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Article

Suppress that algae: Mitigating the effects of harmful algal blooms through preemptive detection and suppression

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SUMMARY
Recently, Harmful Algal Blooms (HABs), e.g., toxic red tide and blue-green algae, have suffocated and plagued coastlines and inland water bodies leading to economic losses. Currently, batch data collection in many areas is inadequate and reactionary following regional fish kills. Therefore, there is an inherent need for a "smart" solution aimed at preemptive detection and mitigation of the impending super bloom through combination of concurrent measurements, modeling, and mitigation using suppression agents. Our hypothesis is if a Seek and Destroy Algal Mitigation System (SDAMS) is engineered with a multitude of capabilities, including remote algal parameter sensing, wireless data transmission, and mitigation using suppression agents, then it will preemptively detect and mitigate HABs. The SDAMS includes (i) a floatation device with a Wi-Fi microcontroller and five sensors for concurrent measurements, (ii) real-time data transmission to the cloud, (iii) data visualization; diagnostic and predictive analysis, and (iv) an algae suppression component. During laboratory testing, physical and chemical agents used for mitigation noticeably suppressed the algae in various ways. Algal suppression occurred by either reducing pH, increasing Dissolved Oxygen (DO), or exerting high mechanical properties. We conducted predictive analytics to quantify the influence of the suppression agent on algae and compared the green spectrum strength (indicating algal intensity) to the DO concentration. Using machine learning, a 4th order polynomial equation with 94% accuracy provided the best curve-fit to explain the green spectrum-to-DO relationship. This cost-effective solution can be applied to instantaneously suppress, or preemptively mitigate, HABs to minimize environmental impacts.

INTRODUCTION
Algae are a beneficial part of our ecosystem; however, select types of algae can be very damaging. Diverse suites of phytoplankton, cyanobacteria, benthic algae, and macroalgae produce blooms in water bodies (1). These blooms pose significant threats to clean water quality and living organisms, and can cause substantial economic and recreational impacts (1). When algae containing toxins grow rapidly and out of control, they form HABs. Toxins produced by algae differ by species and region and have various negative impacts on humans, animals, and the environment. Cyanobacteria, also known as blue-green algae, is a type of photosynthetic bacteria, which like most algae types, mostly blooms in sea and freshwater (2). The HAB report by National Oceanic and Atmospheric Association (NOAA) also states that the most common cyanobacteria HAB toxins in the U.S. are microcystins, a group of liver toxins that can cause gastrointestinal illness in humans and mortality in birds and animals. In addition, dinoflagellates and diatoms, different types of phytoplankton, are the common species in marine and brackish waters. Some of these blooms discolor the water to different shades of red and brown and a few appear bioluminescent. Commonly addressed as red tides, blooms are named due to the red or rust-colored swaths caused by *Karenia brevis* growing in overabundance (3). This NOAA study also points out that harmful *K. brevis* algae are common in the Gulf coast of Florida and bloom episodes occur every year (3).

Harmful Algal Blooms (HABs) are a part of the ongoing water crisis and have consistently plagued U.S. waterways in recent years (4). In every state with marine economies, HABs have caused over one billion dollars in losses during the last decade in these areas that rely on recreation, tourism, and seafood harvesting (4). These blooms have a significant impact on ecological resources, coastal economies, and human health. As recent as 2022, there have been more frequent HAB events across the U.S. and the whole world (3). Dead fish plagued many waterways, and businesses that were reliant solely on tourism were forced to close (5). In addition, the seagrass-based habitat warped into an algae-based habitat, rendering the recovery tedious and costly. The conundrum is clear as seagrass regrowth is prevented by continuous algal blooms. This year, the loss of seagrass has resulted in the deaths of more than 800 manatees in just Florida, and this number is projected to get worse (5). Furthermore, HABs also produce toxins that may result in neurotoxic shellfish poisoning, respiratory irritation in humans, and even affect the internal system of marine animals and birds (3).

Currently, data collection is manual and reactionary, following the bloom episodes, which is too late and insufficient for rapid HAB mitigation. Also, in many areas, data collection related to HAB impacts are based on voluntary reporting and is inadequate (1). Geographic-based images are emerging from the National Center for Coastal Ocean Science (NCCOS), which helps to identify bloom locations in the United States (2). Furthermore, many current mitigation methods are addressing the root cause of algal blooms and are centered on awareness of fertilizer overuse. These methods revolve around nitrogen and phosphorus chemical reduction strategies. Although some organizations are working towards achieving on-demand bloom detection, there is very limited widespread mitigation following a regional HAB

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episode. If proper mitigation methods are used, it can help prevent dissolved oxygen depletion and fish death at an early stage before algal biomass reaches critical thresholds. While there is unanimous consensus on the need for rapid HAB mitigation, suppression activities via mitigation methods, at times, can be controversial due to the unintended ecosystem impacts by agent-doped waters.

Algal mitigation techniques primarily fall under four broad categories: (i) physical or mechanical, (ii) chemical, (iii) biological, and (iv) environmental controls (6). Physical mitigation uses physical means to remove toxins from water ecosystems by using sediment-based methods, for example, clay flocculation (6). Bentonite clay can help remediate water bodies as it has the tendency to adsorb chemicals as well as organisms like algae, which clarifies the surface water (6). Bentonite is a natural mineral formed from volcanic ash, which, when dispersed, has the ability to agglomerate and remove cells such as cyanobacteria and dinoflagellates from water bodies. Limitations include the acceleration of muck formation in the basin of water bodies. Chemical mitigation utilizes artificial chemicals and compounds, e.g., aluminum and copper sulfate (6). Aluminum sulfate (alum), a chemical agent, helps to clarify turbid lakes polluted with algae through precipitation (6). Alum is a flocculant, which has an affinity for phosphorus, an algal nutrient. Flocculation draws phosphorus and other particulates including algae and settles to the bottom of water bodies thereby altering turbidity levels from cloudy to clear. Limitations include chemical contamination of water bodies if used excessively. Biological mitigation is a phenomenon in which an organism, e.g., macroalgae, predator enhancements, bacteria, viruses, and allelopathic organisms, produce biochemicals that impact the germination, survival, growth, and reproduction of another organism (6). Limitations include potential genetic mutation of HABs. Environmental mitigation includes strategies involving physical or chemical modifications of the environment such as dredging in water bodies, aeration, water circulation, and limiting the use of fertilizers (6). This environmental mitigation technique is more reactionary as HABs may still be able to form.

Our hypothesis was if a custom-designed algae mitigation system is engineered with environmental sensors and wireless data transmission abilities, then it will aid in preemptive algae detection and mitigation. We have designed the SDAMS (Seek and Destroy Algae Mitigation System), which includes the following four components. (i) A floatation device that includes a microcontroller connected to five distinct water quality sensors for concurrent measurements of algal parameters. (ii) Continuous real-time data transmission to an interactive cloud. (iii) Data analysis in a visual platform (e.g., a mobile device) to monitor real-time algal parameters, and subsequently conduct desktop Diagnostic and Predictive analytics. (iv) A mitigation component containing an agent dispersal pump controlled via a switch. In this research, we developed a solution for early detection and prediction of an impending HAB episode through a combination of remote measurements, statistical modeling, and suppression agents.

RESULTS

As the type, shape, composition, and color of HABs are different, a singular metric that could be considered as a leading indicator to detect an algal bloom or algal demise cannot be relied upon. It is for that reason, a collection of five algal bloom parameters in conjunction were considered for this research, e.g., Color Spectrum Intensity, Dissolved Oxygen (DO), pH, Photo Intensity (both Ambient and Water), and Temperature. In this research, we used three different agents for algal suppression: Aluminum Sulfate, Copper Sulfate, and Bentonite Clay. The five bloom parameters were measured during the experimentation, and overall, diverging trends were seen on select metrics in isolation. Three key metrics that showed appreciable temporal movements following agent addition include green spectrum (represents the algal growth in a pond), DO, and pH. Our control sample, which was an algae-rich tank with no additional agents yielded an average pH of *Chlorella vulgaris* (culture of green algae that we used during this experimentation) was 8.2, the average, the DO was 5,026 µg/L, and the average green spectrum index was 133. The physical and chemical agents that we used to suppress the algae yielded appreciable results. Based on the laboratory research, the agents suppressed algae via distinct methods and did not vary water quality parameters in the same manner. Agent behavior and interaction following the dispersal in the algal pond simulators are discussed below:

Alum Agent Interactions

We noticed dramatic changes in DO levels in a simulator doped with the alum suppression agent (**Figure 1**). DO had increased temporally due to the influence of alum. Also, after 72 hours from doping the waters with the agent, the pond simulator had the most clarification or most decrease in green spectrum intensity (**Figure 2**).

Copper Sulfate Agent Interactions

Copper sulfate affected the pH of the water in time leading to algal demise and settling. An initial dip in pH can be attributed to acidity, however, algae thrived, and the bloom momentum continued despite agent addition (**Figure 3**). After about 36 hours, a rapid decline in pH was seen suggesting rapid algal demise.

Bentonite Agent Interactions

Clay flocculation and sedimentation were observed. Another key observation noted was that pH and DO did not vary noticeably throughout the course of the experiment, yet suppression of the algal column occurred (**Figures 1-3**).

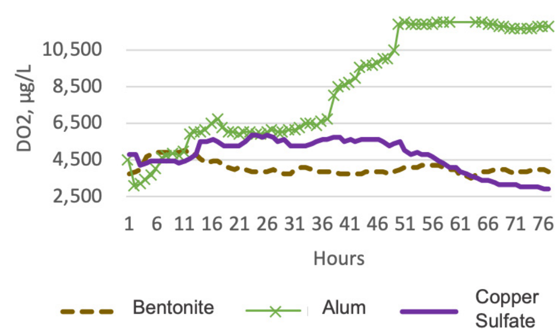

Figure 1. DO_2 variations in C. vulgaris algae with suppression agents. Three suppression methods were evaluated: Bentonite (brown), Alum (green) and Copper Sulfate (purple). Alum had a significant increase in DO_2, while Copper Sulfate had a gradual decline and Bentonite was steady.

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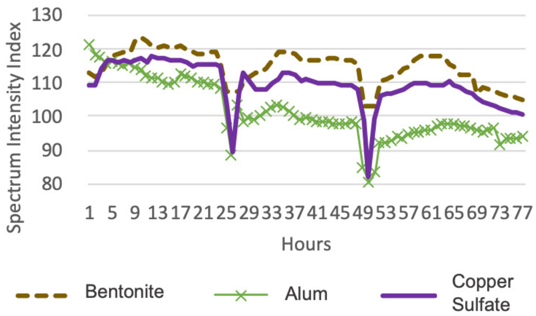

Figure 2. Spectrum variations in C. vulgaris algae with suppression agents. Color and line indicate the suppression method. All suppression agents had a gradual decline in light intensity over time.

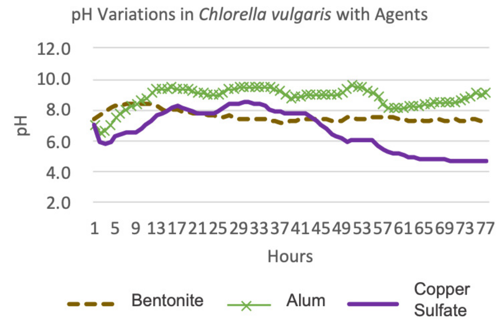

Figure 3. pH variations in C. vulgaris algae with suppression agents. Color and line indicate the suppression method. The pH for both Alum and Bentonite were mostly stable, while Copper Sulfate had a significant decline.

Predictive Analysis (Multiple Regression)

Predictive analytics were conducted to observe the relationship between the alum chemical agent and algal suppression. This finding suggests that 89% of the variability of the green spectrum (dependent variable) can be explained by the entire set of independent variables (pH, DO, light intensity, and temperature). Additionally, the p-value and other statistics indicated a good correlation between the variables ($p = 1.3 \times 10^{-35}$, which is less than 0.05).

Predictive Analysis Using Machine Learning

To enhance the predictive power of the statistical models, Machine Learning (ML) models were created (**Figure 4**). ML models were created to predict the DO based on the green spectrum values over time. We programmed ML models using the train set (60% of the data) and utilized hyperparameter tuning for each model whereby specific parameters were modified multiple times to determine which combination of hyperparameters could yield best performance in terms of Mean Squared Error (MSE), Mean Absolute Error (MAE) and relative error. An optimal model is reached when the best combination of hyperparameters is achieved and found to give best performance on the validation set (20% of the data). This can subsequently be applied to the test set (20% of the data).

The benchmark model attempted to use polynomial functions as its basis. It was used to fit a nonlinear data trend. For this model, hyperparameter tuning was applied by altering the Mth order polynomial. After we conducted hyperparameter tuning, we found that a 4th order polynomial was the best choice for modeling this dataset and the model. Based on the curve fit, the model has a relative error of 6%, which leads to an accuracy of over 94% as determined by dividing the Mean Absolute Error of the green spectrum (2.56) by the range of green spectrum. Additionally, the mean squared error on the validation set was found to be 10.73, the mean absolute error was 2.56 and the root mean squared error was 3.28.

DISCUSSION

We hypothesized that if an algae mitigation system is engineered with environmental sensors and wireless transmission capabilities, then it will help in preemptive algae detection and mitigation. The engineered SDAMS device included four components namely, a floatation device with sensors, real-time data transmission to the cloud, predictive analytics, and a dispersal pump for mitigation. During SDAMS laboratory testing, the physical and chemical agents (aluminum sulfate, copper sulfate pentahydrate, and bentonite clay) used to suppress the algae yielded appreciable results and they suppressed algae through different ways.

Alum, a chemical agent, was also effective in clarifying the algal pond simulator. Alum is a flocculant that suppresses via its strong colloidal properties (7). During coagulation, particles are drawn together by van der Waals forces and they form flocs, which later settle to the bottom thereby altering the turbidity levels from cloudy to clear. The coagulation process is affected by pH, salts, alkalinity, turbidity, temperature, mixing, and coagulant chemicals as the water quality parameters change dramatically after agent dispersal. Aluminum sulfate will also help eliminate odors in addition to removing the algae (7). This can be applicable for usage in larger water bodies. According to a source, aluminum sulfate mitigates algal growth by controlling the amount of phosphorus, a nutrient from fertilizer runoff, available in water (7). The agent reacts with water to form aluminum hydroxide, which binds and removes the phosphorus (7). As the algal mass is devoid of its food supply (phosphorus), they die. Most importantly, the potential for future large-scale algal reproduction would be diminished due to the phosphorus shortage. This chemical agent will not harm marine life or humans if used within thresholds below 52 micrograms g Al/L, and pH should remain within 5.5 to 9.0 (7). Therefore, if used within the threshold, alum is a great chemical agent for instantaneous mitigation efforts in the future.

Copper sulfate was suitable in clarifying the algal pond simulator. Neutral or acidic pH levels can help stunt the growth of algae. Copper sulfate kills algae directly by binding to and damaging the algal cell (6). Copper sulfate reacts with water to form copper carbonate, an ineffective compound, which collects to the bottom of the pond and does not break further. Too much buildup of copper compounds can kill plant life and create ripple effects in the ecosystem (6). Despite substantial reduction in the size of HABs, copper sulfate is considerably lethal and could be harmful to the marine environment if used without a controlled strategy (6). So, it should not be used in waters that support aquatic life as it is more susceptible to chemical changes. As this chemical agent is not biodegradable, it can make runoff hazardous (6). In addition, copper sulfate is not useful in excessive bloom

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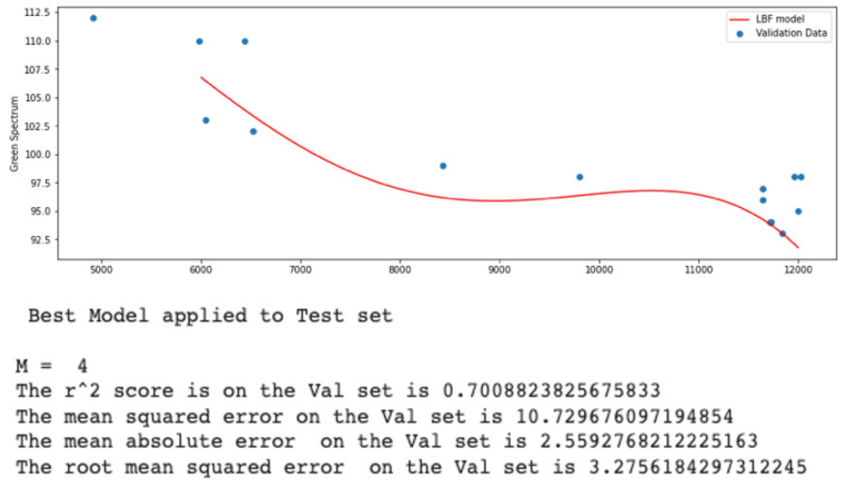

Figure 4. A Linear Regression Benchmark model with a Polynomial Basis. The Regression Model presents a balanced curve fit with an M value of 4, and an R^2 of 0.7. The mean squared error is 10.7, the mean absolute error is 2.6, and the root mean squared error is 3.3. These statistics were concluded after training, validating, and testing the data set. The model represents a balanced curve fit of the test set. These models are used to predict impending super blooms.

situations as it can only eliminate the top algal layer of a water body (6). This might eventually make the bottom very sterile, thereby preventing the growth of beneficial bacteria. Therefore, although copper sulfate is good for future algal suppression, it should be dispersed in very minimal amounts. Bentonite, a physical agent used for the algal suppression in the Laboratory Analysis Test (LAT) was efficient in clarifying the algal pond simulator. The physical agent had a maximum molecular weight of 422 g/mol (8). This indirectly meant that the agent had the highest density among agents tested, which aids in sedimentation. Typically, as the molecular weight increases, mechanical properties of the substance increase and are less chemically reactive (8). Based on research studies, bentonite provides strong adsorption properties (8). The volume of bentonite increases several times when in contact with water, which aids algal particle capture and sedimentation (8). Most importantly, bentonite did not result in dramatic fluctuation in the water quality parameters such as pH and DO. Lastly, bentonite is less susceptible to chemical changes in water quality parameters and can be used in sensitive waters. As evidenced in the results, in the real world, bentonite is strongly applicable and or conducive to select sensitive water bodies for clarification without altering water properties. However, their limitation is related to potential muck formation. This may occur if there is excess and continuous dispersal of the agent. Bentonite poses no dangers to marine life when used appropriately (6).

We conducted predictive analytics to observe the relationship between the alum agent and algal suppression. 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 MSE and MAE. Further, based on the regression statistics, 89% of the data can be explained by this model. Finally, based on the Machine Learning Model, it was observed that the best model obtained during hyperparameter tuning was found to be a linear regression model that uses polynomial basis functions. We found that a 4th order polynomial was the best choice for modeling this dataset.

The SDAMS lab testing was successful. This device was built in a pilot scale, and the concept functioned as expected. This SDAMS cost less than $250 to build and was powered by a 5V rechargeable battery, which only has a 2-week charge life. Furthermore, the SDAMS requires periodic cleaning of the sensors for data quality. Finally, the SDAMS also requires active Wi-Fi for connectivity. In the future, this system can be improved by using Long-Range Wide Area Network (LoRa WAN) technology.

The results of our experiment supported our hypothesis as all aspects of this research functioned successfully, including real-time detection of algal bloom parameters, data visualization in the cloud, algal suppression using chemical and physical sedimentation agents, predictive modeling, and remote mitigation using a pump. In the real world, a scaled-up version of this solution could preemptively detect and predict an impending super bloom episode.

MATERIALS AND METHODS

Floatation Device Shell Engineering and Construction

A 3D model of the custom-designed floatation device was sketched using CAD (AutoCAD Fusion360) (**Figure 5**). The material composition of the floatation device consisted of a 15cm x 10cm x 2cm polystyrene base module wrapped in a cork underlayment. A 5cm hole, three 2cm holes, and a 0.5cm hole were bored through the module. Subsequently, the module was coated with hydrophobic sealant to repel moisture. Using pipe cutters, two PVC pipes 20cm in length and two additional pipes 15cm in length were cut. The pipes were joined to form a rectangular frame using PVC elbows. Then, the waterproof module was mounted on the 20cm x 15cm PVC support frame. The entire engineered assembly was kept afloat by sink-resistant polyethylene tubing around the perimeter. Five transparent polyethylene tubes of suitable sizes were selected and firmly fitted through the bore holes on the module. These tubular containers housed the sensitive electronic sensors and other circuitry.

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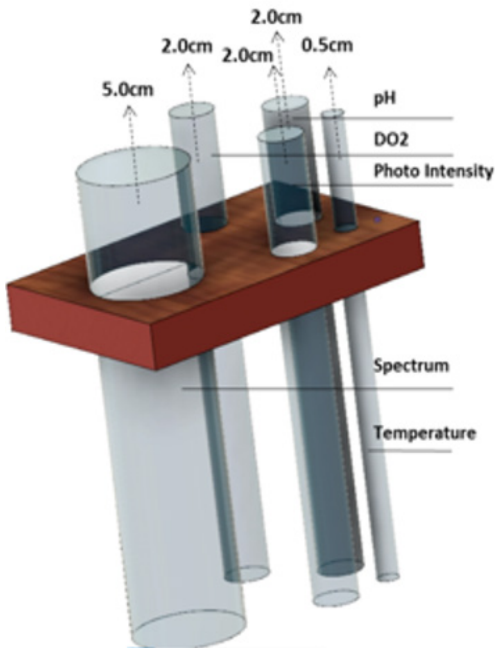

Figure 5. CAD Drawing of SDAMS using AutoCAD Fusion360. Model represents a waterproof shell of a floatation device with bore dimensions and 5 sensor placements.

SDAMS Circuit Design

An Arduino MKR1000 Wi-Fi microcontroller connected to five water quality measurement sensors was used for the device prototype. The five sensors included a spectrum sensor module (Teyleten Robot GY-31 TCS230), dissolved oxygen sensor (DFROBOT Analog DO), pH sensor (GAOHOU pH Electrode Probe), ambient and water photo intensity sensors (Light Dependent Resistors), and a temperature sensor (Songhe DS18B20 Thermal Probe). A circuit diagram was developed using EasyEDA, an electronic circuit design tool. This layout was translated to a microcontroller and sensor circuit connectivity (**Figure 6**). The entire system was controlled by a 5V battery pack.

SDAMS Microcontroller and Sensor Connectivity

The assembly containing all electronic components were subsequently inserted into their respective polyethylene tubes (**Figure 7**). All sensors had the capacity to measure and send data electronically to the programmable microcontroller, which was capable of wirelessly transmitting information.

Pond Simulator Setup

A plexiglass tank with dimensions of 51cm x 26cm x 31cm served as a pond simulator. It was filled with about 27 liters of dechlorinated water. The water tank was then inoculated with a vial containing a *C. vulgaris* algae sample. The solution was left untouched to culture under oxygenated conditions using an aerator. After 3 weeks, the algae-rich tank was used for the lab testing of the SDAMS sensors and circuits. The algal tank was also used for testing various physical and chemical algal suppression agents.

Laboratory Experimentation

27 liters of *C. vulgaris* algae was sufficiently cultured in a pond simulator and 1.5 grams of bentonite was added

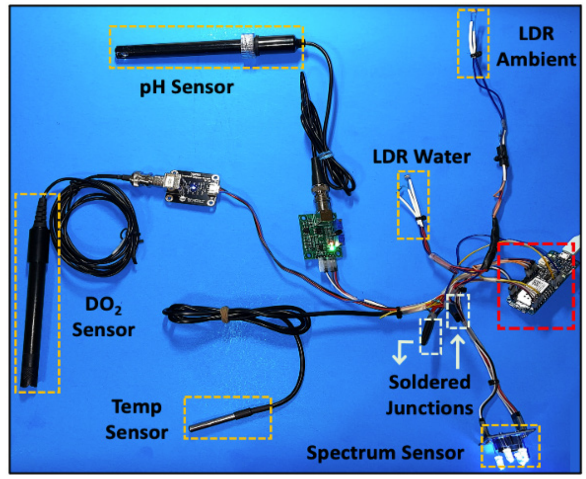

Figure 6. Microcontroller and Sensor Connectivity. This circuit layout contains 5 distinct algal parameter sensors all soldered and taped to a wireless microcontroller (red box). Sensors include Light Intensity Ambient (top right), Light Intensity Water (middle), pH (top left), DO_2 (left), Temperature (bottom left), and Spectrum (bottom right).

to suppress the algae. Subsequently, the experiment was repeated using the same quantities (1.5 grams) of either alum or copper sulfate in constant portions (27 liters) of algae in the simulator. Readings were taken at one-minute intervals continuously for over 72 hours. The algal parameters transmitted wirelessly by SDAMS were recorded in real-time in an Internet of Things (IoT) cloud dashboard (**Figure 8**).

Real-time Data Transmission

Water quality sensors were connected to the digital and analog pins on the Wi-Fi microcontroller supported by Serial Peripheral Interface communication protocol. The microcontroller was programmed using an Arduino to automatically connect to a local Wi-Fi or to a mobile hotspot for wireless connectivity. A unified C++ code was created to control the SDAMS sensors and transmit algal parameter

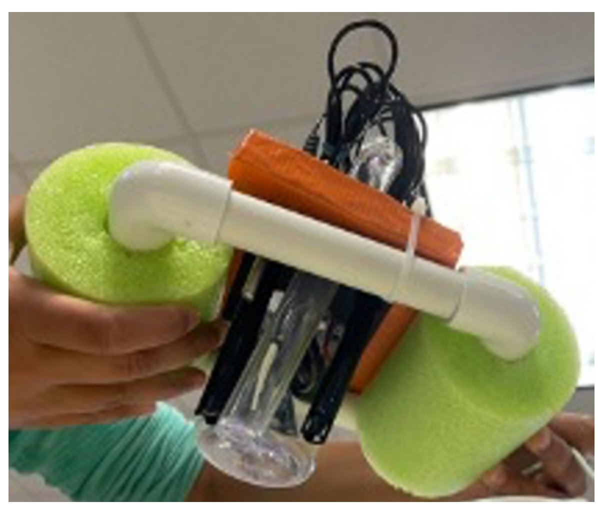

Figure 7. SDAMS Device. This is the completed prototype of the Seek and Destroy Algae Mitigation System. This includes 5 distinct sensors and a microcontroller housed in a custom-designed floatation device.

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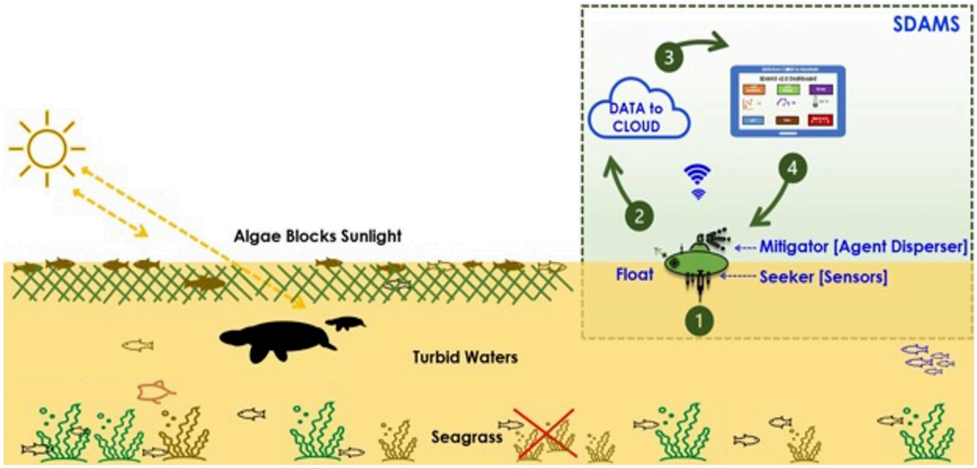

Figure 8. Seek and Destroy Algae Mitigation System in a harmful algae bloom. The Seek and Destroy Algae Mitigation System (inset), contains 4 distinct components: 1) Seeker with 5 sensors to measure algal parameters, 2) Wireless data transmission to the cloud, 3) Dashboard analytics on an IoT visualization platform, 4) Mitigation with a remote agent mitigation pump, which sprays Alum, Copper Sulfate, and Bentonite. These 4 parts systematically work to preemptively detect and mitigate algal blooms, thereby allowing aquatic life to thrive.

variations to an "open source" IoT Thinger.io platform. The IoT platform allowed for cloud visualization including real-time interactive dashboards and charts with on-demand data reports for desktop diagnostics and predictive analytics (**Figure 8**).

Algae Mitigation

As the final element in the SDAMS system, this step attempted to mitigate algae by remotely activating a pump to suppress the algae by spraying an agent based on descriptive (temporal charts) and predictive analytics (regression models) (**Figure 8**). For this step, a separate dispersal pump, relay module, and an activation switch was constructed. When water quality parameters displayed high readings indicating intense algae presence, the pump was activated, which enabled agent dispersal. In real-world applications, a corresponding suppression agent solution can be connected inline to the pump, which can be sprayed remotely.

Statistical Methods

A paired ANOVA test was conducted on the water quality parameter data to determine if there is a statistical difference between the dependent variables. Machine Learning was further used for the data analysis portion of this research to achieve more comprehensive results. All predictive analysis was programmed in Google Colab using Python. The first step was data preprocessing where the datasets were cleaned and organized with independent and dependent variables (DO and Green Spectrum) in their respective columns. 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. We iteratively generated improved linear regression models and for each new model created, its performance was measured by applying it to the validation set. Ten hyperparameter tuning tests were conducted for the Polynomial Basis Function benchmark model. The model was tested by changing the degree of the polynomial to 3, 5, 7, 9 and 2, 4, 6, 8, 10, 12. 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.

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