**Abstract**

Harmful algal blooms (HABs) have become a pressing environmental concern in coastal regions, with climate change intensifying their impacts on ecosystems, public health, and economies. Despite the increasing prevalence of HABs, understanding their formation mechanisms remains incomplete due to the complex interactions between environmental factors. Accurate prediction is crucial for early warning systems and effective mitigation strategies, enabling timely interventions to reduce harmful impacts. While green infrastructure shows promise in mitigating nutrient loading and surface runoff, its role in alleviating HABs remains underexplored. Biscayne Bay, a critical coastal ecosystem in Miami-Dade County, has experienced rising HAB occurrences driven by anthropogenic activities and climate change. This dissertation addresses these challenges by developing predictive models and exploring mitigation strategies through machine learning (ML), temporal decomposition, climate data integration, and nature-based solutions. The overarching goal is to improve predictive accuracy and understanding of HAB drivers and provide actionable solutions for managing their impacts.

The first chapter investigates the spatiotemporal relationship between chlorophyll-a, an indicator of HABs, and environmental variables like land use, nutrients, and climate. Current-month and one-month lead predictive models are developed using multiple ML algorithms. The Extra Tree Regressor performs best for one-month lead predictions, achieving an R² of 0.92 in training and 0.47 in testing. Random Forest Regressor excels in current-month predictions, with an R² of 0.69 in training and 0.44 in testing. SHAP analysis identifies developed land use, total phosphorus, and nitrogen oxides as key contributors to HABs. This study fills a gap regarding upstream land use’s impact on coastal HAB dynamics and offers new insights into feature interpretation within predictive models.

The second chapter enhances predictive accuracy by integrating temporal decomposition methods with ML. Three models are developed: Scenario 1 (S1) with a Support Vector Machine (SVM), Scenario 2 (S2) with a Seasonal Autoregressive Integrated Moving Average (SARIMA) and SVM, and Scenario 3 (S3) with a novel hybrid model combining temporal decomposition with machine learning (TD-ML). Results show that S1 and S2 underperformed, with R² testing values for all stations below 0.5, indicating limitations in capturing the HAB complex dynamics. In contrast, the TD-ML models (S3) demonstrate superior performance, achieving R² values above 0.9 and mean absolute percentage error (MAPE) under 30%. This innovative TD-ML approach captures the complex monthly temporal dynamics of HABs, providing a more accurate predictive framework for environmental management and early intervention.

The third chapter examines future HABs under different climate scenarios using bias-corrected climate data from four global climate models. The SVM model incorporates 12-month lags as features to improve accuracy, alongside forward selection and backward elimination for feature optimization. These climate projections are applied to predict chlorophyll-a concentrations at the BB02 station till 2100. SHAP analysis identifies precipitation, discharge, and temperature as key drivers on HAB dynamics, underscoring the significant influence of climate and inflows. The future simulation results suggest that climate change will exacerbate HABs across all SSP scenarios, with the highest increases projected under scenario SSP126. This highlights the need for climate-adaptive strategies in long-term HAB management to mitigate the intensifying impacts of climate change on coastal ecosystems and human health.

The final chapter assesses the potential of green infrastructure (GI) as a nature-based solution to mitigate downstream HABs by reducing upstream nutrient loads and runoff. iPlantGreenS2 and International Stormwater BMP Database are used to design GI locations upstream of BB02, size, and nutrient reduction efficiency, with Random Forest models estimating discharge post-GI deployment. SVM models estimate that GI interventions (wet ponds and constructed wetlands) reduce nutrient loads and discharge by less than 10%, while chlorophyll-a decreased by only 2-3%. These findings suggest GI has promise for mitigating HABs but achieving substantial impacts in coastal environments likely requires scaling up implementations or combining GI with other complementary approaches.

This dissertation advances environmental management by developing innovative predictive tools and strategies for mitigating HABs. The ML models and hybrid approaches provide accurate and timely HAB predictions, enhancing early warning systems and decision-making processes for stakeholders. Integrating climate data offers a robust framework to predict future HAB trends under changing conditions, addressing the growing threat of climate change. Exploring GI solutions provides potentially practical strategies for reducing downstream HABs by improving water quality and lowering influx. These contributions deepen the scientific understanding of HAB dynamics and offer practical solutions to protect coastal ecosystems, safeguard public health, and support sustainable practices. By addressing key challenges like predictive accuracy and mitigation effectiveness, this research provides valuable insights that will benefit academia and society, contributing to the long-term resilience of coastal regions worldwide.