Project Proposal

Project Title: Computational Modeling of Phytoplankton Dynamics with Climatic and Ecological Implications

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Project Description:

In order to better understand the impact of global-warming induced oceanic changes on phytoplankton populations, the overarching goal of this project is to develop a series of computer models that simulate phytoplankton dynamics, including biomass, growth rate, bloom phenology, exportation, and most notably, migratory patterns. The first model is to incorporate multiple environmental factors (e.g., temperature, dissolved oxygen, salinity, etc.), that impact phytoplankton dynamics as parameters. Initial model validation shall involve using one environmental metric that is widely available (likely water temperature or a micronutrient), and comparing field data to computational data for a particular species. Regression analysis of computational error, as well as other statistical tests, are to quantitatively verify model validity. Other tools, such as hierarchical linear models and principal component analysis, are to then be used to determine any presence of interrelatedness between variables. From this, driving parameters, as well as the factors that influence the driving parameters, are to be determined to observe the overall changes phytoplankton face. Then, the next series of computational models is to be created with the ends of delineating the resulting climatic and ecological ramifications from the predictions of the previous computational model. Using network theory principles, it is planned to develop a food web of phytoplankton genera and other species, thereby illustrating possible impacts higher trophic levels may face. Climatic implications are to be determined by modeling scenarios within the framework of existing climate models (i.e., CMIP5). A major area of application and focus within this project could be on utilizing micronutrient data and predictive modeling to provide insights into the occurrences of algal blooms, which, if proven to be an accurate tool, would be valuable to local, and ideally, national and international policymakers. Overall, it is expected that these models are able to depict the nuances of the impact of changing ocean conditions on phytoplankton, capturing all sources of complexity to produce clear answers to the question of how phytoplankton populations are changing, and what ecological and climatic ramifications those changes implicate.

Keywords: Phytoplankton, Computational Modeling, Migratory Patterns, Global Warming

Background:

Phrase One: How can the complex, multifarious impacts of global-warming induced changes in oceanic conditions on phytoplankton be understood, and how shall these changes in phytoplankton dynamics impact the global climate and marine ecosystems?

Phrase Two: Through developing a series of computational models that identify driving parameters and the factors and interactions between said parameters, and translate those findings into ecological and climatic ramifications using a neural network representation of a food web and existing climate models respectively, the causes and impacts of changing phytoplankton dynamics can be better understood.

An Introduction to Phytoplankton

Phytoplankton encompass a broad range of aquatic, microscopic, and photosynthetic species of viruses, bacteria, fungi, protists, animals, and archaea (Käse & Geuer, 2018). This group of species plays a major role in biogeochemical cycling of crucial nutrients. Phytoplankton are responsible for about half of all global primary production, the production of nutritional organic matter from inorganic compounds via photosynthesis and other metabolic processes. They are also responsible for absorbing 30% of anthropogenic carbon emissions (Rohr et al., 2023). Beyond photosynthesis, phytoplankton carry out carbon sequestration through exportation, a process in which, after death, cellular matter sinks to the ocean floor, forming carbon sinks. Through other metabolic processes, phytoplankton are also an important component of the cycling of nitrogen, phosphorus, silica, and other micronutrients (Sarker et al., 2023). In regulating the flow of nutrients and other substances, especially organic matter, phytoplankton play a major role in climate regulation. Another avenue through which they regulate climate is light reflection. Some groups of phytoplankton produce dimethylsulfoniopropiothetin, a complex, sulfur-containing molecule. This compound decomposes into dimethylsulfide, which in turn decomposes into compounds that reflect solar radiation (Deppeler & Davidson, 2017). It is in fact believed that the biochemical processes of phytoplankton, such as this one, were a cause of some of the first major ice ages on Earth (Käse & Geuer, 2018). Additionally, phytoplankton act as the base of marine food chains, serving as prey for various species of zooplankton and fish (Käse & Geuer, 2018; Loschi et al., 2023).

Therefore, phytoplankton are an integral part of the global climate and environmental systems. With climate change impacting ocean conditions, it is important that the impacts that this facet of the global climate and environmental systems is facing is well understood.

Understanding The Impact of Global-Warming Induced Oceanic Changes on Phytoplankton

With that in mind, the impact global warming has had on oceanic conditions themselves must first be considered. Climate change has led oceans to becoming warmer, more acidic, anoxic, and stratified. Sea levels are rising, while salinity and micronutrient concentrations are losing uniformity. Moreover, ocean currents have begun to slow down (Berwyn, 2018). The thermohaline cycle allows for different layers of water to be mixed by cycling the pelagic water, water at the surface, that is warmer, fresher, and less dense, with the benthic water, water at lower layers of the ocean, that is colder, denser, and saltier. This cycle is crucial in mixing nutrients, distributing heat, and regulating overall climate. Analysis of past climate patterns reveals that a slower thermohaline cycle has been associated with more extreme climate patterns (Berwyn, 2018). It is important to note that changes in ocean conditions are not uniform, but rather, vary extensively by region (Winder & Sommer, 2012).

Similarly, phytoplankton are undergoing some overarching trends. Smaller, more buoyant cells have been becoming increasingly favored, there has been migration towards the poles, and changing bloom times (Ratnarajah et al., 2023). However, there are also more nuanced trends. For example, certain groups of phytoplankton are favored under eutrophic conditions, that is, conditions where there are excessive micronutrients, leading to an unhealthy amount of growth in algal blooms that deplete ecosystem resources, whereas others are favored under fresher, or darker conditions (Winder & Sommer, 2012). There are a voluminous amount of environmental factors (e.g., light, heat, nutrient concentrations, pH, salinity, etc.) that impact phytoplankton dynamics (Winder & Sommer, 2012). Moreover, each species of phytoplankton operates under different sets of ideal conditions. This raises a dilemma. Consider two phytoplankton species living in the same area. Suppose that one species of phytoplankton prefers a pH range of 5.9 to 6.5, whereas another one prefers a range of 6.7 to 7.3. With ocean acidity changing nonuniformly, if one area of the ocean has a pH of 6, and another area has a pH of 7, then each respective phytoplankton species would migrate to that new area to be in a place that matches their respective ideal conditions. However, there are other environmental factors at play, and it is important to consider how those factors impact migratory patterns and other dynamics. Using the example given, would another factor, such as dissolved oxygen, have a precedent over pH when it comes to these species seeking ideal conditions? Moreover, these migrations would leave predators bereft of a major source of food. What implications would that have for the rest of the ecosystem, and how can that be understood? Finally, what climatic implications result from these migrations?

Phytoplankton Genomics and Examples of Parametric Variability

To add another layer of complexity, there are complex processes occurring at the genomic, cytological, and molecular levels that contribute to changes in factors relevant to this project, namely primary production and metabolic rates. For example, biochemical processes like DNA methylation, where a methyl functional group is applied to the third carbon in the carbon ring of the nitrogenous base of adenine, with warming ocean temperatures, has been found to inhibit amino acid metabolism, as well as respiration and photosynthesis in phytoplankton, while enhancing fatty acid metabolism (Wan et al., 2023). This means that there is a slower rate of primary production and carbon sequestration, inhibiting phytoplankton's role both as the base of marine food chains, as well as climate regulators.

Meanwhile, micronutrients also play a major role in influencing metabolic rates. For example, phosphorus is an integral component to all forms of metabolism, so compounds of micronutrients containing it are crucial for phytoplankton. However, as discussed above, varying levels of micronutrients, phosphorus-containing compounds included, impact phytoplankton dynamics in different ways. It has been found that increased phosphorus levels has allowed for all metabolic processes to occur at faster rates, bolstering phytoplankton's ability to sequester carbon and provide greater biomass for its predators. However, excessive phosphorus concentrations can be toxic for phytoplankton and lead to eutrophication (Li et al., 2023). Toxicity and metabolic rates vary across different species as well.

Another example of significant environmental variability is with water temperature. Different genera of phytoplankton exhibit different responses to warming ocean temperatures. For example, using a modified Eppley Curve, an exponential function that models the relationship between growth rates and water temperature, one analysis found that, while growth rates are expected to increase alongside temperature, the rate which the growth rate increases for diatoms was greater than that of dinoflagellates, cyanobacteria, and coccolithophores (Anderson et al., 2023). Moreover, dissimilar thermal attributes are predicted to result in differential migration patterns.

In conjunction with the explanation offered in the previous section, these examples illustrate that for any environmental parameter, there is a great amount of nuance when it comes to the impact that phytoplankton face. This nuance only expands when multiple variables are considered in tandem.

Computational Modeling of Phytoplankton Dynamics: Progress and Current Limitations

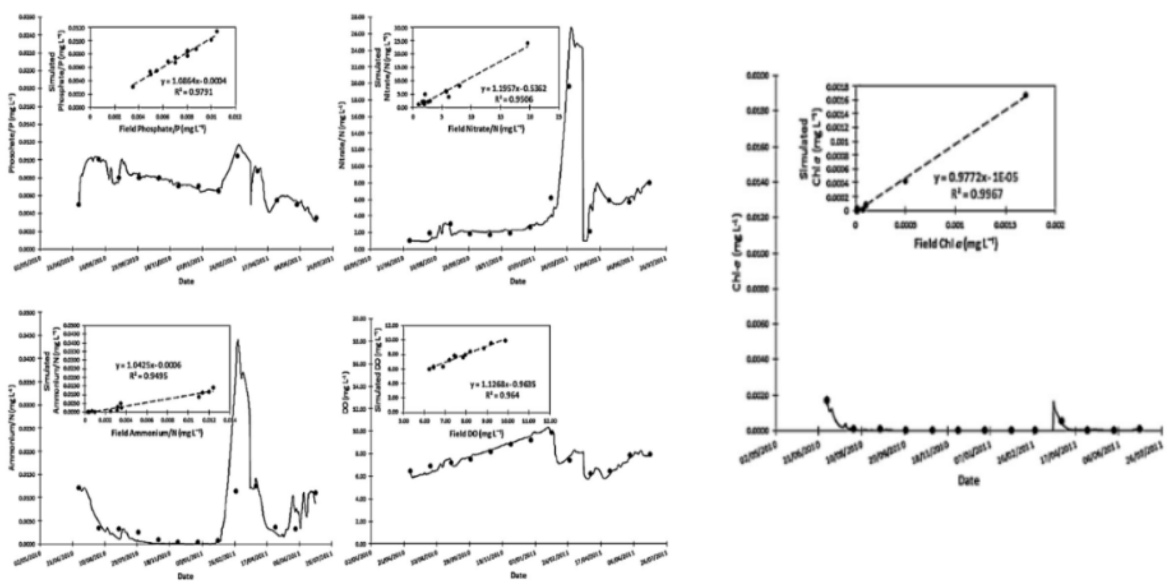
As a result, computationally modeling these dynamics is important, as it can be used to capture these details, and provide greater insight into what the observed results signify. In essence, this is what the goal of this project is: to take the nuanced trends in phytoplankton populations, organize, synthesize, and contextualize them, and provide ramifications of these trends.

Presently, there are many limitations facing computational modeling of phytoplankton dynamics. One major limitation is the misunderstanding of the role zooplankton play in the modeling process. Different models have made different assumptions about how zooplankton interact in ecological systems, leading to different predictions in climate and food web scenarios (Rohr et al., 2023). Indeed, review articles regarding zooplankton dynamics have discussed the need for developing more robust data collection methods and attaining more data (Ratnarajah et al., 2023). Moreover, there are other limitations to current computer models on phytoplankton, such as the fact there is a dearth of relevant data from the Southern hemisphere (Deppeler & Davidson, 2017).

That is not to say that successful models have not been developed. In fact, there have been models developed for small bodies of water, such as the Tucuruí reservoir in Pará, Brazil. This computer model was based off of field data, and through regression analysis including R^2, root mean square error, and the slope of regression lines comparing computer predictions to actual results, it was able to be determined that the model was in fact accurate. Namely, the environmental parameters of chlorophyll a, dissolved oxygen, ammonia, nitrates, and phosphates were all able to be predicted very reliably. Figure 1 (Deus et al., 2013) depicts the linear regression between the predicted and field values of these parameters. The R^2 values for phosphate, nitrate, ammonia, dissolved oxygen, and chlorophyll a were 0.9791, 0.9506, 0.9495, 0.964, and 0.9967, respectively. These extremely high R^2 values indicate that there was a strong connection between the field and predicted data, and thus that the model had good accuracy. This provides a strong example for how the accuracy in computer model predictions can be assessed, by extension allowing for model results and ramifications to be validated.

Figure 1

An Example of Computational Model Validation Techniques: Tucuruí Reservoir as a Case Study



Note. Each parameter contains a larger graph depicting the raw comparison between field data and computer predictions. From lop left to bottom right, the parameters shown are phosphate, nitrate, ammonia, dissolved oxygen and chlorophyll a. Embedded within are the linear regressions that compare the computer model predictions against the actual field data. Therein lie the R^2 values which serve to evaluate model accuracy.

With such examples in mind, this project seeks to perform predictive modeling, using more environmental parameters as input, and projecting findings to a global scale, making use of as much available data as possible. Presently, it is believed that a computer model that takes into account changes among different phytoplankton species, numerous relevant environmental parameters, and uses appropriate statistical tools to be validated can produce results regarding changing phytoplankton dynamics and their drivers, and the climatic and ecological implications. Applications of this model could be widespread, being used as an important tool for decision makers, managing failing aquatic ecosystems, and predicting future climate and ecological conditions.

Relevance/Significance

Since phytoplankton play a major role in biogeochemical cycling, climate regulation, and ecological stability, they are important facets of the global climate and environmental systems. Thus, capturing the complexity of the multifarious stressors they are facing is key to understanding how they will be impacted overall, and in turn, what that means for the environment. If developed to be accurate and efficient, this model would have significant ramifications for policymakers. Namely, since phytoplankton play a major role in the formation and changes of an algal bloom, having a model to predict their population given, for example, micronutrient concentrations, policymakers would be able to make informed decisions about lake management. For instance, one study focusing on lake ecosystems in Wuhan, China devised an accurate computational model that was able to run hypothetical scenarios. From these scenarios, concrete policy recommendations were made, including control of the nutrient stoichiometry between nitrogen and phosphorus, as well as increasing the presence of exclusively zooplankton-feeding fish (Tian et al., 2023). If a model on a larger scale is successfully devised, then policymaking applications would be greater in magnitude, and more versatile to a wider range of different types of bodies of water. Clearly, carrying out this project would have significantly useful and beneficial impacts both in science and policy.

Innovation

Presently, there exists a wide variety of computational techniques to model phytoplankton dynamics. However, different models have different focuses. Some computer models may focus on a specific body of water. For example, computational modeling has been used for phytoplankton dynamics both in the coastal waters of Bangladesh and Wuhan (Sarker et al., 2023; Tian et al., 2023). However, being two very different regions with different conditions, those models had very different structures and made use of very different techniques. Function is another major avenue through which models vary. For instance, while both of these examples aimed to make sense of the multiple stressors phytoplankton face by sifting through many environmental parameters, a model dedicated to depicting a food web between phytoplankton genera and predators would have significantly different architecture.

By seeking to specifically create a series of computational models, these heterogeneously designed computer algorithms may be brought under one central system. Since this project aims to model phytoplankton dynamics on a global scale, taking into account many parameters, the model shall be highly versatile and adaptable to the unique circumstances of a given aquatic ecosystem. Multiple different purposes, including identifying driving parameters, differentiating impact among various species, projecting climatic and environmental implications can also be achieved with this model. Hence, by consolidating many important empirical functions through a large scope, this project shall produce a unique way to computationally model phytoplankton dynamics.

Experimental Design/Research Plan Goals:

Major Parts of the Project (rough outline) will continue to evolve over time and should be updated frequently.

The independent variable shall be the configuration of the computer model with respect to the environmental factors included as parameters, the sources of data used, and the computational techniques employed to produce predictions relating to phytoplankton dynamics, and ramifications for the climate and environment.

The dependent variables shall be the model validity, which shall act as a prerequisite to other dependent variables, which shall include the changing phytoplankton dynamics in their own right, the driving factors behind those changes, as well as the climatic and environmental implications.

There shall be multiple rounds of iteration for the computer model.

Materials List

This study plans to make use of various computational tools to model phytoplankton dynamics such as:

- NetLogo
- TensorFlow and other Artificial Intelligence modeling tools

This study plans to make use of various sources of data to feed into the model as input for predictions and scenarios such as:

- Environmental Protection Agency
- Massachusettes Department of Environmental Protection

- United States Department of Agriculture
- Datasets from previous experiments

Methodology

Specific Aim #1

The first task in constructing the computational model shall be validation of the model. This shall be achieved through the comparison of the constructed computer model with field data, using a widely known parameter. One parameter, and its impact on one particular species, is to be modeled.

Justification and Feasibility. The findings of any computational model offer no value unless it is ensured that the model is accurate. Therefore, devising some plan to implement statistical or computational techniques that verify model validity shall be imperative. This is a highly feasible approach as there exists a wide variety of software tools on which a myriad of statistical algorithms may be run. For example, the above mentioned study regarding the Tucuruí reservoir alone used three metrics, including root means square error, R^2, and the slope of the least squares regression lines, to evaluate model accuracy, thereby allowing for model validation (Deus et al., 2013). It is likely that other error analysis tools, such as a Student's t-test, among other hypothesis tests, may be used to assess the significance of the differences in observed and computer data.

Expected Outcomes. It is expected that once the statistical tool or tools used to validate the model is applied, insight into model validity can be attained. For example, as explained with Figure 1 (Deus et al., 2013) in the introduction, conclusions about model accuracy could be reached using R^2. Thus, it is expected that the metric or metrics within the tool chosen for model validation be indicators of model validity.

Potential Pitfalls and Alternative Strategies. There exist a wide variety of techniques to ensure model validity. Each test offers a unique set of advantages and disadvantages with regards to the factors taken into account. For example, using metrics from a linear regression model (i.e. slope, R^2), that compares predicted data to actual data allows for some aspects of model validity to be captured. However, linear models are often subject to many confounding and lurking factors, which may inhibit its quality as a marker for computational accuracy. However, alternative statistical and computational tools may be used in conjunction with linear regression in order to account for factors that regression fails to. Conversely, linear regression would be able to account for actors these other statistical tools might miss. With this understanding, an approach using multiple validation techniques shall be devised.

Specific Aim #2

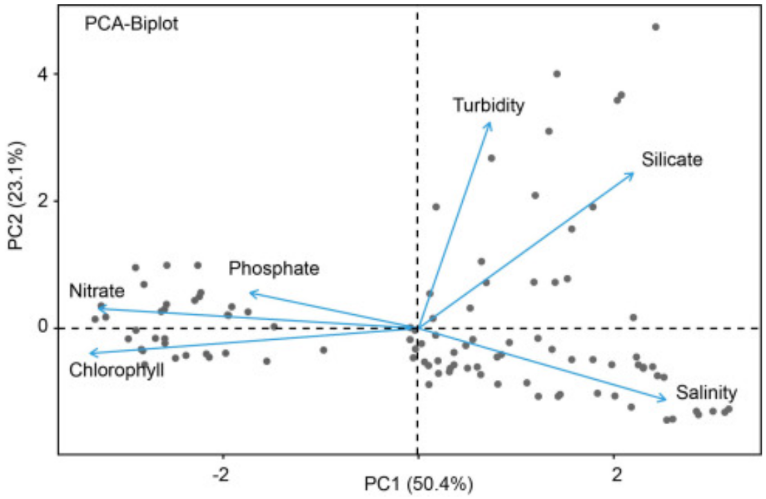
Once the model is validated, implement more species and more parameters. Utilize statistical tools to identify driving parameters in the observed phytoplankton dynamics. In addition, assess the factors that influence what the driving parameters are in different areas, and how all parameters impact one another to exert a net impact on phytoplankton throughout different global regions.

Justification and Feasibility. As previously discussed, there are numerous factors that influence phytoplankton dynamics. Experimenting with these parameters on phytoplankton simultaneously is not viable, as that would lead to too many confounding variables to be able to discern any meaningful relationship or trend. Hence, incorporating all of these factors into a computational model would help eliminate this ambiguity. In order to better understand the observed changes in phytoplankton dynamics, the driving factors behind these changes need to be understood. That way, any possible mitigation strategies to aid ecosystems can be created. Since computational modeling offers the ability to disentangle the driving parameters, as well as their relationships, and the factors behind the driving parameters, it is a viable approach to choose for this project.

Expected Outcomes. Through the use of principal component analysis (PCA), as well as a hierarchical linear model of environmental parameters, driving parameters, as well as their relationship with one another, and the factors that influence them can be detected. Using PCA, multiple different parameters can be condensed into vectors in order to simplify the complex, multi-variable dynamics of a dataset. In doing so, the magnitudes of the vectors can be analyzed, and from there, the driving parameters can be identified. For example, Figure 2 (Sarker et al., 2023) depicts a PCA performed on environmental parameters measured for the impact on phytoplankton for coastal Bangladesh. Turbidity, silicate, and salinity, with the largest magnitude, were identified as the most important driving parameters in the study. PCA is a robust example of how driving parameters may be identified.

Figure 2

An Example of Using Principal Component Analysis to Identify Driving Factors



Note. This graph depicts the PCA performed on the seven parameters measured in coastal Bangladesh. Each vector describes the extent to which each parameter impacts the observed phytoplankton dynamics.

Another way driving parameters, and more importantly, the relationship they hold between one another, can be determined through a hierarchical linear model (HLM). An HLM is a type of multivariable regression that splits up parameters into different levels. For example, for the model created for phytoplankton in Wuhan, China, the broader, ecological parameters were placed at level 2 within the hierarchy, whereas, smaller-scale physicochemical parameters were placed at level 1. This neat assortment of factors allowed the authors to determine the driving parameters by using t-tests for linear regression between the level 1 parameters and the phytoplankton dynamics (which, in this study, was primary production), level 2 and primary production, as well as between levels 2 and 1. It is this comparison that takes place between level 1 and 2 (and higher levels, if used) that allows parameter relationships, and from there, the factors behind the driving parameters, to be determined (Tian et al., 2023). Although, it is important to understand that the factors behind the driving parameters are not deduced by statistics, but rather, by the science of the situation. For example, since the Tucuruí reservoir was man-made, the hydrodynamical forces causing the inflow and outflow of water into the reservoir was what drove phytoplankton population changes. The man-made artificiality of the dam was what made the rapid inflow and outflow the driving parameter (Deus et al., 2013). This simple deduction was done using analysis of the environment rather than statistics. The point, then, of using an HLM, is to help sort the parameters and identify their significance in an organized manner, to help contextualize the driving factors behind the identified driving parameters. In the context of this study, it was found that nitrogen, phosphorus, water temperature, and the *Rotifera* genus of zooplankton were driving parameters (Tian et al., 2023).

Potential Pitfalls and Alternative Strategies. HLMs and PCAs are only two techniques that could be used to disentangle the driving parameters of phytoplankton dynamics. HLMs pose an advantage in that they can compartmentalize, and consequently, draw conclusions not only about what factors are driving parameters, but relationships that lie therein. However, it is harder to integrate a very large number of parameters into an HLM. Conversevely, although PCA does not compartmentalize factors, its vectors provide a more concise and visual way of understanding which parameters are significant. Similar to Specific Aim #1, great care in maximizing the use of statistical tools to achieve the specified end must be taken. That way, overall error is minimized as each test collectively contributes information about all relevant metrics.

Specific Aim #3

Determine climatic and ecological ramifications. Construct a neural network for a food web containing phytoplankton genera and their predators. Climatic ramifications are to be modeled through testing climate scenarios that result from the results from Specific Aim 2 within the framework of current Climate models (i.e., CMIP5).

Justification and Feasibility. At this point, since the impact phytoplankton face would be apparent, with all matters of the parameters being determined, the next step would be to determine what impacts the changes phytoplankton face would have on marine ecosystems as well as the climate. Knowing this information is crucial, given the major role phytoplankton play in biogeochemical cycling, marine food webs, and climate regulation. With marine ecosystems and the climate in a comparatively dire state, any facet of these systems, especially one as important as phytoplankton, being impacted, will have significant ramifications. Understanding what those ramifications are is important. There have been past instances where neural networks and network theory principles have been utilized in constructing and analyzing food webs with phytoplankton. For example, one study of the coastal area around Venice was able to successfully model a food web of the area. Each node was assigned a set of parameters, most of which related to the transfer of energy and organic matter among predators, prey, decomposer, and other ecological players. The authors were able to model how energy transfer was changed due to environmental parameters, and how those changes impacted the ecosystem (Loschi et al., 2023). Meanwhile, for climatic ramifications, CMIP5, known as the Coupled Model Intercomparison Project, is a project that climatologists have used to aggregate data about climate change, as well as climate models. By using this interface of models and predictions as a place for implementing scenarios of phytoplankton-induced changes to climate, climatic ramifications can be discerned.

Expected Outcomes. It is expected that, given some input from relevant parameters, which would include driving parameters identified from the previous subtask as well as those relevant to energy transfer, the neural network would present how energy transfer from phytoplankton to the higher parts of the trophic pyramid would be modified. It is expected that the change in abundance of the species is noted. Other ecological ramifications of the observed changes in the food web should also be either reported, or inferred from the neural network model. It is expected that, when phytoplankton-induced climate scenarios are modeled within the existing CMIP5 framework (and potentially other climate databases), that climatic implications of changes in phytoplankton dynamics can be attained.

Potential Pitfalls and Alternative Strategies. Network theory could potentially be a tenuous way to computationally model a food web. The use of a neural network would necessitate the use of numerous other correcting mechanisms and other functions in order to be operational and accurate. If the neural network is too complex, which, given the complex nature of this scenario, this is likely to be the case, then making a neural network may be immensely difficult. It may be fruitful to search for an alternative approach to computationally modeling a food web. Finally, CMIP5 may not be the ideal software by which to model the ramifications of phytoplankton-induced climate scenarios. It may be necessary to research other climate modeling software in order to model these ramifications.

Risk/Safety/Ethical Concerns:

Given that the scope of this project is computational, it should not pose any safety concerns. No individuals, animals, nor any other facet of the natural or anthropological environment should be harmed by this project. Changes in ocean conditions are all simulated. Consequently, there are no artificial modifications to any actual water body will undergo. The planned methodologies for this study strongly deter any possible risk with regards to ethics and safety.

Data Analysis:

The data collected from computer simulations is planned to be subject to a series of statistical tools in order to assess model validity. Previous instances of computational models of systems of phytoplankton system used regression analysis, comparing actual data to model predictions. Metrics like root means square error, R^2, and the slope of the least squared regression lines have been used to evaluate model accuracy, thereby allowing for model validation (Deus et. al. 2013). A Student's T-test, among other hypothesis tests, may be used to assess the significance of the differences in observed and computer data. Moreover, in order to identify driving factors of phytoplankton dynamics, it is planned to use ANOVA tests to compare the significance of the impact of different parameters on phytoplankton dynamics. Subsequent Post-Hoc tests would be performed to investigate this further, as has been done in previous instances (Sarker et. al. 2023). Similar statistical tools may have to be applied to the networks created for depicting ecological ramifications. Additionally, with so many parameters at play in this study, performing procedures such as principal component analysis, as well as non-metric multidimensional scaling, are to be imperative in order to simplify data so as to make it understandable, and thereby reveal all of its insights. One way climatic ramifications could be assessed empirically is through looking at rates in metabolism, primary and export production, light reflection, among other metrics. Climatic implications can also be determined more indirectly through factors including biomass, diversity, and chlorophyll concentrations. Overall, the above outline of the methodology provides a solid base of information for the data analysis to be performed.

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Timeline: (with action steps identified- sub-deadlines will continue to evolve):
Rough timeline of major phases. As these phases get established, specific tasks under these phases will be defined further.

September
- Brainstorming Project Ideas
- Establishment of Phytoplankton as an Area of Focus
- Establishment of Dual-Focus
    - Modeling Phytoplankton Biochemistry and Genomics Given Micronutrient Concentrations and other Environmental Factors
        - Impact on primary production, metabolic processes, among other areas
    - Computationally Modeling Phytoplankton Dynamics (biomass, phenology, migratory patterns, etc.)
        - Impact on climate and food web
        - Using environmental conditions as parameters.

October
- Narrowing Down Project Focus
    - Identifying Computationally Modelling as Primary Approach
- Researching on Computational Techniques, Software, Possible Sources of Data For Input
    - NetLogo
    - TensorFlow and other Artificial Intelligence Modelling and Machine and Deep Learning Tools
    - Network Theory, Neural Networks, Louvain Method,
    - EPA, MassDEP, and other potential databases

November
- Choosing Software Tools and Sources of Data
- Initial Model Validation
    - Done using one wide-known variable, such as Dissolved Oxygen of Water Temperature
    - Establishing statistical tools used to validate model for this project, such as R^2, RMSE, hypothesis tests, among other tools
- Develop Testing Strategy. This should begin to be performed. It should follow this vague outline:
    - Once model is validated, incorporate more parameters
        - Salinity, pH, micronutrients, turbidity, zooplankton, among other factors
    - Incorporate data for multiple species of phytoplankton
    - Utilize techniques such as network theory, multi-agent programming, among other tools, to model the impact of changing phytoplankton dynamics
        - Apply parameters to these models to assess trophic ramifications.
    - Employ chosen statistical tools to evaluate results with the following metrics:
        - Model accuracy
        - Driving Factors of the Observed Changes in Phytoplankton Dynamics
        - Impact on Higher Trophic Levels

December
- Continue executing the developed test strategy. Ensure that:
    - Phytoplankton dynamics, including
    - Changing phytoplankton dynamics can applied and/or parameterized into network models including higher level organisms in order to assess ecological impact
- Begin to statistically analyze results
    - Use tests and techniques to identify driving factors
- Provide Data/Evidence on Climatic Ramifications as well
- Models should be being iterated upon, and data should be being collected across different models.

January
- Finalize models and results

- Complete data analysis on ecological and climatic ramifications, identifying driving factors
- Applying these procedures through the lens of tracking eutrophication and local, ideally even higher level, policymaking.
- Identify future areas of focus

February

- Develop necessary products (clean up Project Notes and Logbook, STEM Fair poster, etc.)
- Present results