

## Machine Learning-Based Harmful Algal Blooms (HABs) Modeling in the Sacramento-San Joaquin Delta

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## Highlights

- Environmental data influencing *Microcystis* abundance at 16 Sacramento-San Joaquin Delta (Delta) locations has been considered for Harmful Algal Blooms (HABs) modeling.
- Correlation analysis showed water temperature, pH, dissolved organic nitrogen, and phosphorus had a positive correlation, and antecedent flow, dissolved oxygen, and dissolved ammonia had a negative correlation with *Microcystis* (Average cells/ml)
- Initial data analysis inferred water temperature greater than 19 °C, pH range between 7.25 and 8.25, low flow, dissolved oxygen range of 7-9 mg/L, and increasing availability of organic nitrogen and phosphorus contributed to higher Microcystis abundance.
- The southern part of Delta experienced several HABs episodes.
- Since Microcystis (Avg. cells/ml) data was skewed, the values were log-transformed for HABs modeling. The Microcystis (Avg. cells/ml) data was divided into two categories: (1) Low and (2) High (Caution), with 4,000 cell/ml as the threshold per California Voluntary Guidance.
- ☐ Five Machine Learning (ML) models, including logistic regression, decision tree, random forest, **XGBoost**, and **artificial neural network**, were used to simulate *Microcystis* (Avg. cells/ml).
- The 70% data was randomly selected for models' training. The remaining 30% of the data was used for model evaluations. Model accuracy, precision, recall, and F1 score were used for model evaluation.
- The random forest (RF) model predicted *Microcystis* (Avg. cells/ml) to be the most accurate among the selected five models with 0.88 accuracy, 0.89 precision, 0.99 recall, and a 0.93 F1 score.
- RF model accurately predicted High Microcystis (Avg. cells/ml) on 87% of occasions and Low Microcystis (Avg. cells/ml) on 93% of occasions.
- This continuous modeling effort will provide information to help monitor and control HABs, thereby supporting both the ecological health and the long-term resilience of the Bay-Delta ecosystem.

## **Background and Motivation**

- HABs started becoming a critical concern for the Delta since 1999.
- Microcystis, a Cyanobacteria genus, is the primary reason behind HABs.
- Prior study initiatives closely collected relevant data influencing HABs abundance.
- This study aims to statistically analyze available HABs-related environmental data and develop an HABs modeling framework for the Delta.

## Methods

- Data Source: CA DWR and UC Davis
- Data Locations: 16 HABs locations in Delta
- Data Collection Period: 2014 2019 Data Availability: 381 days
- Predictor variables: 14
- Target Variable: *Microcystis* (Avg. cells/ml)

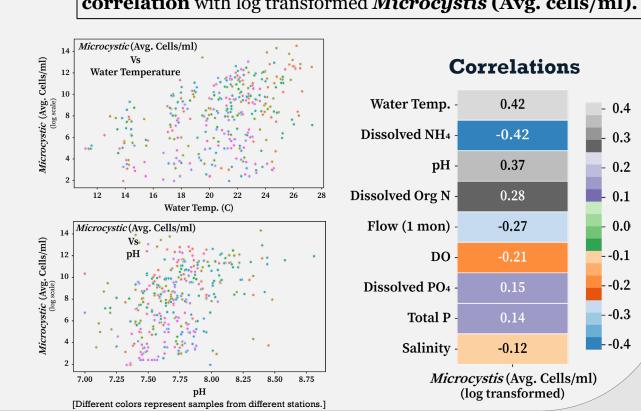
Available *Microcystis* (Avg. cells/ml) data is **highly skewed**, given the variability of relevant environmental variables.

# **Predictors Target**

#### **Workflow**

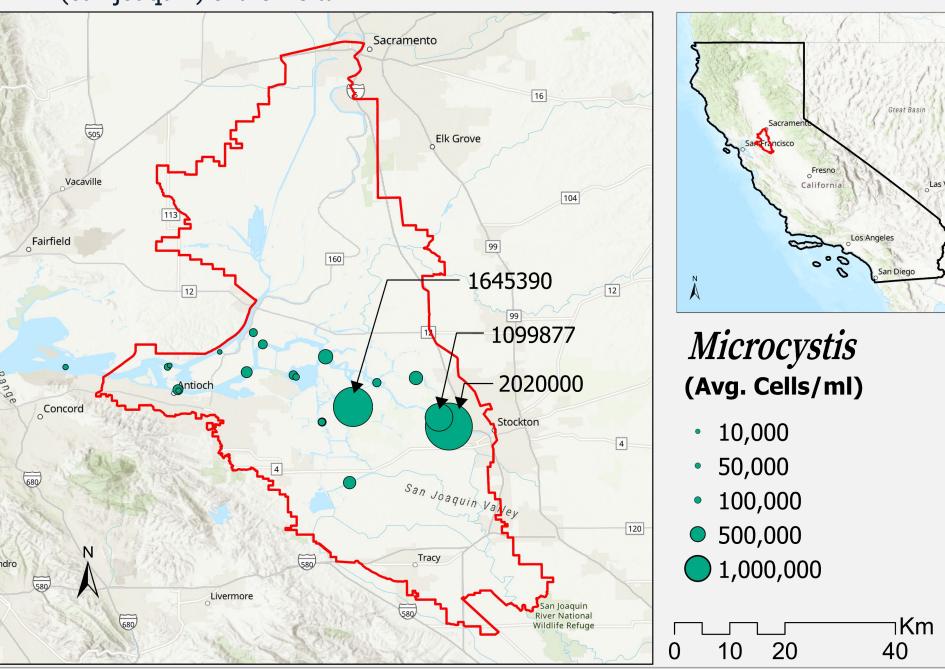
**Problem Definition** Literature Review Data Analysis Model Selection Model Development Model Evaluation

Water temperature, dissolved NH4, and pH had higher correlation with log transformed *Microcystis* (Avg. cells/ml).



## Study Area

Major Cyanobacterial Microcystis abundance events happened in the southern part (San Joaquin) of the Delta.



## Model Selection and Development

- ☐ ML model development
- ✓ This study treated **HABs modeling** as s classification problem (using 4,000 cells/ml as the threshold)

22+22

Random Forest Model: An

ensemble of multiple decision

by averaging the outputs of all

by majority voting (for

classification).

datasets

decision trees (for regression) or

XGBoost Model: A highly efficient

boosting algorithm that builds

models sequentially, where each

new model corrects the errors of

the previous one. It uses gradient

descent to optimize predictions,

**Artificial Neural Network (ANN)** 

interconnected nodes (neurons) that

**Model**: ANNs consist of layers of

process data. They predict by

backpropagation.

learning complex patterns and

relationships between inputs and

outputs through multiple layers and

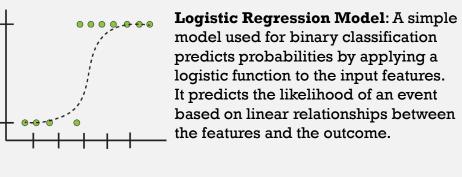
making it robust for large, complex

trees that improves accuracy and

reduces overfitting. It is predicted

- ✓ **Five** popular **ML** models are selected to solve classification problems.
- ✓ Based on the correlation matrix and initial data analysis, water temperature, pH, DO, dissolved NH<sub>4</sub>, dissolved organic N, dissolved PO<sub>4</sub>, total P, antecedent flow, and salinity were selected as predictors for **ML model development**.
- √ 70% Training and 30% Testing Data
- ✓ Data were **selected randomly** for modeling.
- ✓ Hyperparameters were tuned using the grid search method.

#### ☐ ML model used



**Decision Tree Model**: This model makes predictions by splitting data into branches based on feature values, forming a tree-like Act2 structure. It classifies by moving down the tree to a decision point Act3 (leaf) based on feature splits. Output

#### ☐ Evaluation Metrics:

- **Model Accuracy**: How often the model's predictions are correct overall.
- Model Precision: Of the predictions made for a specific category, how many were actually correct.
- **Model Recall**: Out of all true cases in a category, how many were correctly predicted.
- Model F1 Score: A balance between precision and recall showing overall model performance.

**Train** 

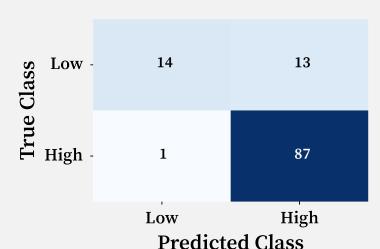
☐ The higher the values of all performance metrics (accuracy, precision, recall, and

Fl score), the better.

RF model most accurately predicted Microcystis (Avg. cells/ml) among five considered ML models.

RF model demonstrated the highest accuracy (0.88), highest recall (0.99), and highest F1 score (0.93) on the testing dataset, making the model appropriate in classifying the Microcystis (Avg. cells/ml) responsible for HABs.

### **Confusion Matrix**



- ✓ RF model correctly predicts the Low category 93% of the time (14 out of 15 times) on the testing dataset.
- ✓ On 87% of occasions, the model predicts the **High** category correctly.

Low category: *Microcystis* (Avg. cells/ml) < 4,000\*

**High** category: *Microcystis* (Avg. cells/ml) > 4,000 \*

- ✓ The **RF model** predicts **Low** category on one occasion, though the **True** class is **High** (which implies underprediction and undesirable).
- ✓ The model predicts **High** on **13** occasions (**13**%), but the True class is Low.

## **Future Direction**

**Initial Results** 

Expand the dataset to enhance the generalization capability of the proposed ML models.

\* California Voluntary Guidance

Develop an interactive dashboard that enables users to instantly simulate Microcystis under user-defined environmental conditions.

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## References

- 1. Hartman R, Rasmussen N, Bosworth D, Berg M, Ateljevich E, Flynn T, Wolf B, Pennington T, Khanna S. 2022. Temporary Urgency Change Petition of 2021 and Emergency Drought Salinity Barrier: Impact on Harmful Algal Blooms and Aquatic Weeds in the Delta. Sacramento (CA): California Department of Water Resources. October 2022. 188 pp. + appendix.
- 2. Bouma-Gregson K, Bosworth D H, Flynn T M, Maguire A, Rinde J, and Hartman R. 2024. Delta Blue(green)s: The Effect of Drought and Drought-Management Actions on Microcystis in the Sacramento–San Joaquin Delta. San Francisco Estuary and Watershed Science. https://doi.org/10.15447/sfews.2024v22iss1art2
- Environmental Protection Agency, US. (2019). Recommended Human Health Recreational Ambient Water Quality Criteria or Swimming Advisories for Microcystins and Cylindrospermopsin (EPA Document Number: 822-R-19-001). https://www.epa.gov/sites/default/files/2019-05/documents/hh-rec-criteria-habs-document-2019.pdf

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