REAL-TIME DATA DRIVEN FORECAST SYSTEM FOR COASTAL ALGAL BLOOMS

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ABSTRACT

We present a new modeling system for prognostic daily forecasting of algal bloom (Chlorophyll-a > 10 mg/m^3) risks in weakly flushed coastal bays. According to a vertical stability theory (Wong et al. 2009), a necessary condition for an algal bloom is determined by the ratio of a bulk vertical turbulent diffusivity (E) relative to a critical value (E_c) dependent on the algal growth rate and photic depth. Based on 3D hydrodynamic modeling and data driven models, the turbulent diffusivity E for a given semi-enclosed water on any given day can be estimated from the predicted tidal range and hydro-meteorological data – and accounting for effects of density stratification. The critical diffusivity E_c can be determined from water temperature and light extinction data. This bloom forecast framework has been validated against extensive biweekly and monthly water quality data (1986 to 2018).

Using high-frequency data (10 min) on salinity and temperature at various depths, together with readily available hydro-meteorological data (solar radiation, air temperature, wind speed and rainfall) the vertical density gradient on the next day can be predicted using an artificial neural network (ANN) model - and hence the water column stability risk (E/E_c). Combining the stability risk with a nutrient availability factor estimated from water quality monitoring, the algal bloom risk on the next day can be predicted. The forecast system has been validated against 4 years of high frequency data for the Yim Tin Tsai marine fish culture zone in Tolo Harbour, Hong Kong.

Keywords: Coastal algal bloom, Water column stability, Real-time prediction, Daily forecast system, Fisheries management

1. INTRODUCTION

Harmful algal blooms (HAB) in eutrophic coastal waters can give rise to serious environmental and economic impacts and is a complex global issue. Under favorable environmental conditions, population of microscopic phytoplankton can grow rapidly to bloom levels (Chlorophyll-a > 10 mg/m^3) and persist for weeks or even months. HAB causes harmful impacts including water discoloration, severe dissolved oxygen (DO) depletion, beach closure, massive fish kills or shellfish poisoning. The ability to provide a prognostic forecast of algal bloom can be very useful for fisheries management – and yet this is a notoriously difficult problem. In recent years, proactive water quality management using data driven models has been attempted (e.g. Coad et al 2014). Nevertheless, successful attempts of algal bloom forecasting using real time data has hitherto not been reported.

A simple prognostic model for prediction of coastal algal bloom has been proposed by Wong et al. (2009) and Lee et al. (2012). The model was validated by data from continuous tracking of a number of algal bloom events. However, the theory has not been incorporated into an operational daily forecast system – largely due to the lack of high frequency data. In recent years, high-frequency (10 min interval) water quality data has become available in a number of marine fish culture zones in Hong Kong. We present herein a hybrid forecast model based on the combination of the vertical stability theory with a data driven artificial neural network.

2. VERTICAL STABILITY THEORY FOR ALGAL BLOOM

2.1 Bloom Criteria

Field observations of algal bloom events in Hong Kong show that a stable water column is necessary for an algal bloom to form. Fig. 1 shows a schematic diagram of a two-layer system that considers phytoplankton growth in the upper photic layer, vertical mixing and sedimentation, and loss rate. The time evolution of the vertical distribution of algae under nutrient non-limiting conditions can be predicted from solving the advective-diffusion equation accounting for algal growth kinetics (Wong et al. 2009). A necessary hydrodynamic stability condition for algal bloom to form can be shown to be:

$$E < E_c = \frac{4\mu l^2}{\pi^2} \tag{1}$$

where E = vertical eddy diffusivity of water column; E_c = critical turbulence threshold above which a bloom cannot be formed, μ = algal growth rate, and l = euphotic layer depth derived from Secchi depth measurement. A bloom is likely to occur when Eq. 1 is fulfilled and the nutrient threshold is reached (i.e. total inorganic nitrogen $> 100\ mg/m^3$ and orthophosphate$> 15\ mg/m^3$).

2.2 Estimation of Turbulent Diffusivity

In order to check the bloom criteria, it is necessary to estimate the vertical diffusivity E. Extensive 3D model computations have shown that the tidal current U on any given day at a fish culture zone can be estimated from the predicted tidal range. The vertical tidal mixing can be estimated from $E \sim U\ H$, where H is the depth; the wind-induced mixing can be estimated from the wind speed (Wong et al 2009). The reduction of vertical mixing due to density stratification can be estimated by the classical Munk and Anderson equation (Fischer et al 2013):

$$E = \frac{E_{0T} + E_{0W}}{(1 + \alpha Ri)^{\beta}} \tag{2}$$

Where α and β are empirical constants; E_{0W} and E_{0T} are the tidal- and wind-induced turbulent diffusivities respectively; Ri = bulk Richardson number estimated from a combined surface current (i.e. $U_s = U_{sW} + U_{sT}$). Alternatively, the effect of stratification on wind- and tidal-induced mixing can be assessed separately due to the existence of a pycnocline in stable water column (Fig. 1):

$$E = \frac{E_{0T}}{(1 + \alpha Ri_T)^{\beta}} + \frac{E_{0W}}{(1 + \alpha Ri_W)^{\beta}} \tag{3}$$

In both Eq. 2 or Eq. 3 an upper limit of $Ri = 15$ should be applied, above which there is no further reduction of diffusivity (Fernando, 1991).

The vertical stability theory (Eq. 1) is validated using long term biweekly and monthly water quality data (1986 to 2018) in Tolo Harbour, Hong Kong. Fig. 2a shows the corresponding E and E_c for the recorded bloom events; it is seen the stability criterion is well-validated. In comparing the estimation of vertical diffusivity E based on Eq. 2 and 3, we note that: (i) under neutral stability condition, E_{0W} is about one order of magnitude larger than E_{0T}, hence indicating that wind effect is dominant; (ii) Eq.3 generally gives a smaller estimation of E leading to a higher risk; and gives a better agreement of the predicted stability with observations.

$$\text{Hydrodynamic stability factor } (R) = \frac{critical\ turbulence\ (E_c)}{estimated\ diffusivity\ (E)} = \frac{4\mu l^2}{E\pi^2} \tag{4}$$

2.3 Bloom Risk Forecast

A probabilistic forecast framework (Lee et al. 2012) is adopted to give an assessment of the likelihood of an algal bloom to occur. Based on historic data, the cumulative distribution of observed algal bloom as a function of the stability risk factor $R = E_c/E$ (Eq. 4) and nutrient concentration (N or P) can be obtained (Fig. 2b). By considering the combined effect of hydrodynamic stability risk and nutrient availability, a prognostic probability, $P(B)$, indicating the algal bloom risk on the next day, can be predicted as:

$$P(B) = P(B|R) \cdot P(B|N,P) = P(B|R) \cdot \min[P(B|N), P(B|P)]$$
$$P(B|R) = \frac{1}{1 + \mu_R \cdot R^{-a}}, \qquad P(B|N) = \frac{1}{1 + \mu_N \cdot N^{-b}}, \qquad (B|P) = \frac{1}{1 + \mu_P \cdot P^{-c}} \tag{5}$$

where $\mu_R = 5.86$, $\mu_N = 1.45$, $\mu_P = 1.26$, $a = 1.12$, $b = 1.61$, $c = 1.33$.

3. DAILY ALGAL BLOOM FORECAST SYSTEM

Based on the vertical stability theory, a truly predictive forecast system is developed using (i) a 4-year (2014-2018) high-frequency temperature and salinity (surface and bottom) for the Yim Tin Tsai Fish Culture Zone; (ii) regular biweekly data of nutrient concentrations and Secchi disc depth; and (iii) daily meteorological data including solar radiation, air temperature, wind speed and rainfall.

Fig. 3 shows the framework of the daily bloom risk forecast system. A three-layer artificial neural network (ANN) model based on back-propagation algorithm (one hidden layer of three neurons) is developed to predict the surface temperature (SST), vertical temperature and salinity gradient (i.e. accuracy = 0.38°C, 0.2 °C/m and 0.2 psu/m) on the next day. The data input includes meteorological data (global solar radiation, air temperature, wind speed, rainfall) and the SST, vertical temperature and salinity gradient of the current day. The ANNs for predicting temperature, vertical temperature and salinity gradients are trained using data from Feb 2014 to Jun

2016, and tested against data from Jul 2016 to Jun 2018. In accordance with Eq. 5, the ANN output is coupled with the predicted tidal range and meteorological data to calculate the water column stability risk factor and combined with the nutrient availability factor to give an algal bloom risk for the next day.

Fig 4 shows an example of daily alga bloom risk forecast during June to July in 2017. The nutrient risk in this period is high (nutrient unlimiting) and hence the bloom risk is mainly controlled by the hydrodynamic stability, R. A stable water column ($E < E_c$) is observed starting from early June and the bloom risk ranges from medium to high during this period ($P(B) = 0.5 \sim 0.7$). On the other hand, the observed chlorophyll fluorescence and a marked DO differential between surface and bottom (indicative of photosynthetic production in the surface layer) clearly indicates an algal bloom event from around June 20 to end of June – with a secondary bloom around the first week of July. The bloom occurrence is clearly correlated with the predicted algal bloom risks.

4. CONCLUSIONS

We have presented a daily algal bloom forecast system for use in semi-enclosed coastal waters – where fish farms are usually located. The forecast is based on the combination of a deterministic vertical stability theory and a data driven ANN model and has been demonstrated to be robust and suitable for field implementation. It should be emphasized that the algal bloom forecast does not rely on any chlorophyll measurements (which are typically not available). The forecast system is the first of its kind and has great potential for application in coastal water quality and fisheries management.

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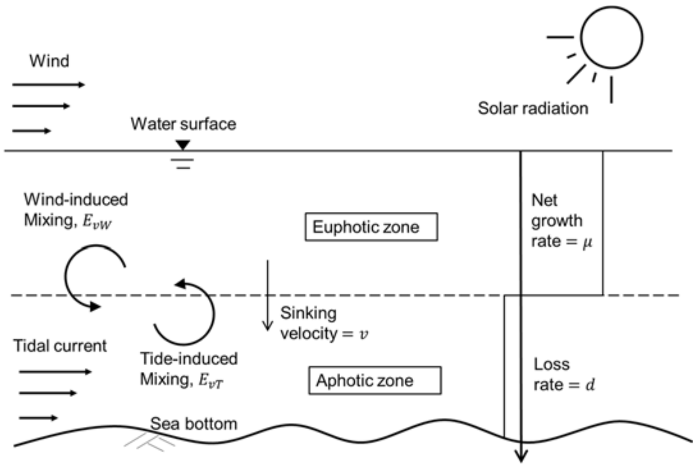
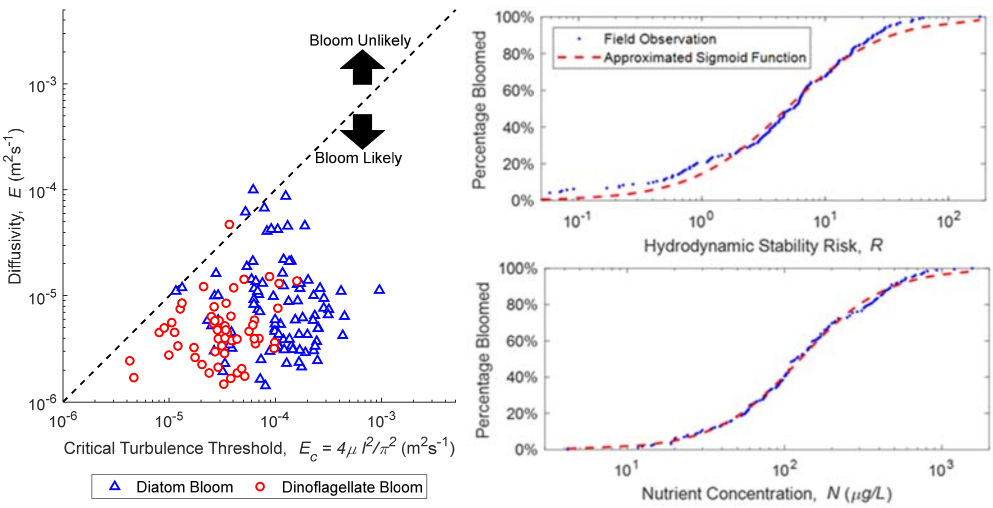


Figure 1 *Simplified 2-layer system for algal bloom dynamics*



(a) *(b)*

Figure 2 *(a) Validation of stability theory for algal blooms with field data; (b) Probability of bloom occurrence as a function of hydrodynamic stability and total inorganic nitrogen concentration*

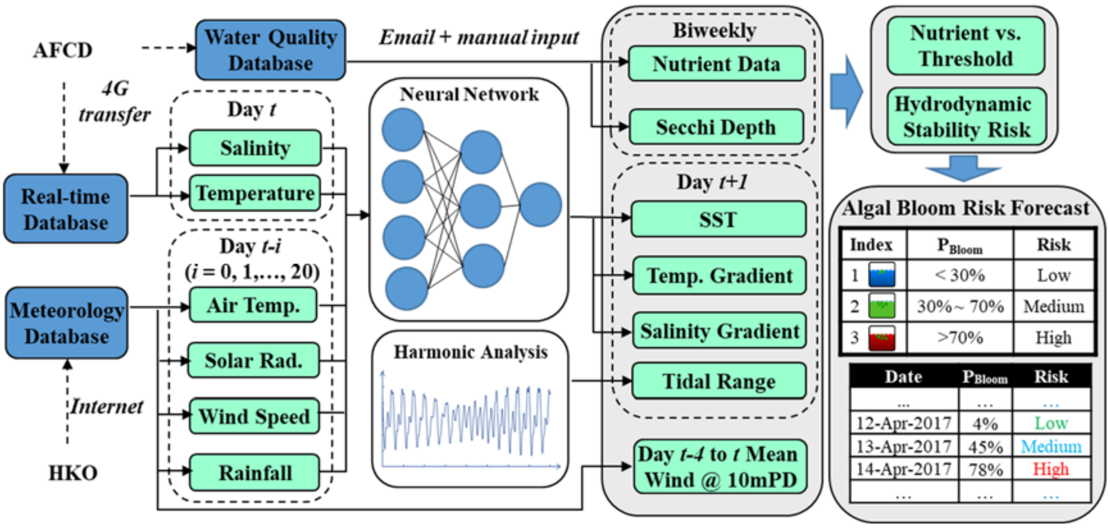
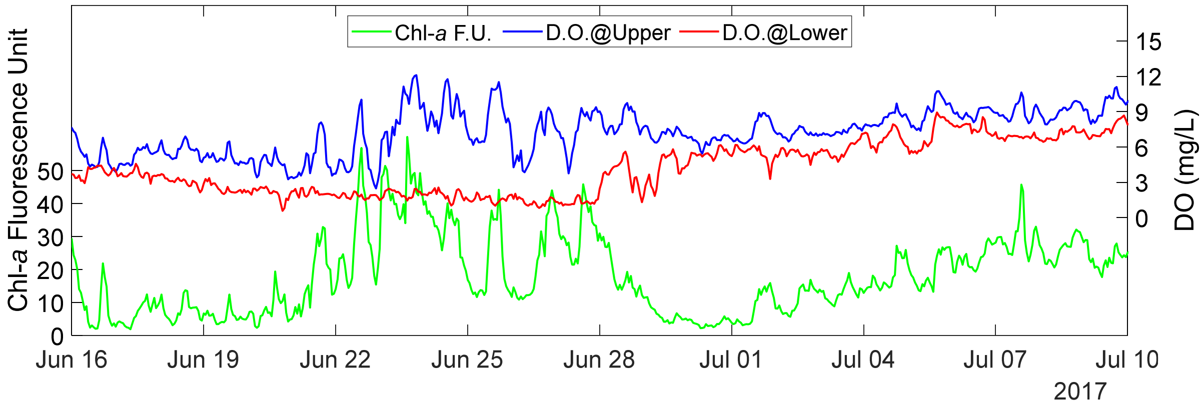
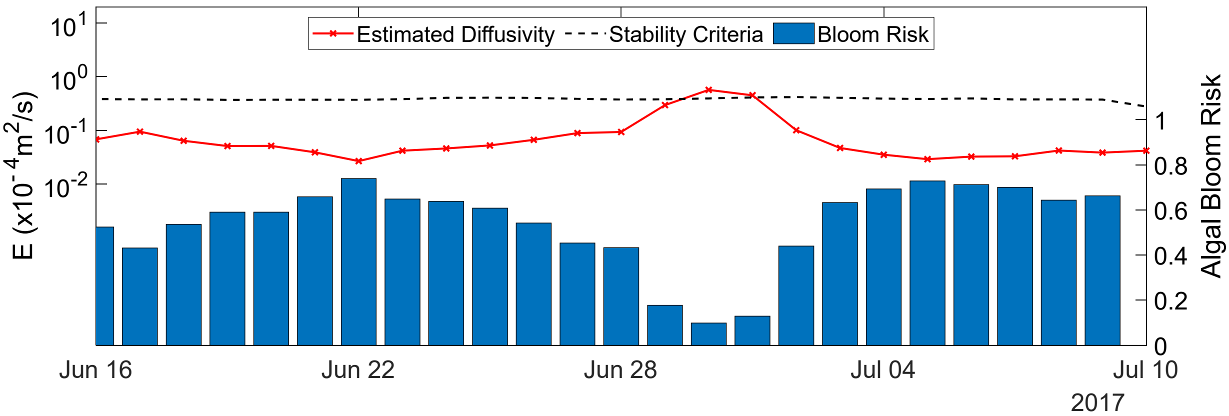


***Figure 3**. Framework of algal bloom risk forecast system*



(a)



(b)

***Figure 4** Forecast and monitoring of algal blooms at Yim Tin Tsai Fish Culture Zone: (a) surface and bottom DO and surface chlorophyll fluorescence; and (b) daily bloom risk forecast in June-July 2017*

REFERENCES

1. Coad, P., Cathers, B., Ball, J. E., & Kadluczka, R. (2014). Proactive management of estuarine algal blooms using an automated monitoring buoy coupled with an artificial neural network. *Environmental modelling & software*, 61, 393-409.
2. Fernando, H. J. (1991). Turbulent mixing in stratified fluids. *Annual review of fluid mechanics*, 23(1), 455-493.
3. Fischer, H. B., List, J. E., Koh, C. R., Imberger, J., & Brooks, N. H. (2013). *Mixing in inland and coastal waters*. Elsevier.
4. Lee, J. H. W., Wong, K. T., & Choi, K. W. (2012). Forecasting and Management of Coastal Water Quality. In *Handbook of Environmental Fluid Dynamics* (Ed. H.J. Fernando), Vol. 1, pp. 93-108, CRC Press.
5. Wong, K. T., Lee, J. H. W., & Harrison, P. J. (2009). Forecasting of environmental risk maps of coastal algal blooms. *Harmful algae*, 8(3), 407-420.