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Incorporating Viveka: A Bayesian Decision Framework For Harmful Algal Bloom Risk Under Rising Temperature

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Abstract: Harmful algal blooms (HAB) pose increasing threat to coastal areas with climate change and global warming intensifying their impact. The aquatic ecosystem is one among the most severely affected specifically marine life. Aquaculture is increasingly vulnerable to the consequences of HAB's. This proposal introduces a Bayesian decision model for assessing harmful algal bloom (HAB) risk in aquatic systems under climate-driven warming, enriched with a *Viveka* (discernment) which is inspired by Shanti Parva from Mahabharata. Beyond standard probabilistic updating, the model includes a meta-judgment module that adjusts evidence based on its reliability, context, and consistency. This enables refined, wise decision outputs like warnings. This paper elaborates the model's structure, assumptions, and decision logic, without performing experimental regulation.

Keywords

HAB, Viveka, Bayes, Algal Blooms

I. Introduction

HAB problems are serious, and in some areas of the world are growing worse, but capabilities and knowledge exist that help to minimize impacts and protect public health and marine resources as never before. This scientific and management community, and the HABs they respond to and investigate, now face a world that is changing in many ways due to population growth, pollution, and climate change, to name but a few stressors. Even the current global economic crisis can be viewed as a factor that will affect the future of HAB science and management due to reductions in funding or diversion of scientific teams to other topics, for example. Of equal importance, perhaps, perceptions of HABs are changing, affecting the behaviour, needs, and priorities of the public, funding agencies, and those charged with managing these diverse phenomena. [1] Freshwater HABs impact aquatic food production, recreation and tourism, and drinking water supplies, leading to economic losses of $4.6 billion annually in the United States alone (Kudela et al. 2015). Climate change is hypothesized to impact the proliferation of HABs in lakes and reservoirs through a number of mechanisms (Paerl and Huisman 2009; Visser et al. 2016; Huisman et al. 2018). First, increased temperature is hypothesized to lead to selection for more harmful species. This occurs through increased growth rates of harmful cyanobacterial species relative to other species (Paerl and Huisman 2008; Carey et al. 2012; Visser et al. 2016), through extending of the summer growing season (Anneville et al. 2005; Deng et al. 2014; Visser et al. 2016) and through increased vertical stratification resulting in greater fitness by cyanobacteria that are able to regulate their buoyancy (Wagner and Adrian 2009; Carey et al. 2012; Posch et al. 2012; Taranu et al. 2012; Visser et al. 2016). [2] According to – Mahabharata, Shanti Parva, Chapter 30 He who foresees the danger in time and prepares accordingly, his victory is assured. The one who is always prepared is truly virtuous and attains success [3] This stands a proper inspiration for being prepared for the foreseen danger and taking actions to help the farmers from mitigating losses. There is a need for early warning systems and foresight to help reduce the losses faced by the aquaculture. Bayes theorem can be used to estimate the likelihood of algal blooms based on measured temperature of the water. Conventional models often rely on deterministic or correlation-based methods that fail to capture the evolving nature of ecological systems. Where in contrast Bayesian framework helps to predict in probabilistic framework the likelihood of bloom occurrences as the water temperature rises.

This combined framework—Bayesian probability as the measureable core and *Viveka* as the qualitative compass—advances all-inclusive approach to algal bloom management. It allows for probabilistic estimation while maintaining ecological and moral discernment. By embedding discriminative awareness within statistical modelling, researchers can not only predict blooms more accurately but also interpret them within the broader context of ecosystem health, human responsibility, and sustainable foresight. Ultimately, this integration bridge's ancient philosophy where according to Viveka be aware about the foreseen danger and act wisely and modern data science, offering a paradigm that is both empirically robust and ethically grounded.

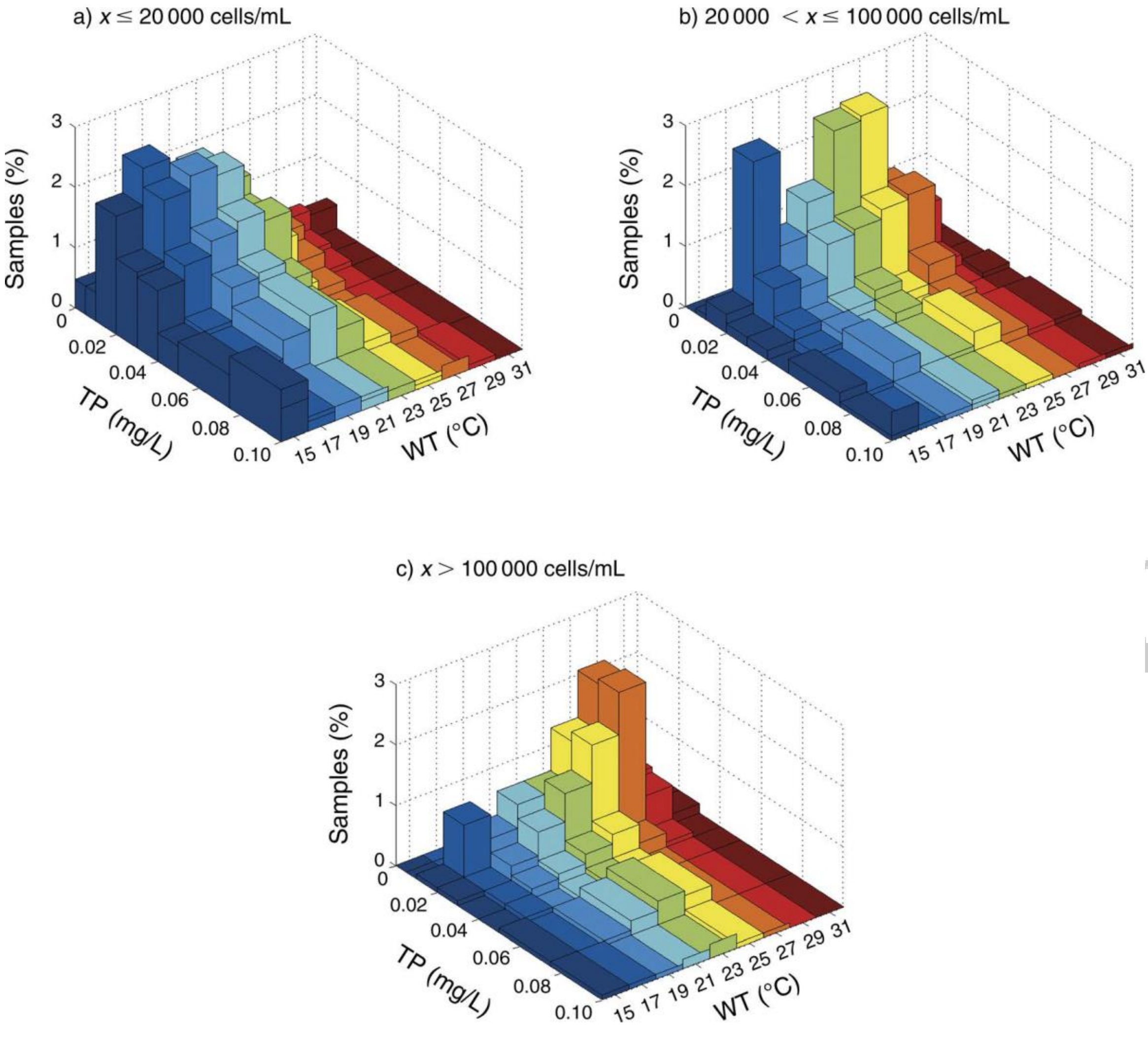
2. Literature Review

Temperature is a key factor driving the dynamics of HABs, influencing their growth rates, duration, toxin production, and species composition. With ongoing climate change and rising global temperatures, HAB events are becoming increasingly frequent and severe. Research conducted in 2020 by Ho and Michalak found that higher spring air temperatures were correlated with reduced microcystin concentrations, suggesting that while warmer conditions may extend the growing season and boost cyanobacterial abundance, they could simultaneously lead to lower toxin production. Observations have also indicated that longer summers are associated with shifts in phytoplankton communities, favouring nontoxic taxa. Regarding total abundance, there is evidence that elevated temperatures enhance the growth rates of Microcystis aeruginosa, although the resulting strains may be less toxic.[4]

It is seen noticed that Elevated pCO2 and warming may promote algal growth and toxin production, and thereby possibly support the proliferation and toxicity of harmful algal blooms (HABs). Here, we tested whether empirical data support this hypothesis using a meta-analytic approach and investigated the responses of growth rate and toxin content or toxicity of numerous marine and estuarine HAB species to elevated pCO2 and warming. Most of the available data on HAB responses towards the two tested climate change variables concern dinoflagellates, as many members of this phytoplankton group are known to cause HAB outbreaks. Toxin content and toxicity did not reveal a consistent response towards both tested climate change variables, while growth rate increased consistently with elevated pCO2 . Warming also led to higher growth rates, but only for species isolated at higher latitudes. The observed gradient in temperature growth responses shows the potential for enhanced development of HABs at higher latitudes. Increases in growth rates with more CO2 may present an additional competitive advantage for HAB species, particularly as CO2 was not shown to enhance growth rate of other non-HAB phytoplankton species. However, this may also be related to the difference in representation of dinoflagellate and diatom species in the respective HAB and non-HAB phytoplankton groups. Since the proliferation of HAB species may strongly depend on their growth rates, our results warn for a greater potential of dinoflagellate HAB development in future coastal waters, particularly in temperate regions. [5]

In a lake database analysis Histograms were generated for the percentage of cyanobacteria abundance corresponding to specific hazard classes (low, moderate, and high; Chorus and Bartram 1999) vs. total phosphorus and surface water temperature (Fig. 1). The cases characterized by low, moderate, and high hazard were, respectively, 52%,28%, and 20%in the 20 lakes. Fig. 1c shows, for example, that at low total phosphorous (TP) concentrations the cases of high hazard were more frequent if water temperatures were high (.238C). Low cyanobacterial abundances (classified in the low hazard category) occurred more frequently at lower temperatures (,218C) (Fig.1). Graphical results obtained representing the current database suggest that the effect on cyanobacterial abundance of interactions between nutrients and water temperature (WT) is not additive, although few cases with high TP were available in the data set. It is notable that there appears to be a high dependence of cyano-bacterial abundance on WT at lower TP concentrations. The number of blooms classified as high hazard changed with different combinations of WT and TP in the lakes. Eighty-two per cent of the high hazard events occurred when WT was between 208C and 308C and about 60%of these occurred when TP was between 0.01and 0.03 mg/L. This suggests that blooms classified as high hazard are much less likely to occur if phosphorus concentrations are low, i.e., TP,0.01 mg/L. Moreover, when TP was low, blooms were most likely to occur when WT was high; however, as TP increases, cases of hazardous blooms were still observed in the database at relatively low temperatures (WT<15^{o}C)[10]

PROBABILITY OF CYANOBACTERIAL BLOOMS



Fig(1). Percentage of samples (cases) from all the lakes classified as (a) low, (b) moderate, and (c) high hazardous blooms based on the cyanobacterial abundance (x) observed. Each bin represents a particular combination of the environmental conditionsobserved (total phosphorus and water temperature).

3.Conceptual Model Structure

3.1 Conceptual Working

[Sensor Data]
(Temperature)
↓
[Viveka]
(Validation on data)
↓
[Bayes Theorem]
(Calculating probability of occurrence of Algal Bloom)
↓
[Decision]
(Will the bloom occur ?)
↓
[Learning]
(Update data using new data)

3.2Viveka

Derived from the Sanskrit roots *vi-* (to distinguish) and *vic-* (to separate), the word *Viveka* signifies "the faculty of discernment" (Monier-Williams, 1899). It is the faculty that enables individuals to identify what is righteous (*dharma*) versus unrighteous (*adharma*), what is eternal versus temporary, and what ultimately fosters harmony versus destruction.[12] Viveka layer will help to focus on validation on the sensed data and to check if the data is correct or even does it make any sense.

3.3 Bayes Therom

$$P(H/E) = \frac{P(E/H).\,P(H)}{P(E)}$$

P(H/E): Posterior Probability →The probability that the hypothesis H is true given evidence E.
P(E/H): Likelihood → The probability of observing evidence if H is true.
P(H): Prior Probability → Your belief in H before seeing the evidence.
P(E): Evidence → The overall probability of observing E under all possible hypotheses.

The Bayes theorem is probability that helps us update our belief about an event or hypothesis when new evidence is found. It helps us connect to what we already know (the prior probability) with the new information (the evidence) to give us an updated probability (the posterior probability).

Bayes Reasoning and wisdom of Viveka assists in prediction of algal blooms enabling farmers to take preventive action. A farmer knows from experience that algal blooms happen unpredictably. As per historical records from nearby ponds suppose show that blooms occur in 15 % of weeks during the production season:

$$P(H)= 0.15$$

This represents his prior belief which is like Arjunas confusion from Mahabharta on battlefield when he faces confusion about his targeted strategy.

AI algorithms and especially **machine learning (ML)** models can **integrate Bayesian reasoning** to continuously update bloom probabilities as new data arrives.

For example:

- Initially, the system uses historical data to set **priors** (e.g., "blooms usually happen at 30°C").
- As new sensor data comes in, AI updates these probabilities automatically using **Bayesian updating**.
- The model becomes smarter over time — learning **local patterns** specific to each pond.

AI plays a role of acting as the *automated Viveka* — continuously exercising discernment by updating beliefs based on evidence.

3.4 Decision / Utility Layer

Utility Layer acts as and operational supervisor to ensure the task is performed safely and efficiently.It works as a monitor for issuing warning ,delay for actions.The Viveka concept suggests that threshold should not be rigid but they should be adujustable based on wisdom of signals. It suggests that if as per hard logic the check on the algal blooms is to be done after 3 days but the contextual logic says that there are developments seen under the water which reflect the growth of algal blooms than one should take early measures to eliminate the growth throughout.

4. Model Assumptions & Theoretical Justification

It is assumed that Viveka helps in tuning as per the evidence sources with varying reliability .The indicators are also assumed to be situationally independent, where Bayesian Network helps to predict using Probabilistic Logic.The meta-judgment weights are set by respective domain experts or based on sensor history.The model symbolises Viveka idea from Mahabharta where it says that one should not act hurriedly instead measure ,analyse,direct and then act accordingly.

5.Future Work/Validation

Future enhancement for this model can be:

1.To collect real sensor and satellite datasets

2.Comparison of Viveka Enhanced Bayesian model with threshold model.

3. Extend judgement model with meta learning.

6.Conclusion

The model demonstrates how **increased water temperature** acts as evidence that updates the **probability of algal blooms** using **Bayesian inference**.By integrating continuous monitoring and probabilistic reasoning, farmers can **anticipate bloom risk**, apply **timely mitigation measures**, and **minimize production losses** in freshwater aquaculture.

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