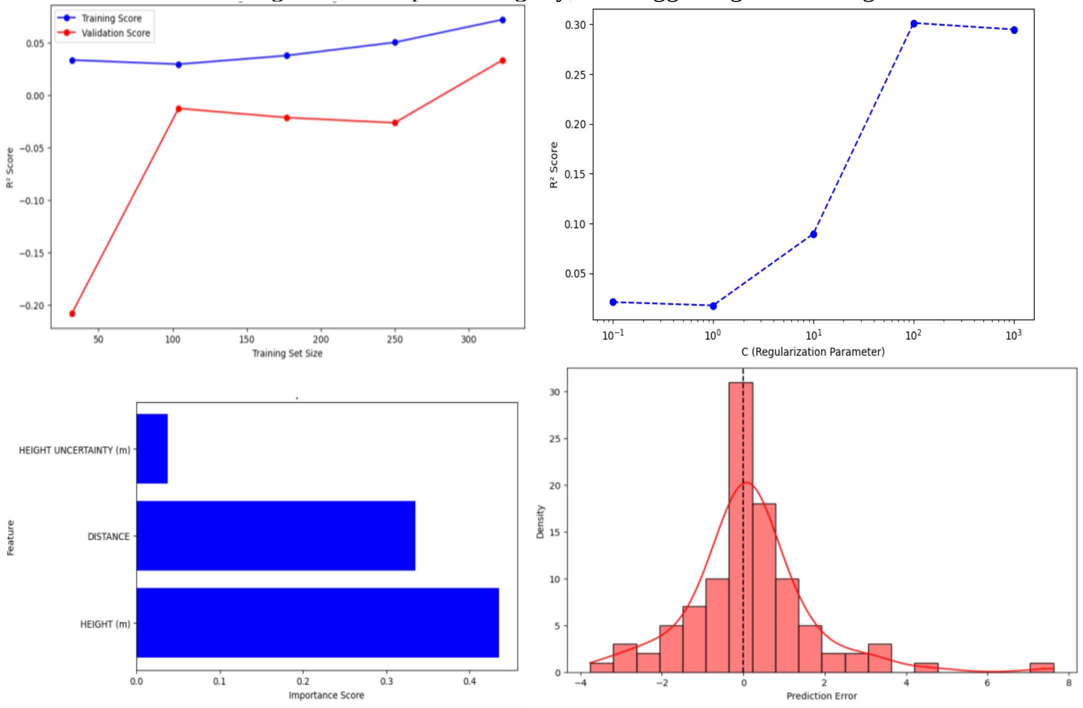

Figure 11: Model Learning Behaviour: Various plots in SVM

Figure 11 shows the Hyperparameter Impact (C Value)

- Small C values (10^{-1} to 10^0) lead to high bias (underfitting), with R^2 scores around 0.02–0.03.
- Larger C values (10^1 to 10^2) significantly improve performance, reaching $R^2 \approx 0.3$.
- C > 10^2 shows minimal additional improvement, indicating a plateau.

Feature Importance in SVM

- Height (m) (~0.45 importance score) is the most significant feature.
- Distance (~0.35) plays a notable role.
- Height Uncertainty (m) (~0.05) has minimal influence.

Residual Analysis

- Residuals are centered around zero, indicating a reasonably accurate model.

- A slight right skewness suggests some under-predictions, with a few extreme errors needing further refinement.

Model Comparison

In Figure 12, a comparison is made between Random Forest and Support Vector Machine (SVM) classifiers, and it is revealed that Random Forest has superior accuracy, precision, and recall metrics over SVM. Random Forest's superior overall classification performance is evident by its higher accuracy (about 78% vs. 71%). The advantage is furthered by the higher precision of Random Forest (approximately 74% vs. 70%), which means it makes fewer false positive predictions.

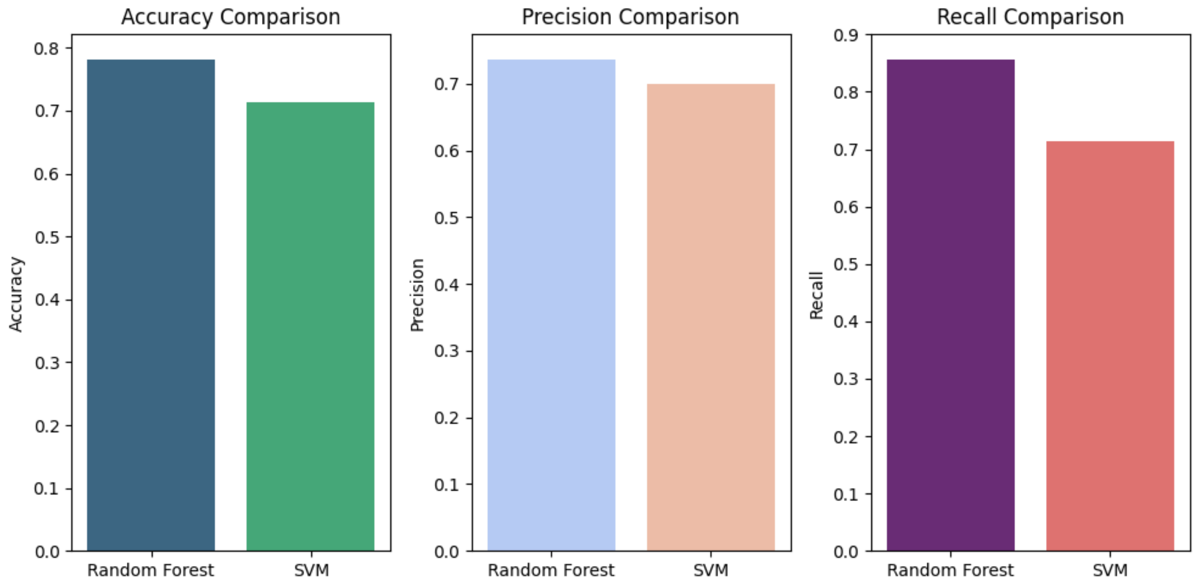

Figure 12: Model Comparison

Random Forest's recall is significantly higher than 71%, which is a testament to its ability to identify a larger percentage of actual positive cases. The results indicate that Random Forest is a more effective classification tool for this particular task.

In Figure 12, the comparison of Random Forest and SVM models shows that Random Forest performs better, with an accuracy of 78%, while SVM only achieves 72%. Random Forest's precision is 0.75, which is slightly higher than SVM's 0.72, indicating a more reliable prediction. This is further supported by the recall metrics, as Random Forest scored 0.86 compared to SVM's 0.71, indicating that it identifies more relevant instances and reduces false negatives.

The correlation heatmaps for both models are shown in Figures 9 and 10. Random Forest exhibits stronger associations between crucial variables, such as a 0.32 correlation between rate uncertainty and height uncertainty. The model's generalization and predictability are improved by stronger correlations. SVM is less effective at detecting complex patterns in the data, because it shows weaker correlations on the other hand.

These results indicate that Random Forest is the better choice for predicting sea-level trends, which is important for coastal planning and disaster preparedness. However, while it performs better statistically, further analysis is needed to determine how well it applies to real-world scenarios and whether its predictions are easy to interpret for long-term environmental forecasting.

CONCLUSION

In conclusion, the study highlights that the Random Forest model outperforms SVM in predicting sea-level rise, with higher accuracy (78% vs. 72%), precision (0.75 vs. 0.72), and recall (0.86 vs. 0.71). These results suggest that Random Forest can provide more reliable predictions, making it a valuable tool for coastal planning and climate adaptation. However, further research is needed to assess its real-world applicability and interpretability to ensure its effectiveness in long-term environmental decision-making.

These predictions are crucial for designing flood defences, optimizing land use policies, and improving disaster preparedness strategies. The results suggest that Random Forest is a valuable tool for climate adaptation strategies, despite the absence of Logistic Regression evaluation in this comparison. Future research will focus on incorporating additional climate indicators and exploring deep learning techniques to enhance prediction accuracy and resilience modeling further

Future research should focus on improving model interpretability to increase trust among policymakers and stakeholders, even though Random Forest has strong predictive capabilities. To improve prediction accuracy even further, it could be beneficial to incorporate ensemble learning techniques, hybrid models, and real-time geospatial data. Incorporating socio-economic factors into the modeling process will make it possible to conduct comprehensive climate risk assessments, guaranteeing that adaptation policies address not only environmental threats, but also their societal impacts.

Future research should prioritize enhancing model interpretability to build trust among policymakers and stakeholders, despite Random Forest's strong predictive performance. Further improvements in accuracy could be achieved by integrating ensemble learning techniques, hybrid models, and real-time geospatial data. Additionally, incorporating socio-economic factors into the modeling process would enable more comprehensive climate risk assessments, ensuring that adaptation strategies address both environmental challenges and their societal impacts.

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