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Climate Change Impacts on Harmful Algal Blooms: An Integration of Data-Driven and Downscaling Approaches

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Background & Problem Statement

Algae can help sustain aquatic life by contributing to food and O_2.

What conditions?

In certain conditions, may cause the rapid growth of harmful algae, an HAB

HABs will **do harmful on**:

Human health (Food, Drinking water...)

Economics (Tourism, Fisheries industry…)

Environment (Fish die-offs, Seagrass degradation...)

There is no final & consistent conclusion on the mechanism of HAB formation

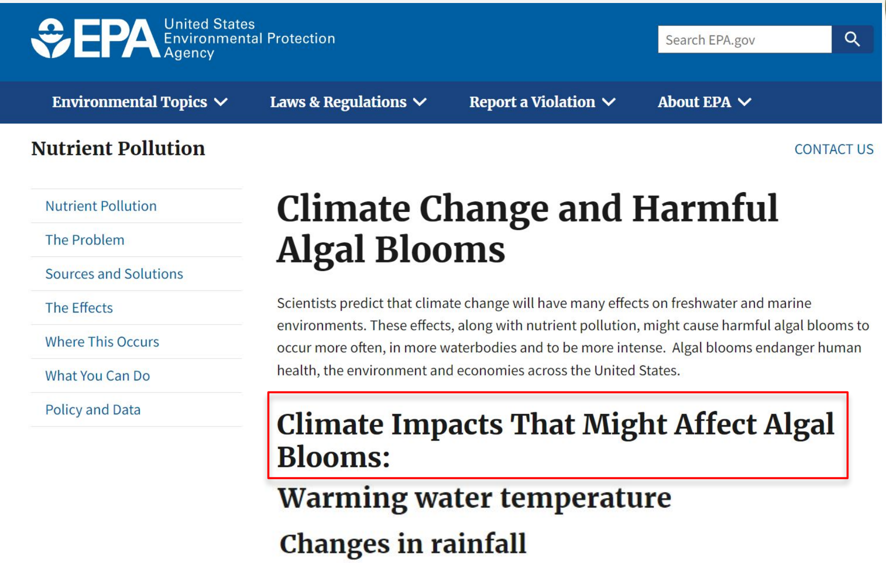
Chemical Factors?	Physical Factors?
Biological Factors?	Climatic Factors?

Prediction → Find out important features; Early-warning and prepare in advance

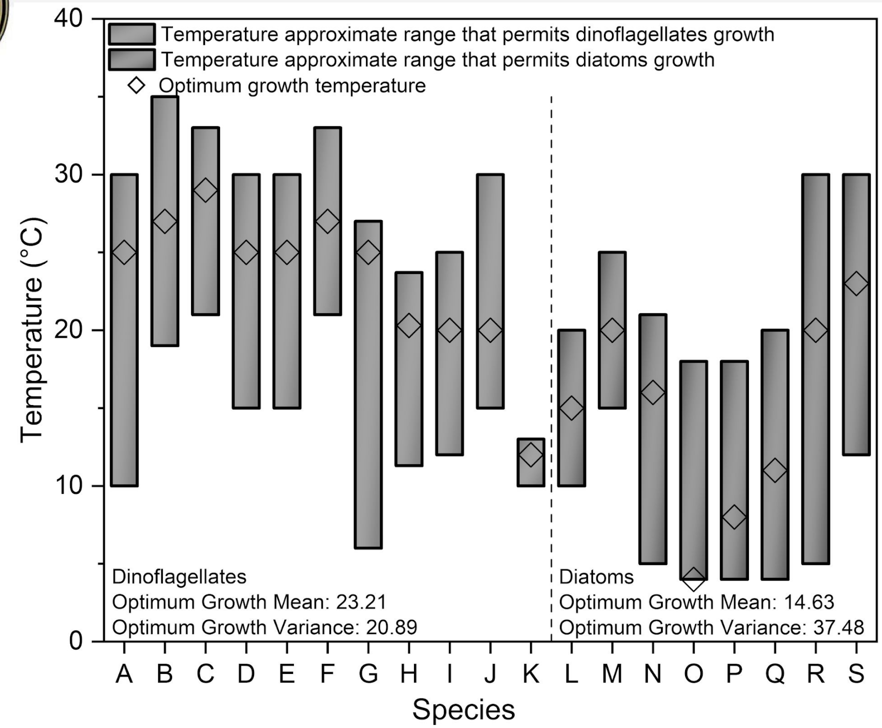
A green and brown algae bloom in August 2020

North Biscayne Bay, bloom of Anadyomene spp.
https://www.miamiwaterkeeper.org/fish_kill,

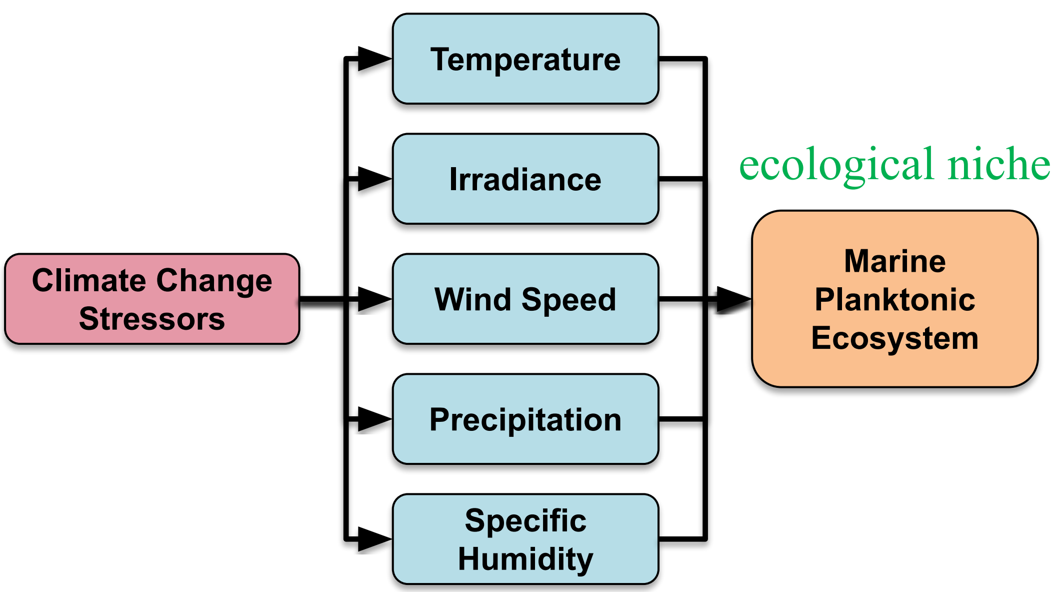
Background & Problem Statement



https://www.epa.gov/nutrientpollution/climate-change-and-harmful-algal-blooms



A summary of the suitable and optimal temperature for the growth of some harmful algae species



Experiments Or Data-Driven?

Objective

Evaluate the climate change impacts on HABs based on different climate models and future scenarios.

Assumptions

1. Machine learning models can conduct small-magnitude extrapolation tasks.
2. The biases in a climate model's output can be corrected by aligning the modeled data's statistical distribution with the observed data's distribution for a historical reference period.
3. Future water quality data are considered as same as the historical data.

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Methodology

Case study research area

Variables

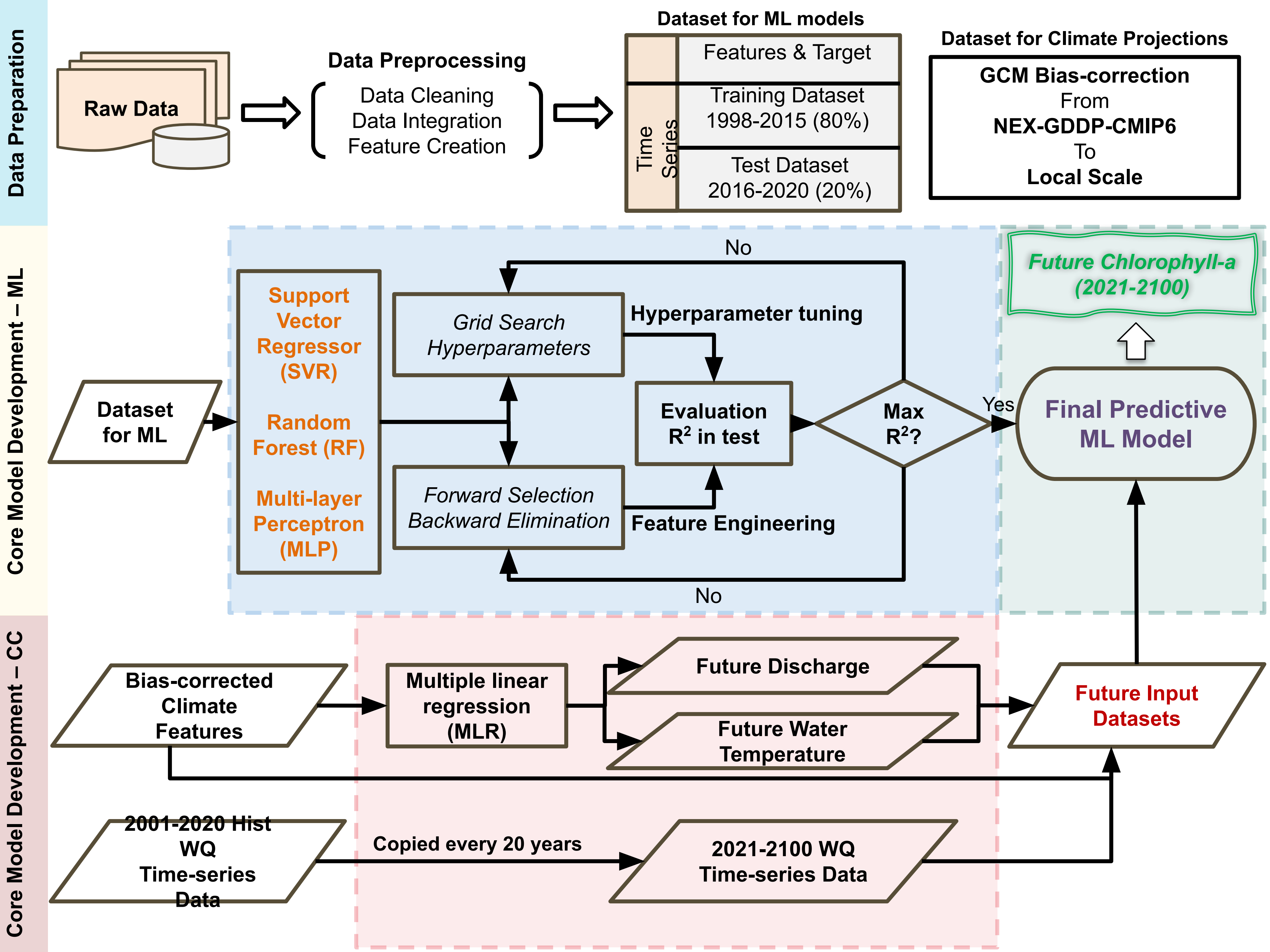
Variable Type	Name of Variable	Unit
Dependent Variable	Chlorophyll-a	mg/m3
Independent Variables	Ammonia Nitrogen	mg/L
	NOx	mg/L
	Dissolved Oxygen	mg/L
	pH	-
	Total Phosphorus	mg/L
	Turbidity	NTU
	Water Temperature	C
	Discharge	cfs
	Specific Humidity	kg/kg
	Wind Speed	m/s
	Precipitation	kg/m2
	Shortwave Radiation	W/m2
	Min, Max, Air Temperature	C
	Developed Percent	%

Water Quality data

Hydrological data

Climate data

Land use data



Data Preparation
Raw Data
Data Preprocessing
Data Cleaning
Data Integration
Feature Creation
Dataset for ML models
Features & Target
Time Series
Training Dataset
1998-2015 (80%)
Test Dataset
2016-2020 (20%)
Dataset for Climate Projections
GCM Bias-correction
From
NEX-GDDP-CMIP6
To
Local Scale
Core Model Development – ML
Dataset for ML
Support Vector Regressor (SVR)
Random Forest (RF)
Multi-layer Perceptron (MLP)
Grid Search Hyperparameters
Hyperparameter tuning
Forward Selection Backward Elimination
Feature Engineering
Evaluation R^2 in test
Max R^2?
No
Yes
No
Future Chlorophyll-a (2021-2100)
Final Predictive ML Model
Core Model Development – CC
Bias-corrected Climate Features
Multiple linear regression (MLR)
Future Discharge
Future Water Temperature
Future Input Datasets
2001-2020 Hist WQ Time-series Data
Copied every 20 years
2021-2100 WQ Time-series Data

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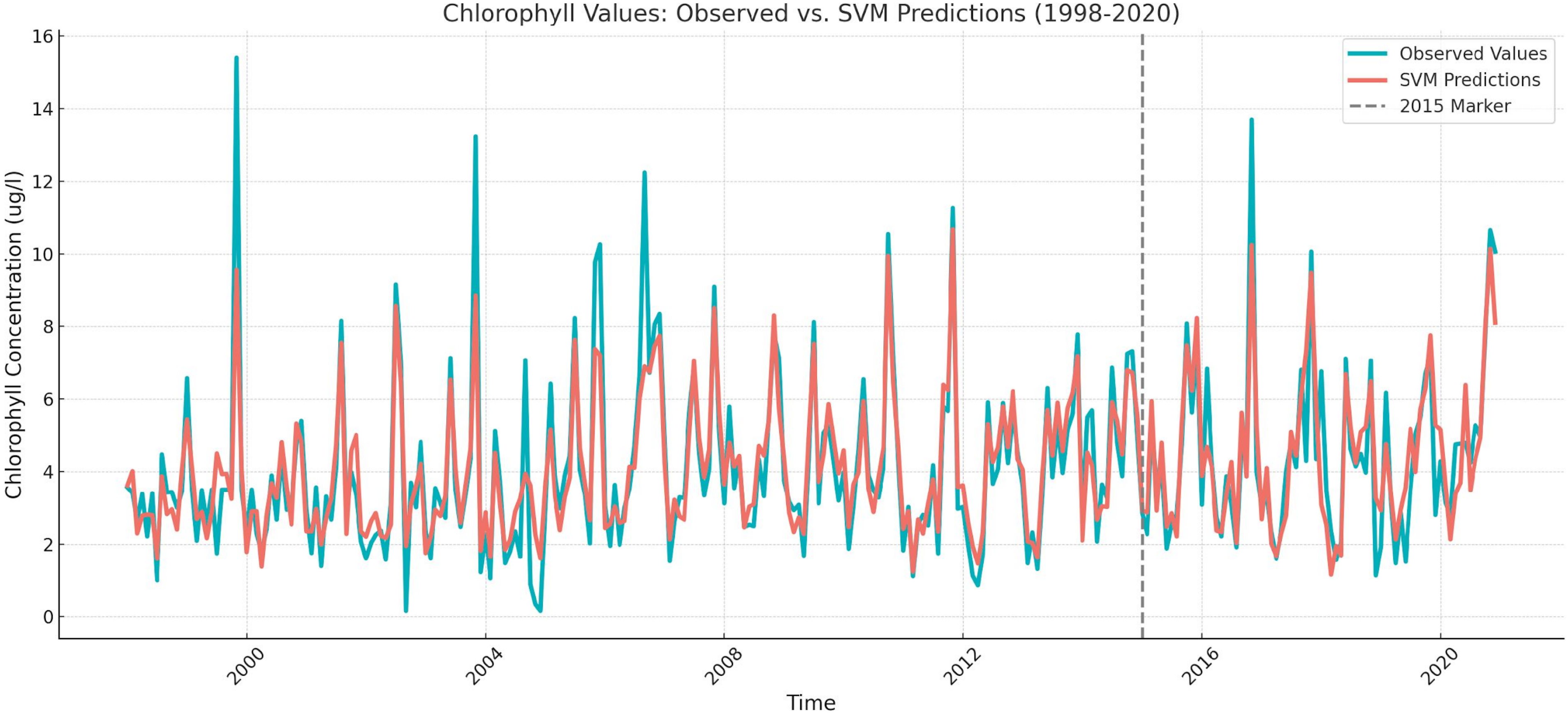
Preliminary Results

Predictive model metrics

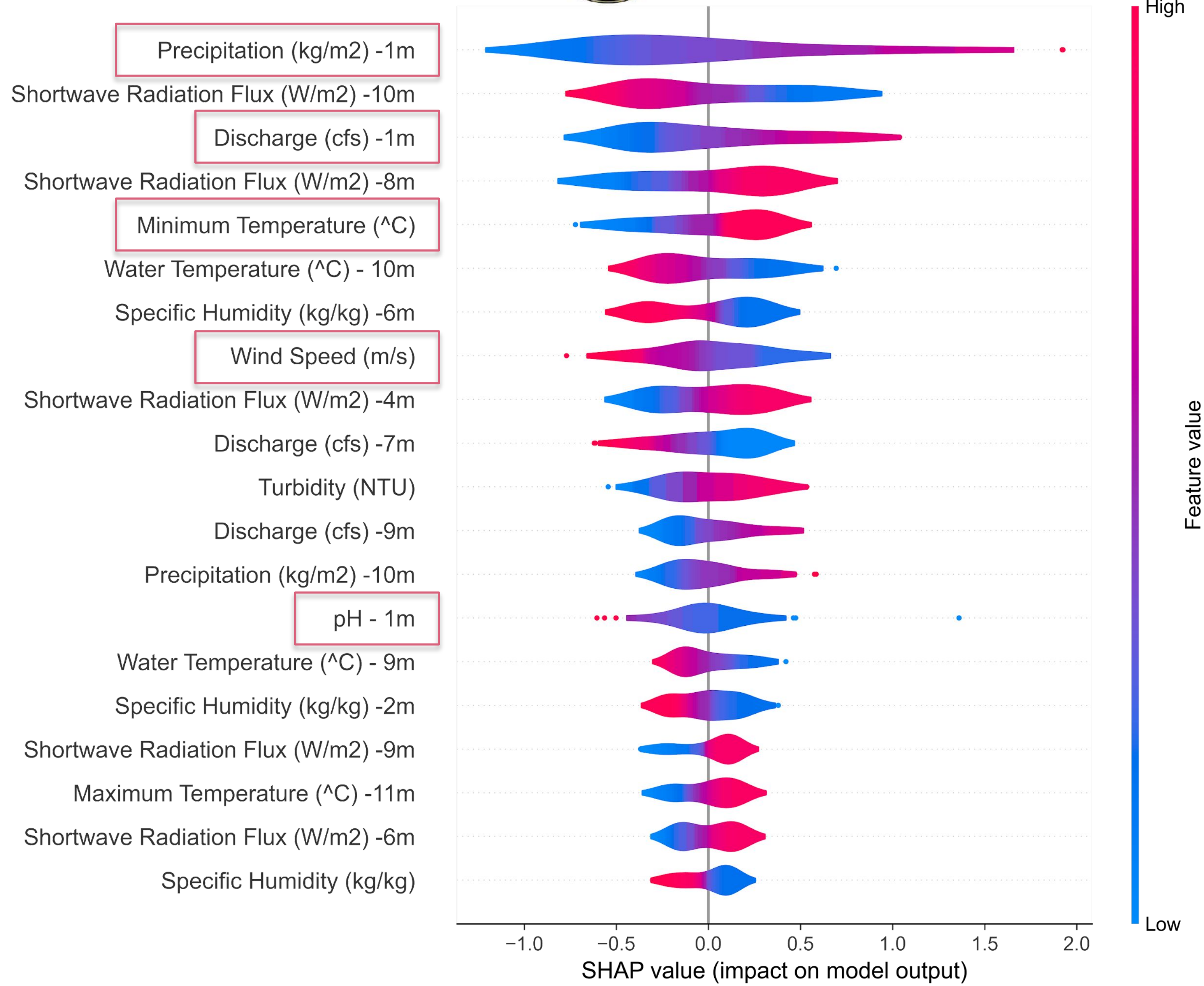
Metrics	SVM Chl-a	RF Chl-a	MLP Chl-a	MLR WT	MLR Discharge
R^2 in train	0.82	0.80	0.64	0.89	0.83
R^2 in test	0.74	0.62	0.66	0.91	0.83
MAE in train	0.69	0.70	0.99	0.92	83.2
MAE in test	0.92	1.18	1.12	0.71	105.9
MAPE in train	0.33	0.34	0.48	0.04	0.16
MAPE in test	0.26	0.33	0.32	0.03	0.31

Predictive model metrics



This SVM predictive model will be applied to predict future Chlorophyll-a concentration

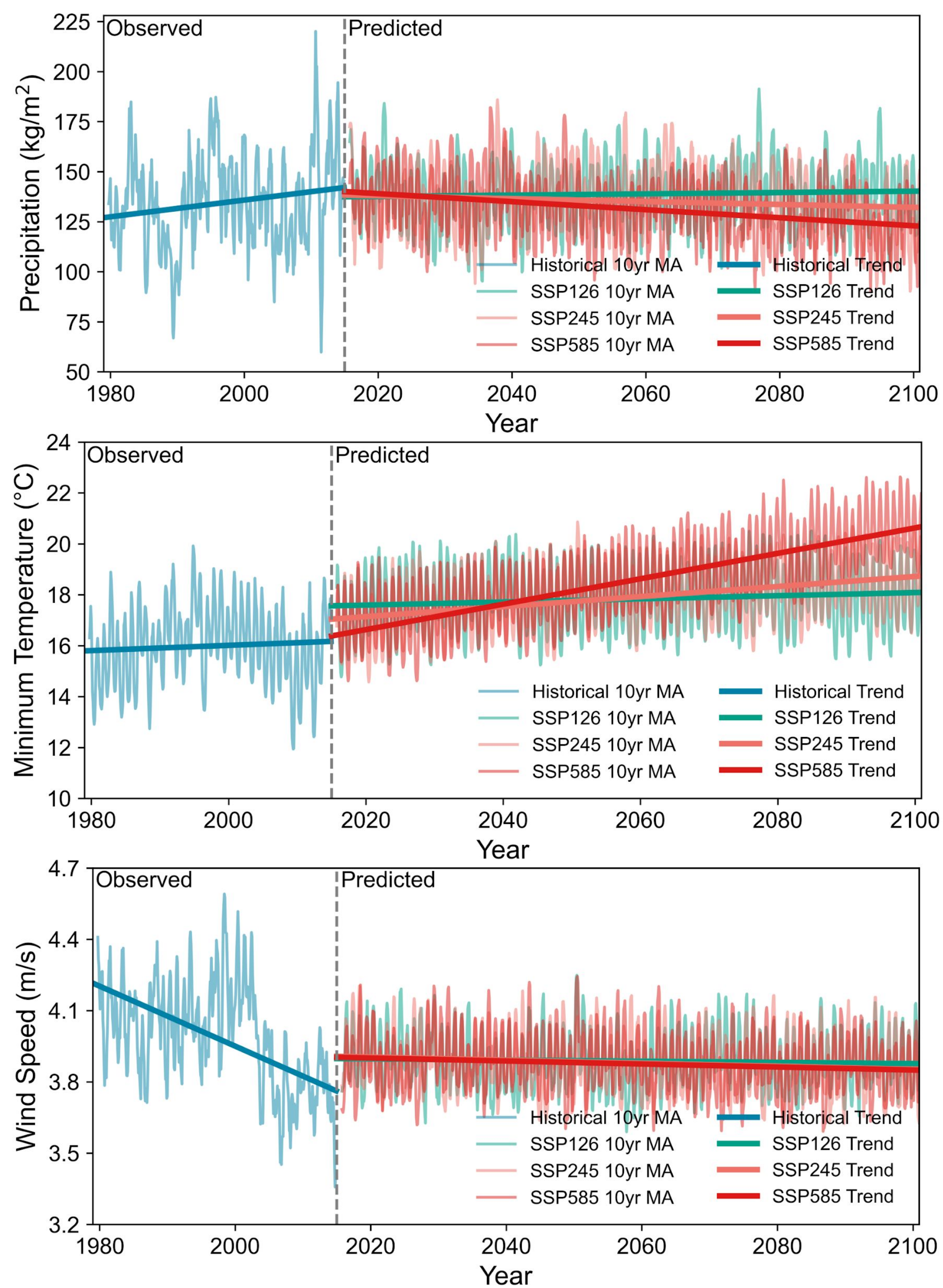
Feature Importance



liminary Results

NEX-GDDP-CMIF
(0.25*0.25)

BCC-CSM2-MR
CNRM-ESM2-1
MPI-ESM1-2-LR
MRI-ESM2-0



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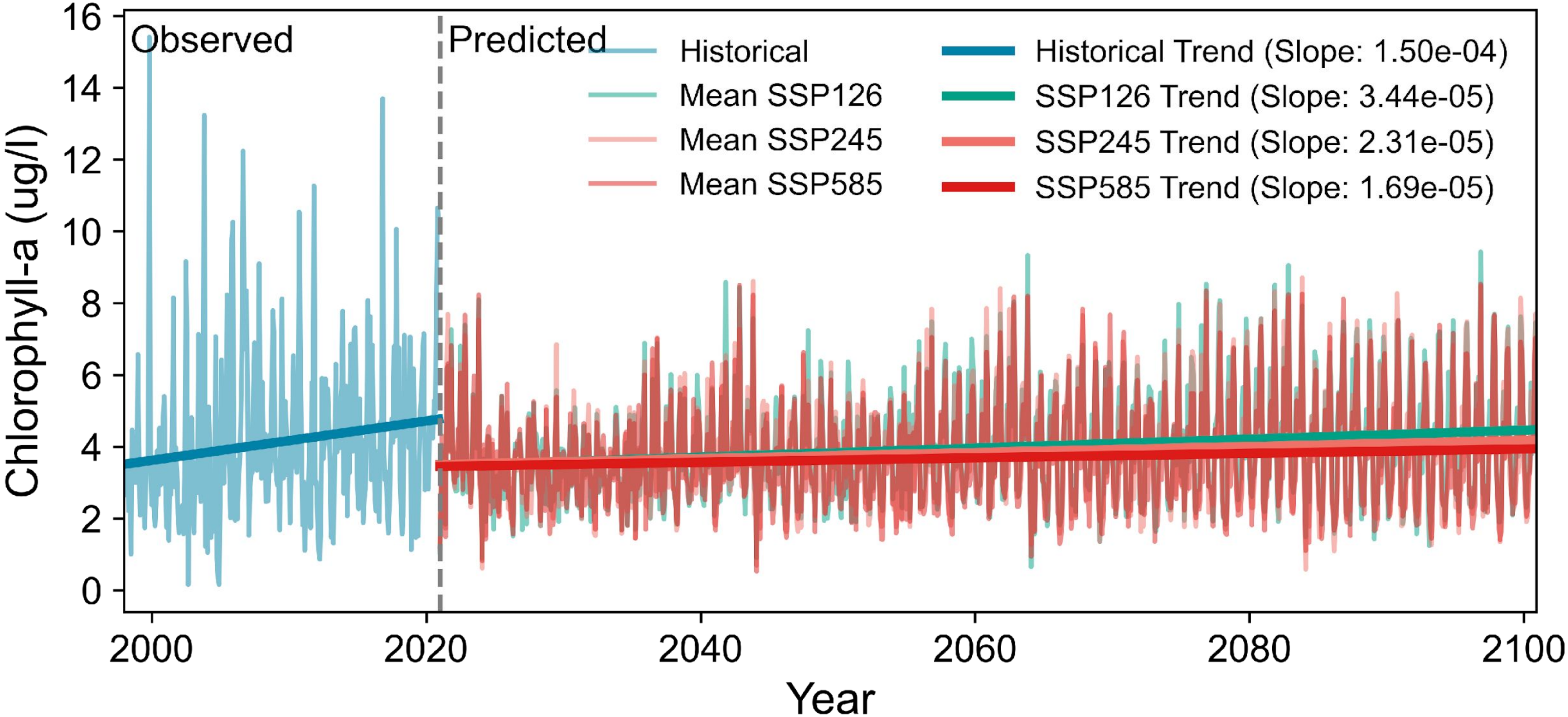
Preliminary Results



The observed trend has a steeper slope compared to the predicted SSPs, suggesting that future scenarios (SSP126, SSP245, and SSP585) may have slower trends compared to historical data.

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Thanks for your listening and suggestions!

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