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An Engineered Hub & Spoke System to Seek and Destroy Toxic Photosynthetic Organisms in Water Bodies

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ABSTRACT

Algal blooms have plagued waterways causing significant losses to Florida's economy. Currently, bloom data collection is reactionary and inadequate, following regional fish kills. Algal mitigation efforts are minimal and centered around fertilizer usage. Hence, there is a need for a smart solution aimed at preemptive detection and mitigation of impending blooms. The goal is to engineer an integrated Hub & Spoke (H&S) algae mitigation system for remote algal measurements, analytics, and mitigation. The system had three Spokes and a Hub. First, the 1st Mover, includes an aerial drone surveillance system, multispectral imagery, and post-processing using software. Second, the Verifier, an engineered floatation device for real-time algal measurements with a microcontroller and six sensors (pH, DO2, TDS, Photoresistor, Color Intensity, and Temperature). Third, Destroyer, a proactive mitigation system with algal suppression agents and a camera. Lastly, a centralized Hub to observe descriptive analytics visually in a cloud dashboard. H&S-engineered prototype tests were successful. 1st Mover visuals were converted as orthomosaic images and differentiated green zones from others. The Verifier passed leak checks, sensor-microcontroller interactions were seamless, measured data, and transmitted to the Hub continuously. Destroyer submersible pump dispersed mitigation agents via a remote on/off switch from the Hub dashboard. Per lab testing, a physicochemical agent (Alum-Bentonite combo) suppressed Chlorella vulgaris algae by flocculation and sedimentation. TDS, pH, and DO2 declined dramatically signifying the suppression. A 4^{th}-order polynomial machine learning model predicted TDS with 84% accuracy. This solution can be applied in the real world to mitigate algal blooms, saving our coastlines.

Introduction

Ensuring safe and clean water bodies is essential for natural ecosystem balance. Yet, cases of algal blooms plaguing both marine and freshwater bodies have been rapidly increasing. In a push to aggressively improve the water quality nationwide, federal, state, and local agencies are considering various options to overcome this environmental menace, which has impacted all 50 states in recent years.

Algal Life Cycle

Algae are a diverse group of photosynthetic microorganisms, which are a beneficial part of the aquatic food web as they form the energy base for that ecosystem. However, when certain toxin-producing suites of phytoplankton, cyanobacteria, and other microalgae grow excessively, Harmful Algal Blooms (HABs) are produced in the water body (1). Favorable environmental conditions such as extended photo periods, limited mixing conditions, stagnant flow hydrology, and favorable water chemistry e.g., pH, salinity, and conductivity help bloom development (1). HAB proliferation in marine environments is accelerated by nutrient enrichment from anthropogenic sources, coupled with rising temperatures over 80° F (1). Upon development, blooms block sunlight, resulting in the premature demise of aquatic plants and animals, and as the biomass dies and decays, dissolved oxygen is consumed, creating dead zones (1). Here the aquatic life struggles to thrive and the eutrophication cycle throws the regional ecosystem in dramatic disarray.

HAB Types

Toxins produced by blooms differ by species and region and have various negative impacts on humans, animals, and the environment. Cyanobacteria, known as blue-green algae, is a type of photosynthetic bacteria that blooms in sea and freshwater (2). Another common HAB type is the microcystins, which are a group of liver toxins that result in neurotoxic shellfish poisoning and affect the internal system of marine animals and birds (3). Dinoflagellate types and phytoplankton species appear in brackish waters. Some of these blooms discolor the water to shades of red and brown and some appear bioluminescent. Addressed as red tides due to the rust-colored swaths, the harmful Karenia brevis algae are a common sight on Florida's Gulf coast (3).

Problem

HABs have recurrently posed significant threats to water quality and marine organisms. Reported in all 50 states, HABs have caused billions in losses during the last decade, especially in areas that rely on tourism and seafood harvesting (3). Health and environmental problems from HABs have been pricey. According to the CDC, algal blooms cost $65 million per community and just the human digestive and respiratory issues alone cost up to $14.6k per illness (4). Recently in Florida, dead fish plagued regional waterways like the Indian River Lagoon (IRL) estuary, which spans 181 miles across Florida's East Coast and ranges through six counties (5). The watershed includes brackish water lagoons, freshwater rivers, ocean inlets, wildlife refuges, and ocean inlets. It is also known as the most bio-diverse habitat in North America and houses around 4,000 plant and animal species (5). Anthropogenic impacts have accelerated algal blooms in the IRL rendering parts of the estuary unnavigable and have devastated the local eco-tourism (5). Also, the IRL seagrass-based habitat has warped into an algae-based habitat, causing a tedious and costly recovery. Furthermore, unpleasant red tide episodes occur every year especially in Central Florida, choking off food sources for marine life (3).

Current Work

While initiatives to limit HAB proliferation, are centered around awareness of fertilizer overuse, there are no widespread proactive mitigation efforts. Data collection related to HAB impacts is largely based on voluntary reporting (6). Marine engineers collect water quality data from sensitive bloom-prone areas and aggregate the data in batches. The current monitoring system relies on the aggregation of disjointed data to provide information on the magnitude of a bloom – geolocation, satellite imagery, field observations, models, public health reports, and buoy data (6). However, the process is manual and minimal e.g., data collection once a month, which is late and insufficient for proactive HAB mitigation (6). These measurement techniques do not solve the requirement for continuous measurements. Broad access to research, advanced technologies, and funds are needed to make rapid strides toward a proactive algal mitigation and remediation effort.

Algal Mitigation

Currently, there is no singular algal suppression methodology. They are case-dependent, very selective, limited to water bodies, and fall under four broad categories. Physical Mitigation uses sediment-based methods such as flocculation to remove harmful toxins from water bodies (7). Limitations include the propensity of muck formation. Chemical Mitigation utilizes synthetic compounds to clarify turbid lakes through precipitation. Limitations include chemical contamination potential (7). Biological Mitigation uses biochemicals produced by organisms, which impact the growth and survival of another organism (7). Limitations include genetic mutation potential. Environmental Mitigation includes physical or chemical modifications of the environment such as dredging and limiting the use of fertilizers (7). This technique is more reactionary.

Need

There is an inherent need for a smart solution aimed at preemptive detection and mitigation of impending super blooms, which can be achieved through technology. It is imperative to continuously monitor using IoT (Internet of Things) principles and advanced technologies to solve current environmental issues (8). Hence, the goal of this research is to engineer a Hub & Spoke (H&S) system for remote algal measurements, analytics, and mitigation.

Methods

Hub & Spoke System

The goal of this research is to engineer an integrated Hub & Spoke (H&S) system for remote algal measurements, analytics, and mitigation using intelligent data. The system (Figure 1) has the following features:

1. 1st Mover System: This system consists of programmed surveillance coupled with multispectral image capture, storage, and post-processing.
2. Verifier: This is an engineered floatation device for algal parameter measurements, real-time data capture, and data transmission to a cloud.
3. Destroyer: This is a proactive algal mitigation system with a submersible pump to disperse algal suppression agents activated remotely and a remote camera.
4. Hub: This is an actionable centralized virtual system to observe instantaneous data in real-time and descriptive analytics on a visual dashboard.

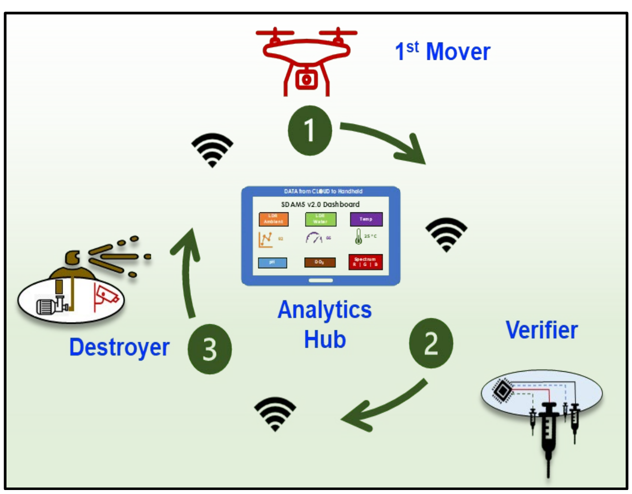

Figure 1. Hub & Spoke Algae Mitigation System showing major components. Schematic diagram by the researcher.

(1) 1st Mover

Aerial Surveillance

To execute an aerial scan, a multispectral camera was fitted in an aerial vehicle. The camera was strategically positioned in the aerial vehicle through a custom-designed arm and holder. They were both subsequently 3D printed and attached to the aerial vehicle. A MAPIR camera was mounted on the holder and secured with bands for redundancy support. The drone navigation was custom-programmed. Waypoints were plotted by strategically selecting coordinates such that the drone could fly at a certain altitude, aerial scan at defined locations, and traverse up and down at select intervals.

Image Capture & Post-Processing

A multispectral camera was programmed to capture pictures at programmed intervals and geotag them accordingly. The camera was fitted in the custom holder and the drone was launched. The drone followed the waypoints and returned to the base station. The camera captured multispectral images and stored them in an SD card and pictures were retrieved and processed in MAPIR Cloud through software. Individual photos were stitched and converted as orthomosaic and Digital Surface Model (DSM) images. Geometric distortions and colors were corrected and balanced to produce a seamless mosaic dataset. Natural and artificial features in the environment were captured by the digital surface model. Final mapped images differentiated green zones from others and unraveled a potential algal bloom in select areas.

(2) Verifier System [Floatation Device]

Verifier Shell Engineering

A custom-designed floatation device was sketched using CAD (Figure 2). A plexiglass container (shell) module with a diameter of 18cm was taken. Four 3.8cm equally spaced holes were bored through the shell module and four O-rings were inserted into the borehole perimeter. Subsequently, four rubber stoppers were firmly fitted into each O-ring. The stoppers and O-rings were applied with a thin coat of petroleum jelly, a strong hydrophobic sealant to repel moisture and provide a secure fit. A transparent plexiglass lid to fit the open top was used to protect the electronics in the module from water splash. Further, the lid allowed light through the shell module for solar power.

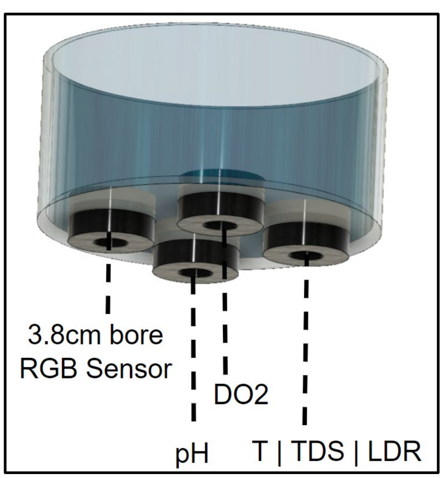

Figure 2. Verifier - CAD diagram of floatation device showing sensor placement locations. Diagram by the researcher.

Verifier Frame Engineering

Two PVC pipes of lengths 24cm, and two additional pipes of lengths 22cm were cut using pipe cutters. Using four PVC elbows, the pipes were joined to form a rectangular frame of dimensions approximately 26cm x 22cm. To keep the PVC frame afloat, sink-resistant polyethylene tubing was cut to fit and inserted around the frame's perimeter. Finally, the shell module was positioned and mounted on the PVC support frame and secured with zip ties.

Verifier Circuitry

An Arduino MKR1000 WiFi microcontroller connected to six water-quality measurement sensors was used for the device prototype. The six sensors included a water Photo Intensity sensor (light-dependent resistors), a Spectrum sensor module (Teyleten Robot GY-31 TCS230), a Temperature sensor (Songhe DS18B20 thermal probe), a Dissolved Oxygen sensor (DFROBOT Analog DO2), a pH sensor (GAOHOU pH electrode probe), and TDS sensor (DFROBOT Analog TDS). A circuit diagram was first developed using an electronic circuit design tool (Figure 3). Subsequently, sensors were connected per the circuit diagram and powered using a 5v solar-powered battery.

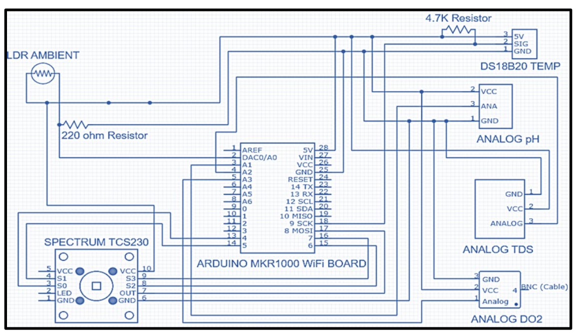

Figure 3. Verifier - Circuit diagram showing sensors and connectivity. Schematic by the researcher.

Stoppers in the Verifier shell module were drilled to fit sensors. All sensors were inserted into their respective stopper holes and the electronics and microcontroller were placed strategically inside the Verifier shell. Sensors were connected to the digital and analog pins on the WiFi microcontroller supported by the SPI (Serial Peripheral Interface) communication protocol. The microcontroller was programmed using Arduino to automatically connect to a local WiFi or to a mobile hotspot for wireless connectivity. A unified C++ code was created to control the sensors and transmit algal parameter variations to an open source IoT Thinger.io platform.

The final completed Verifier system included the shell containing electronic circuitry and a floatation frame around the perimeter (Figure 4).

Figure 4. Verifier – Completed Verifier floatation system placed in the pond simulator.

(3) Destroyer

Destroyer Shell & Frame Engineering

Similar to the Verifier shell, a plexiglass container (shell) with a diameter of 18cm was taken. A 100 ml size bottle representing an algal mitigating agent tank was placed inside the shell. A hole was drilled in the bottle cap and flexible tubing was inserted completely. The other end of the tubing was connected to a 3.5v submersible pump. About 3.5g of alum (algal mitigation agent) was added to the bottle and dissolved in 75ml of water. The bottle was secured inside the shell with 3M tape.

Destroyer Circuitry

A mitigation circuit diagram was developed using an electronic circuit design tool. An Arduino MKR1000 WiFi microcontroller was connected to a 3.3v submersible pump to disperse the mitigation agent upon remote activation. Components of circuitry included a relay, which functioned as an electrical switch to open and close the circuit to turn the submersible pump on/off, a voltage regulator to supply exactly 3.3v to the submersible pump from a 5v supply, a capacitor which stored small quantities of electrical energy to drive the submersible pump and to maintain the power supply. Circuitry also included transistors which acted as a gate and regulated the current and voltage flow. Circuit connectivity was made based on the diagram and was housed inside the Destroyer shell. The final completed Destroyer system included the shell containing electronic circuitry and a floatation frame around the perimeter (Figure 5).

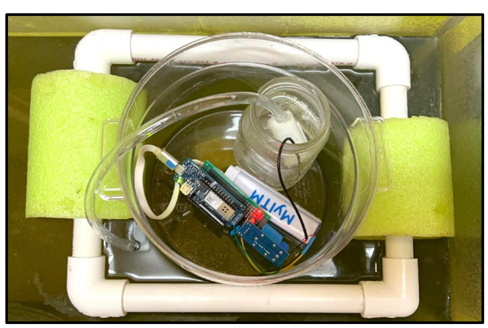

Figure 5. Destroyer system engineered with a submersible pump and electronics for remote algal mitigation.

(4) Hub

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Virtual Software

This is an actionable centralized virtual IoT platform defined by software. The hub contains dashboard visualization showing instantaneous data on algal parameters along with select descriptive analytics (Figure 6). It also included a digital on/off switch to activate algal mitigation remotely. The source of the analytics is the Verifier. Data from the sensors (in the Verifier) are gathered and transmitted by the WiFi microcontroller to a cloud database, where analytics are performed in real-time. Instantaneous values and temporal trends were displayed 24/7 for end-user knowledge of the health of the water body. A unified C++ program drives the hub. Customized dashboard widgets to display algal parameters uniquely were designed for display. If parameters exceed thresholds, a digital switch allows for remote pump activation in the Destroyer system to disperse mitigation agents in algal waters.

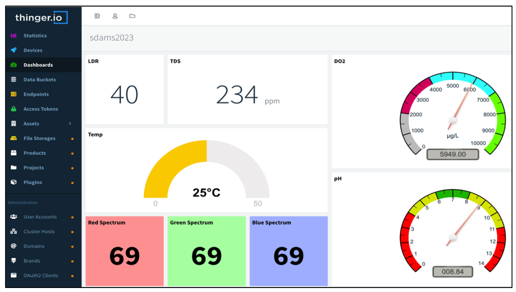

Figure 6. Hub data visualization dashboard showing real-time algal parameter variations.

Lab Analysis Testing (LAT) of H&S System

Pond Simulator Setup and Algae Culturing

Three plexiglass tanks of dimensions 51 cm x 26 cm x 31 cm functioned as pond simulators. They were filled with 27 L of dechlorinated water. The water tanks were then inoculated with Chlorella vulgaris algal samples. Tanks were left untouched to culture under oxygenated conditions using an aerator. After about three weeks, the algae-rich tanks were used for lab testing of the H&S System.

Lab Experimentation

The experiments were conducted with predetermined proportions of the physical (bentonite) and chemical agents (alum) to suppress the algae. In all cases, about 3.5g of agent were doped in 27 L of Chlorella vulgaris. This significantly higher proportion of suppression agent quantities was used to accelerate the reaction time in the lab. Three separate tests namely, (i) 100% alum (3.5g), (ii) 50% alum and 50% bentonite (1.75 g each), and (iii) 100% bentonite (3.5g) were conducted. Readings were taken at one-minute intervals continuously for about 60 hours. Notable variations and inflection points of algal parameters were observed due to algal suppression. Algal parameters were transmitted wirelessly by the H&S System and were continuously displayed on the cloud dashboard (Figure 7).

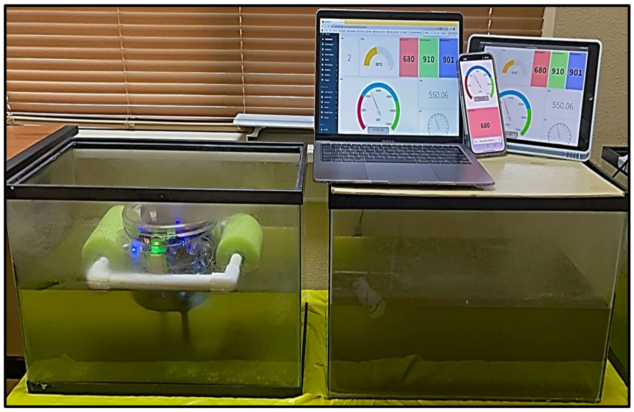

Figure 7. Lab Analysis Testing (LAT) – Full H&S system showing floatation device in pond simulator transmitting real-time algal parameter metrics to computer and handheld devices.

Field Analysis Testing (FAT) of H&S System

This was conducted at the Indian River Lagoon, Florida using the Verifier System. The system was carefully placed in the river and the Verifier floated with no leaks and was stable. The WiFi microcontroller was connected via a hotspot. The Verifier system collected algal parameter data of the Indian River and transmitted it to a mobile device seamlessly. Collocated testing was carried out with existing instrumentation from St. Johns Water Quality Management District. Both systems measured identical pH, DO2, and temperature metrics, the difference being, that the H&S System was more technologically advanced with visuals.

Results

Temporal variations in key metrics such as TDS, pH, and DO2 were observed over 60 hours in the pond simulator. Alum, a chemical agent showed the most dramatic change (blue line) based on the trend line on all key metrics. The pH and DO2 algal parameters had the most profound changes. Bentonite, a physical agent also showed variations (black line), however, they were far more muted versus the alum agent. The results for 50-50 alum-bentonite physicochemical combo agents (orange line) fell in between pure alum and bentonite agents based on the slope of the line.

Multiple regression and ANOVA analysis were achieved on the 50-50 alum-bentonite suppression agent. This was to analyze the relationship between a single dependent variable (TDS) and several independent variables (DO2, pH, Light intensity_H2O, and Temperature). The objective was to predict the value of the TDS dependent variable (y) using known values of select independent variables (x) as a set.

A machine learning model was created to observe the curve of best fit between a single dependent variable (TDS) and an independent variable (pH) instead of forcing a closed-form solution.

Discussions

Suppression was noted when agents were doped in algal waters. However, the chemical and the physical agents suppressed the algae by distinct methods. They did not vary the water quality parameters by the same measures.

Aluminum Sulfate (Alum)

This chemical agent suppressed the Chlorella vulgaris algae by decreasing the pH of the aqua environment, thereby making it less conducive for the algae to thrive. DO2 also declined steadily. This resulted in algal suppression in the simulator over the 60-hour time frame. A steep decline in the total dissolved solids (TDS) concentration (blue line) over time indicated the algal waters were going through the clarification process in the simulator (Figure 8). Per scientific studies, alum is a flocculant with a positive charge, which accelerates precipitation owing to its strong colloidal properties (9). They interact with algal particles, which have a negative surface charge and create a gelatinous viscous substance (9). During this process of coagulation or flocculation, suspended solid particles are drawn together by Van der Waals force, forming a floc, and precipitate to the bottom. Consequently, turbidity levels are altered from cloudy to clear. The coagulation process is affected by various other properties such as pH, alkalinity, and temperature. In this research, based on Figure 8, it can be implied that pH did affect the coagulation. Water parameters changed dramatically after alum dispersal thereby making the ecosystem optimum for coagulation and precipitation. This solution can be applied to the real world for a couple of reasons, as alum will not harm marine life or humans if used within thresholds (<52 micrograms/L, and pH 5.5 - 9.0). Further, alum mitigates algal growth by controlling the amount of phosphorus, a nutrient from fertilizer runoff. Aluminum sulfate reacts with water to form aluminum hydroxide, which binds and removes the phosphorus, thereby starving the algal food supply. Most importantly, the potential for future large-scale algal reproduction would be diminished as the ecosystem is devoid of phosphorus. In the real world, alum can be useful in recreation zones, e.g., smaller water bodies and local ponds where rapid suppression is warranted to save localities from economic impact. Overall, alum might disturb the ecosystem, but could offer the luxury of instantaneous suppression that would rapidly clarify the water body.

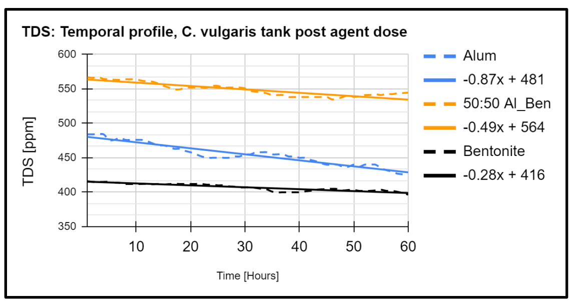

Figure 8. Total Dissolved Solids (TDS) - Temporal profiles following agent dosage in C. vulgaris pond simulator

Bentonite

This physical agent used for the algal suppression was efficient in clarifying the algal pond simulator. The physical agent had a maximum molecular weight of 422 g/mol. This indirectly meant that the agent had the highest density among the agents tested, which aided in sedimentation. When a substance's molecular weight increases, the mechanical properties also increase and are less chemically reactive. This aspect was very evident in this research. pH and DO2 did not vary noticeably (black line) throughout the experiment, yet suppression of the algal column occurred (Figure 9, 10). TDS came down marginally highlighting slow, but steady algal suppression. Based on research studies, bentonite provides strong adsorption, swelling, and viscosity properties. Bentonite's volume increases several times when contacted with water, which facilitates algal particle capture and sedimentation. In the real world, bentonite can be useful to suppress algae in sensitive waters, e.g., rivers and large lakes where aquatic animals and mammals thrive. Bottomline, bentonite can suppress the algae without disturbing the ecosystem. This can be used on water bodies preventively where HAB occurrences are annual.

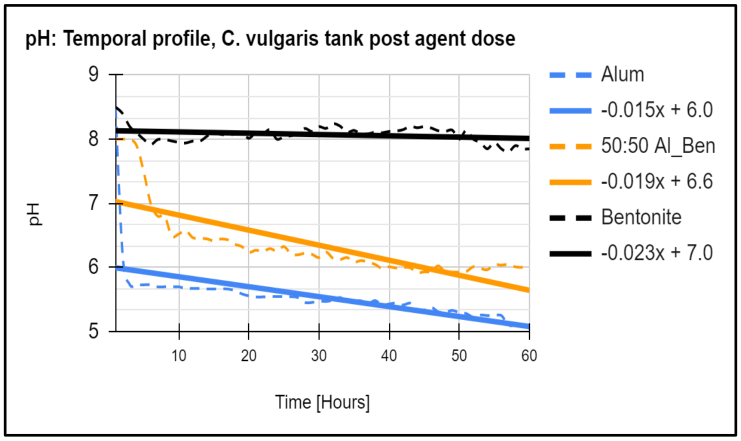

Figure 9. pH - Temporal profiles following agent dosage in C. vulgaris pond simulator

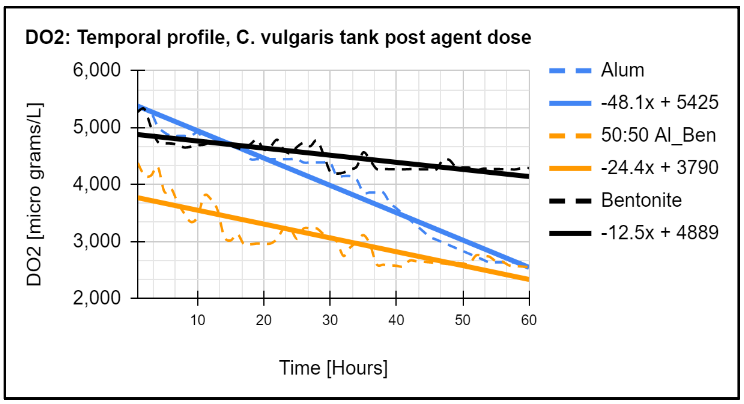

Figure 10. Dissolved Oxygen (DO2) - Temporal profiles following agent dosage in C. vulgaris pond simulator

50:50 Alum-Bentonite

This physicochemical agent provided a balanced suppression. Temporal variations on key algal parameters were observed to lie in between alum and bentonite (Figure 8, 9, 10). Algal suppression occurred both mechanically (due to bentonite properties), and chemically (due to alum properties). Bentonite suppressed the algae without applying too much disturbance to the ecosystem. In the real world, this balanced suppression agent can especially be used when combined with predictive analytics.

Multiple Regression Model

Based on multiple regression analyses on the physicochemical agent, an R^2 of 0.9 indicated the strength of the relationship between TDS dependent or response variable and other independent or predictor variables (Table 1). This also demonstrated the importance of each predictor variable. Further, the relationship between TDS versus the rest of the independent variables can be explained by the equation:

$$TDS = 0.01(DO2) - 5.4(pH) - 7.9(Photo\_H2O) + 0.3(T) + 593$$

Table 1. Multiple Regression Model for Alum-Bentonite Physicochemical Agent. The model shows the relationship between TDS and other algal parameters.

Regression Stats						
Multiple R	0.95					
R^2	0.90					
Adj. R^2	0.90					
Std. Error	3.13					
Obs.	60					
ANOVA						
	df	*SS*	*MS*	*F*	*Sig F*	
Regression	3	4999	1666	169.8	4.3E-28	
Residual	56	549.3	9.80			
Total	59	5548				
	Coeff.	*SE*	*t Stat*	*P-val*	*Lower 95%*	*Upper 95%*
Intercept	604.2	18.32	32.96	0.00	567.52	640.96
pH	-5.77	2.02	-2.84	0.006	-9.84	-1.71
DO2	0.008	0.00	3.14	0.00	0.003	0.01
LDR	-8.34	1.36	-6.10	0.00	-11.08	-5.61

Machine Learning Model

To enhance the predictive power of the statistical models, machine learning models were created to predict the algal TDS based on pH values over time (Figure 11). pH and TDS are among the leading indicators of algae. The models were created on Google Colab and programmed in Python. The first step was data preprocessing where the datasets were cleaned and organized with the Independent and Dependent variables in their respective columns. The two parameters tested are pH, x-values (independent variable), and TDS, y-values (dependent variable). Then, the lab data was split into train, validate, and test datasets.

A 60-20-20 split was assumed for this experimentation, where 60% of the dataset was used to train the model, 20% to validate, and 20% to test the data. To train the data, a simple model was created as a benchmark to initialize the regression model and to subsequently curve fit the data. The benchmark model was a linear regression model with a straight-line equation. Upon training, it was observed to not be effective as the spread of this data cannot be modeled using a straight line and had a poor Mean Square Error (MSE) and Mean Absolute Error (MAE). The second step of the machine learning process is to iteratively generate improved linear regression models. For each new model created, its performance was measured by applying it to the validation set. Then hyperparameter tuning was utilized for each model whereby specific parameters were modified multiple times to determine which combination of hyperparameters could yield the best performance in terms of MSE, MAE, and relative error. An optimal model is reached when the best combination of hyperparameters is achieved and found to give the best performance on the validation set. This can subsequently be applied to the test dataset.

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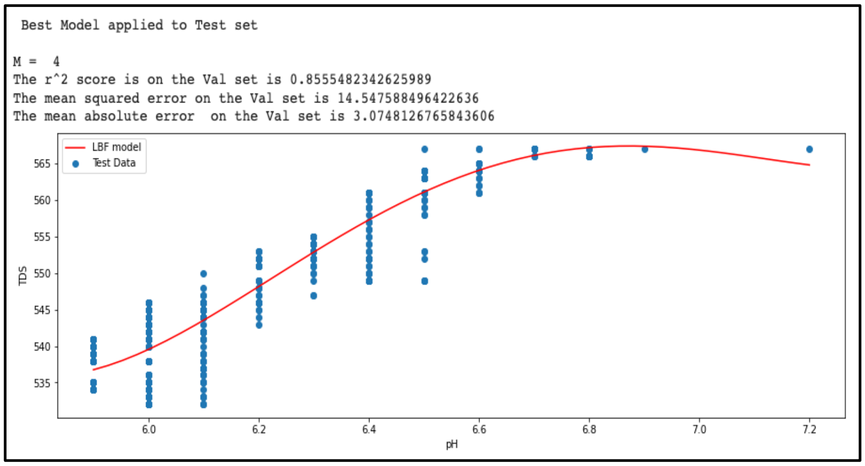

Figure 11. Machine learning 4th order polynomial regression showing best fit curve - pH [x-axis] vs. TDS [y-axis] with R^2 of 0.84

The first benchmark model attempted to use sinusoidal as its basis. For this model, hyperparameter tuning was applied by altering the x value in the sine function as shown by the formula:

$$f(x) = sin(i \bullet x)$$

For the sinusoidal function, 5 hyperparameter tuning tests were conducted. The model was tested by changing the degree of the polynomial to 2, 5, 10, 15 with a sigma of 20. This function however did not model the data properly.

The second benchmark model attempted to use polynomial functions as its basis. It was used to fit a nonlinear data trend. This is a common and very effective model that shows a relationship between the independent and dependent variables to the nth degree. For this model, hyperparameter tuning was applied by altering the Mth order polynomial in the Polynomial Basis formula:

$$f(x) = x^M + x^{(M-1)} + x^{(M-2)}...$$

In this research, 4 hyperparameter tuning tests were conducted for the Polynomial Basis Function benchmark model. The model was tested by changing the degree of the polynomial to 2, 3, 4, and 5 with a sigma of 10.

Finally, it was observed that the best model obtained during hyperparameter tuning was found to be a linear regression model that uses polynomial basis functions. A 4th order polynomial was found to be the best choice for modeling this dataset and the model is as shown:

$$f(x) = 77997 - 47128 + 10697(x)^2 - 1073(x)^3 + 40(x)^4$$

Based on the curve fit, the model has a relative error of 8.77% which leads to an accuracy of 91.23% as determined by dividing the Mean Absolute Error of TDS (3.07) by the Range of TDS (35). Additionally, the mean squared error on the validation set was found to be 14.55, the mean absolute error was 3.2 and the root mean squared error was 3.81.

Conclusion

Harmful Algal Blooms have plagued Florida waterways and caused significant losses to coastal economies. Batch data collection in most areas is reactionary, inadequate, and follows regional fish kills. Further, mitigation methods are centered around N2 & P fertilizer chemical reduction strategies. Hence, there is a need for a proactive smart solution aimed at preemptive detection and;/ mitigation of the impending super bloom via a combination of remote measurements, modeling, and followed by mitigation.

The goal is to engineer an integrated Hub & Spoke system for remote algal measurements, analytics, and mitigation using IoT. The system has three spokes, and a hub as follows:

1st Mover included surveillance via an aerial vehicle, multispectral image capture, and post-processing using software. The 1st Mover drone included a 3D printed arm and housing for the camera, which withstood high altitude and speed. Waypoints were plotted on the map in the software for navigation from takeoff to touchdown and the drone was programmed to trace the points. During post-processing, images were converted to an orthomosaic and a Digital Surface Model. This differentiated green areas from others. Images showed clarity concerning height and depth.

The verifier was an engineered floatation device for algal parameter measurements using a microcontroller and six sensors (pH, dissolved oxygen (DO2), color intensity, photoresistor, total dissolved solids (TDS), and temperature. The Verifier float was intact with no water leaks under various conditions. Sensor handshakes with microcontroller and power management were seamless. They were all enabled by customized C++ coding.

Destroyer: This was an engineered proactive mitigation system. The design included a submersible pump, algal suppression agents, and a wireless camera. The submersible pump dispersed mitigation agents via a remote activation switch from the cloud dashboard. Agents were predetermined based on descriptive analytics and the speed needed for mitigation. The remote camera enabled visual confirmation and the images were automatically captured and stored in the cloud.

Lastly, a Centralized Hub was created in the cloud. Descriptive analytics of algal parameters were shown in a visualization platform 24/7. The Hub also received data from the Verifier and displayed instantaneous values as well as temporal trends of the algal waters. Further, the Destroyer was controlled from the Hub via a digital switch to remotely disperse suppression agents.

Based on lab testing, both physical and chemical agents suppressed Chlorella vulgaris algae in their ways. For example, alum colloidal properties suppressed the algae by flocculation. The pH reduced instantly. TDS and DO2 also sharply declined. However, bentonite's mechanical properties suppressed the algae via adsorption and accelerated sedimentation. Unlike alum, no dramatic changes in pH or DO2 were observed. A 50-50 alum-bentonite engineered combo agent provided balanced results.

A multiple regression model to predict TDS explained 90% of the time. Further, a machine learning best-fit model, namely a 4^{th}-order polynomial curve predicted TDS using pH with 84% accuracy.

This H&S System was very successful in lab and field analysis testing. In the real world, although alum can disturb the ecosystem, it offers instantaneous suppression that would rapidly clarify the water body. Bentonite can be used on sensitive water bodies preventively where HABs have more chances of forming annually. Finally, the 50-50 alum-bentonite engineered combo provides a balanced suppression and can especially be used when combined with predictive analytics.

Limitations

The researcher encountered hardware and software challenges during the experimentation due to the dependence on Bluetooth connectivity. Hence to eliminate the Bluetooth distance constraint, the researcher intends to introduce a Long-Range Wide Area Network (LoRa WAN) for data transmissivity in the future. In addition, there were power constraints during lab testing, and the battery power was limited to 16 hours. To mitigate this issue, the researcher plans to introduce solar panels for uninterrupted renewable power. Furthermore, to improve the predictive behavior of the impending super blooms the researcher plans to achieve Convolutional Neural Network (CNN) Modeling using imagery captured through a camera.

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