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Fractal and Machine Learning-Based Analysis of Shoreline Change in Storm-Affected Coastal Environments

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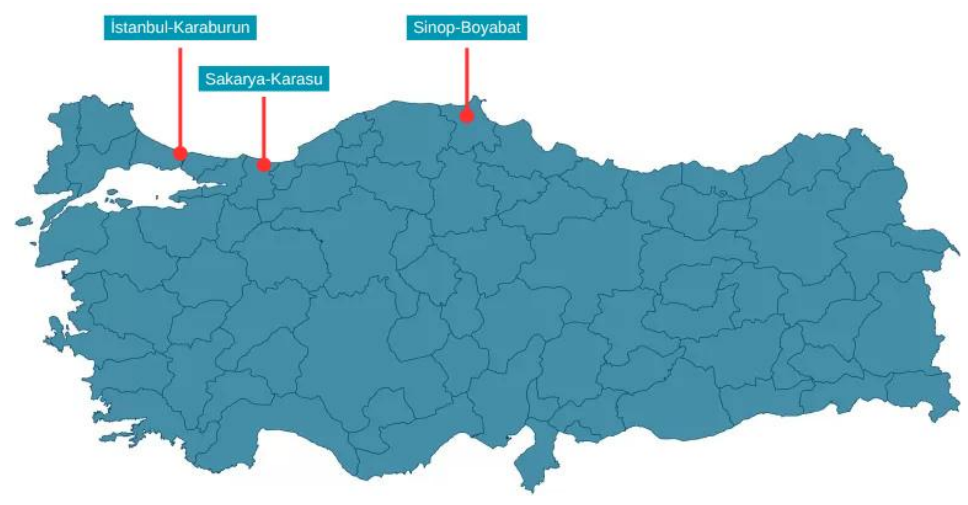
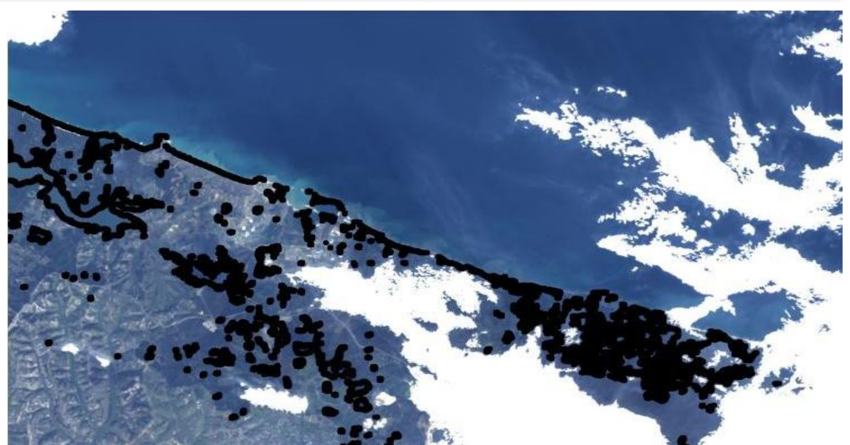
INTRODUCTION & AIM



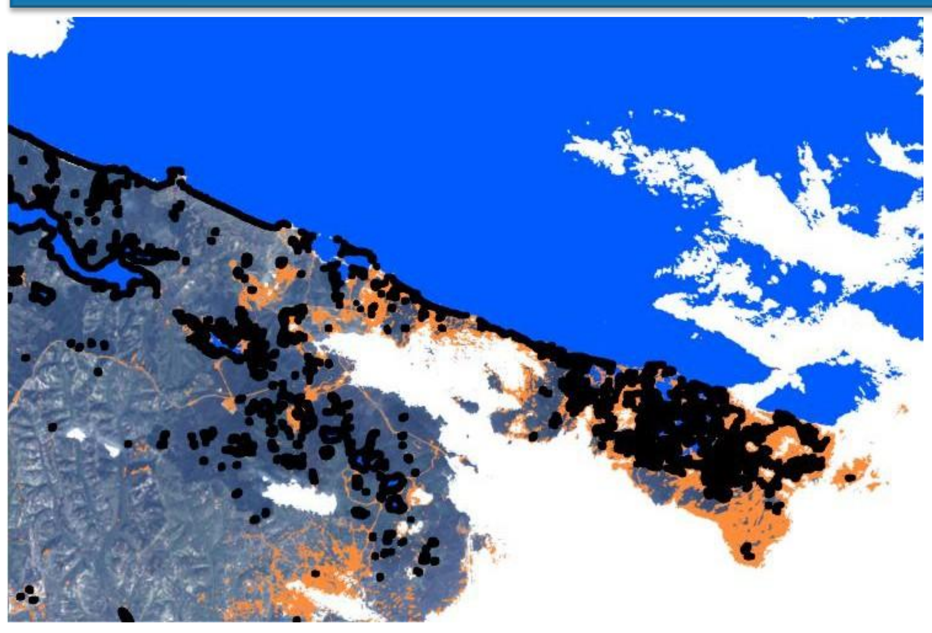
Study areas along the Turkish Black Sea coastline.



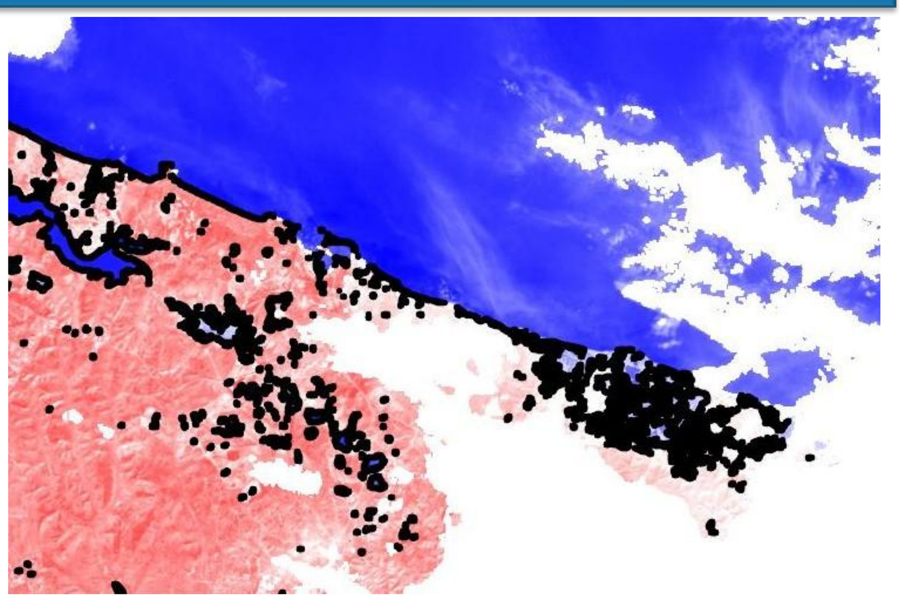
Example of shoreline extraction (Istanbul–Karaburun).

Coastal environments are highly dynamic and strongly influenced by storm events, leading to significant shoreline changes. Accurate prediction of these changes is essential for coastal management and risk mitigation.
This study focuses on three coastal regions along the Turkish Black Sea coastline: Istanbul–Karaburun, Karasu (Sakarya), and Sinop–Boyabat, selected for their differing geomorphological characteristics.
Satellite imagery is used to extract historical shorelines. The example shown represents shoreline extraction for the Istanbul–Karaburun region.

METHOD

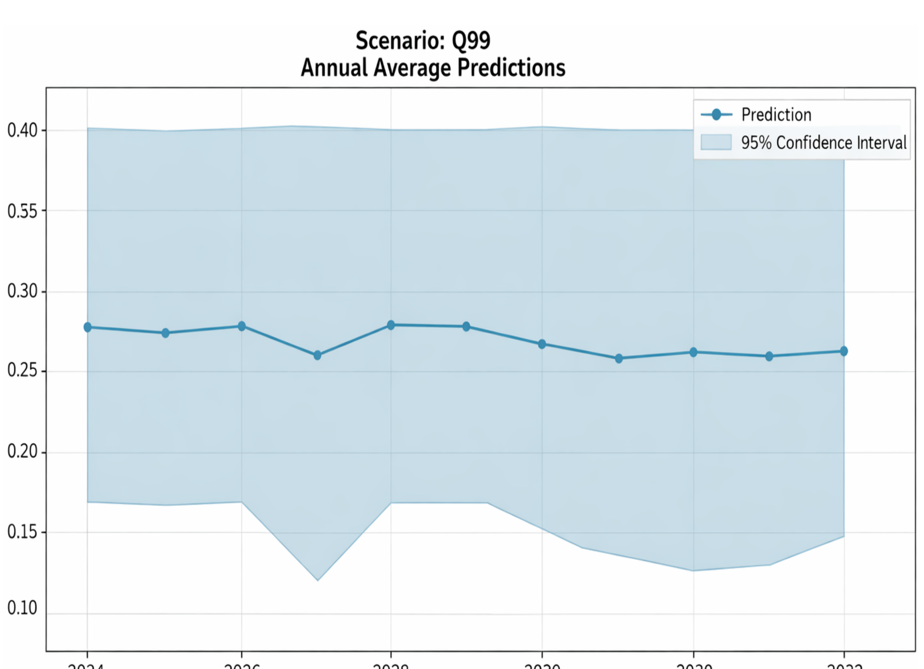


Satellite-based shoreline extraction Istanbul–Karaburun.



Landsat-8 (Copernicus) satellite image of the Istanbul–Karaburun.

Satellite imagery from Landsat-8 (Copernicus) and Sentinel-2 was used to derive shoreline positions for the study areas. Shoreline extraction was performed using remote sensing-based techniques to obtain multi-temporal coastline data.
The example images illustrate Landsat-8 data for the Istanbul–Karaburun region, demonstrating the initial stage of coastline detection from satellite observations.
In addition to Landsat-8, Sentinel-2 imagery was also processed to extract shoreline boundaries with higher spatial detail, enabling more accurate representation of coastal morphology.



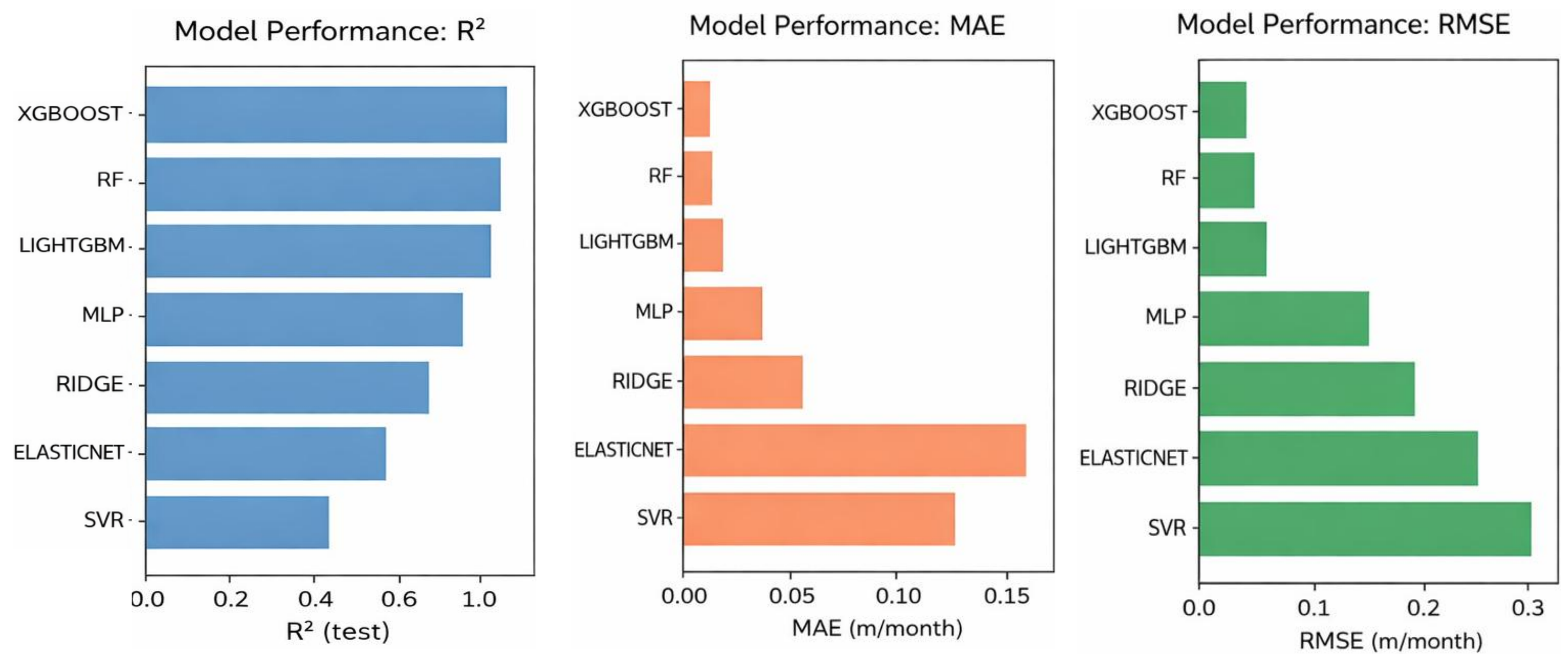
Scenario Q99 (Annual Average Predictions)

Scenario-based predictions (Q90, Q95, and Q99) were generated to evaluate potential shoreline changes under varying storm intensity conditions. The figure illustrates annual average predictions with associated uncertainty bounds (95% confidence interval).

RESULTS & DISCUSSION

Time-series shoreline change predictions for the Karasu coastline using different machine learning models.

The figure shows time-series shoreline change predictions for the Karasu region using multiple machine learning models. The models generally follow a consistent trend and closely match the actual shoreline variations over time.
A significant drop is observed at a specific time step, where all models capture the sudden shoreline retreat, indicating their ability to detect extreme events. Among the models, Random Forest and MLP demonstrate closer alignment with the observed values, while SVR shows larger deviations in certain periods.



Comparison of machine learning model performance using R^2, MAE, and RMSE metrics.

The figure presents a comparative evaluation of machine learning models based on R^2, MAE, and RMSE metrics. Ensemble-based models, particularly Random Forest and XGBoost, demonstrate superior performance with higher R^2 and lower error values.
In contrast, simpler models such as SVR and ElasticNet exhibit lower predictive accuracy and higher error rates. Overall, the results indicate that ensemble methods provide more reliable and robust predictions for shoreline change modeling.

CONCLUSION

This study demonstrates that shoreline changes in storm-affected coastal environments can be effectively predicted using a data-driven framework integrating satellite imagery, fractal analysis, and machine learning models.
Among the tested models, ensemble methods—particularly Random Forest—achieved the highest predictive performance. The results confirm that combining multi-source data enables accurate and robust modeling of complex coastal dynamics.

FUTURE WORK / REFERENCES

Future work will focus on improving long-term prediction accuracy and incorporating deep learning approaches. Additionally, model interpretability methods will be explored to better understand the role of environmental factors.

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