We wish to thank the editor and referees for the constructive comments and suggestions which are helpful to the revision of our manuscript. Detailed response to all comments are given below (responses are shown in blue below the questions).

Anonymous Referee #1

General Comments

Chen et al. evaluated long-term patterns in DO in the eastern Pearl River Estuary (PRE) across seasons and regions, computed an aggregated metric of low DO, and then tested possible controlling factors of it with multiple regression. They found dissolved nitrogen and wind speed were the most explanatory variables for interannual variations and long-term trends. They use additional water quality observations to evaluate the changes to the system over time and hypothesize shifts in the system dynamics. Overall, this is a very interesting study making good use of a long-term data set to evaluate long-term change. I appreciate their thorough treatment of the data both spatially and temporally. My major comments involve clarifying the methods and what is represented in some of the graphics. Clarification is needed throughout as to which months of data are included in different average results and how the data is aggregated to represent "summer". In addition, more clarification is needed on the PCA approach as well as some re-organization of which information is presented in the Methods or Results.

Response: We are grateful to the reviewer for the positive comments and recognition of our work. We will revise the manuscript as suggested (please see details in our responses below).

Specific Comments:

1. **Lines 60 – 81:** Within this section, please incorporate the reasoning for your focus on the Eastern PRE. Can you describe whether this region was selected from the larger PRE because this is where the longest term data is, or is it because this is where the lowest oxygen occurs? It would provide more context if you included some description in the Introduction about how water quality in this eastern region compares to the rest of the estuary.

Response: Thank you for your comment. As Hu et al. (2021) pointed out, observational data on DO and other water quality parameters in the PRE were generally scarce in time and space, while the sampling time periods and sites and sometimes the water quality measurement methods were quite different between available datasets. These limitations and uncertainties inherent in the historical data (including the observations during 1976-2017 compiled by Hu et al. 2021) brought out great obstacles for quantifying the long-term deoxygenation trend in the PRE. By comparison, the monthly data used in our present study, collected in the coastal waters off Hong Kong, have significant merits in terms of temporal coverage (over three decades) and consistency of sampling locations. Therefore, these data with good spatiotemporal continuity enabled us to better estimate the long-term and interannual variations in low-oxygen conditions without concerns on the uncertainties that would arise from the usage of different data sources. Besides, various oxygen-related parameters (e.g., chlorophyll-*a* concentrations) were measured as well and could be used to discern the key factors controlling the long-term oxygen changes. More importantly, the sampling sites in use were mostly located in the eastern side of the PRE, where prominent low-oxygen conditions at the bottom together with surface phytoplankton blooms have been frequently reported (Li et al., 2021; Li et al., 2020; Qian et al., 2018; Lu et al., 2018). Observational data from these coastal sites off Hong Kong (e.g. station SM18), which were close to a hotspot area of low-oxygen conditions in the eastern PRE (Hu et al., 2021), were often adopted as a representative to depict the water quality and oxygen conditions in the region (e.g. *see* Qian et al., 2018). Collectively, we considered that by utilizing the valuable dataset from Hong Kong waters, our study could provide a good insight into the long-term oxygen changes and the underlying drivers in the eastern PRE (especially from a quantitative perspective) and could be a significant part of low-oxygen researches for the whole estuary.

Based on the reviewer's suggestion, we will provide more descriptions for selection of the dataset and water quality conditions in the eastern PRE in our revised manuscript as follows:

"… Nevertheless, due to the scarcity of observations in both time and space, a clear understanding of the long-term trend and interannual changes in hypoxia in the PRE as well as the associated drivers is still lacking, especially from a quantitative perspective. However, the spatiotemporally continuity of observational data, collected by the Environmental Protection Department of Hong Kong (HKEPD) in the eastern waters of the PRE, allowed us for a more accurate understanding of interannual and long-term low-oxygen conditions without concerns on data quality control and comparability due to uncertainties of difference dataset sources. Although the level of nutrient and terrestrial organic matter was relative lower than in the western PRE (e.g. Modaomen Bay)(Chen et al., 2020b; Yu et al., 2020), the eastern PRE was also a hotspot area of low-oxygen due to joint effects of physical and biogeochemical conditions (Li et al., 2021; Lu et al., 2018), in which research within this region could be an significant part of low-oxygen researches for the whole estuary.

In this study, we perform a quantitative analysis on the long-term oxygen changes (trend and interannual variability) by utilizing observational data from HKEPD…"

2. **Line 104:** Please describe what spatial interpolation approach was used in MATLAB for the interpolations. Also, since you have land in between some of the stations, how did the method deal with that? It would be helpful to show what the region looks like in vertical cross-section as a 2nd panel of Figure 1 with the sample locations and depths indicated with dots. This would be like one of the panels of Figure A2, showing which depths each station is sampled at. This would be a helpful way to visualize the depths at each station.

Response: We estimated the vertical distribution of each water quality variable by using the "Natural-Neighbor" method, which has been widely applied in geophysics studies for its high spatial autocorrelation, in MATLAB. Regarding the island between stations NM8 and SM20, we first performed the spatial interpolations directly with all the observed data and then masked out the area cover by the island, which was roughly estimated based on its size (please note that the topographic data of the island was not available). Such a treatment has little influence on the estimation of vertical low-oxygen areas because low-oxygen conditions were seldom found in stations NM8 and SM20. Moreover, same treatment procedure was applied in each year to make it consistent when investigating the interannual variations in low-oxygen conditions.

As suggested by the reviewer, we will update Figure 1 by adding a subgraph to show the location and depth of each station.

3. **Lines 108-120:** This discussion of the PCA needs modification. Please include a table of the variables used in the PCA. I kept having to look back in the text to see how "low oxygen", "Area3," etc, were defined. I'd suggest including just that table and a description of the approach here in the Methods section. The resulting equation (Line 117) and description of it should probably be moved to the Results section. Also, please summarize the rest of the PCA results (in an appendix table), such as what % of variance the other components had, and what their weights were.

Response: Thank you for the suggestion. As suggested, we will add a table of the input variables used in the PCA (please see Table r1 below) and move Equation (1) and its associated description to the Results section (section 3.2) in our revised manuscript. In addition, we will provide more details on the rest of the PCA results in Appendix as suggested.

Table r1 Description of variables in PCA analysis

Variables in PCA	Description
DO_{mean}	Spatial average value of DO in bottom of each year during 1994-2018
DO_{min}	Spatial minimum value of DO in bottom of each year during 1994-2018
$Area_4$	Low-oxygen cross-sectional area (DO<4 mg/L) of each year of each year during 1994-2018
$Area_3$	Oxygen-deficiency cross-sectional area (DO<3 mg/L) of each year of each year during 1994-2018
$Thickness_4$	Low-oxygen cross-sectional thickness of each year of each year during 1994-2018

$Thickness_3$	Oxygen-deficiency cross-sectional thickness of each year of each year during 1994-2018
Low-oxygen Index (LOI)	First principal component of PCA dimension (86.40% of variation), measuring interannual variations in scope and intensity of oxygen conditions

4. **Line 125:** show an equation to describe this standardization

Response: We will show an equation to describe this standardization it as suggested.

5. **Lines 123-134:** There need to be some discussion of these different test results in the Results section.

Response: As suggested, we will provide more details on different test results of regressions (please see Figure r1 and Table r2 below). It can be seen from Figure r1 that the ensemble means of fitting Low-oxygen Index (LOI) for different combinations of training and testing datasets were similar, but the variance explained by the fitting and the regression coefficients were different (please see Table r2). For the regression models with lower coefficients of determination (R^2) (Figure r1c), the fitting LOI both in training dataset and testing dataset varied in a relatively larger range. To provide a more robust data fitting result, we chose the cases with excellent performances (indicated by R^2 over 0.6 both in the training and testing datasets) for formal analysis. Based on the reviewer's suggestion, we will add the above discussion on different test results in section 4.1 in our revised manuscript and provide Figure r1 and Table r2 in Appendix.

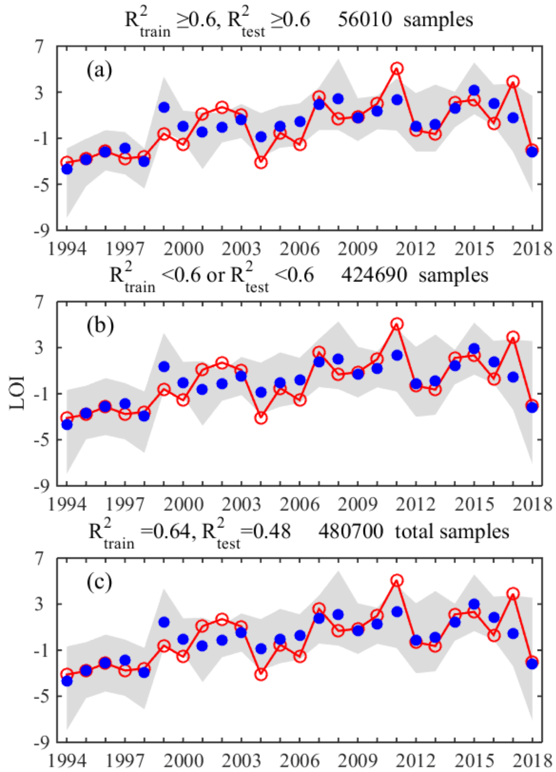

Figure r1. Combined fitting results of the regression models with different combinations of training and testing datasets. R^2 in (a) were greater than or equal to 0.6 both in training and testing datasets. R^2 in (b) were less than 0.6 both in training and testing datasets. Fitting results of total samples were in (c). Note that the red hollow dots denote the LOI estimated based on observational data, while the blue solid dots and the gray patch represent the mean values and ranges of the fitted LOI in the selected regression cases, respectively.

Table r2 Regression coefficients of different sample datasets (Mean±Std)

Fitting cases	WS	flow	T	DIN
R_{train}≥0.6,R_{test}≥0.6	-0.39±0.12	-0.14±0.12	-0.11±0.08	0.49±0.12
R_{train}<0.6 or R_{test}<0.6	-0.37±0.14	-0.17±0.17	-0.12±0.11	0.44±0.15
Total samples	-0.37±0.14	-0.16±0.16	-0.12±0.11	0.45±0.14

6. **Figure 4a:** can you describe the values plotted here more? Is the minimum, mean and range just from the bottom observations, or is it generated from the interpolation?

   Figure 4 (b) and (c)– We need information on the spatial interpolation to get the area and thickness. Also, if samples are collected every month, it is unclear what the bars in (b) and (c) represent. Are they the average of each month's spatially-aggregated values? If so, please put range bars on each bar to show the range across the summer months. Or pick one month to show.

Response: The mean and minimum DO values shown in Figure 4a are the spatiotemporally average and minimum DO concentrations for the bottom observations (using all the data from 10 stations in June, July, and August, i.e. 30 data points in total for each year). Also, the grey patch showed the minimum-to-maximum range of the observations in each year during 1994-2018. We will clarify this in the revised manuscript.

With respect to the areas and thickness of oxygen conditions, they were estimated by interpolation. Specifically, we calculated the areas and thicknesses in June, July, and August of each year, respectively, and then computed the corresponding summer means (results shown in Figure 4b-c) by averaging the areas and thicknesses of the three months. As suggested, we will clarify these estimations and revise the Figure 4b-c by adding range bars to show the range across the summer months (please see the revised figure below):

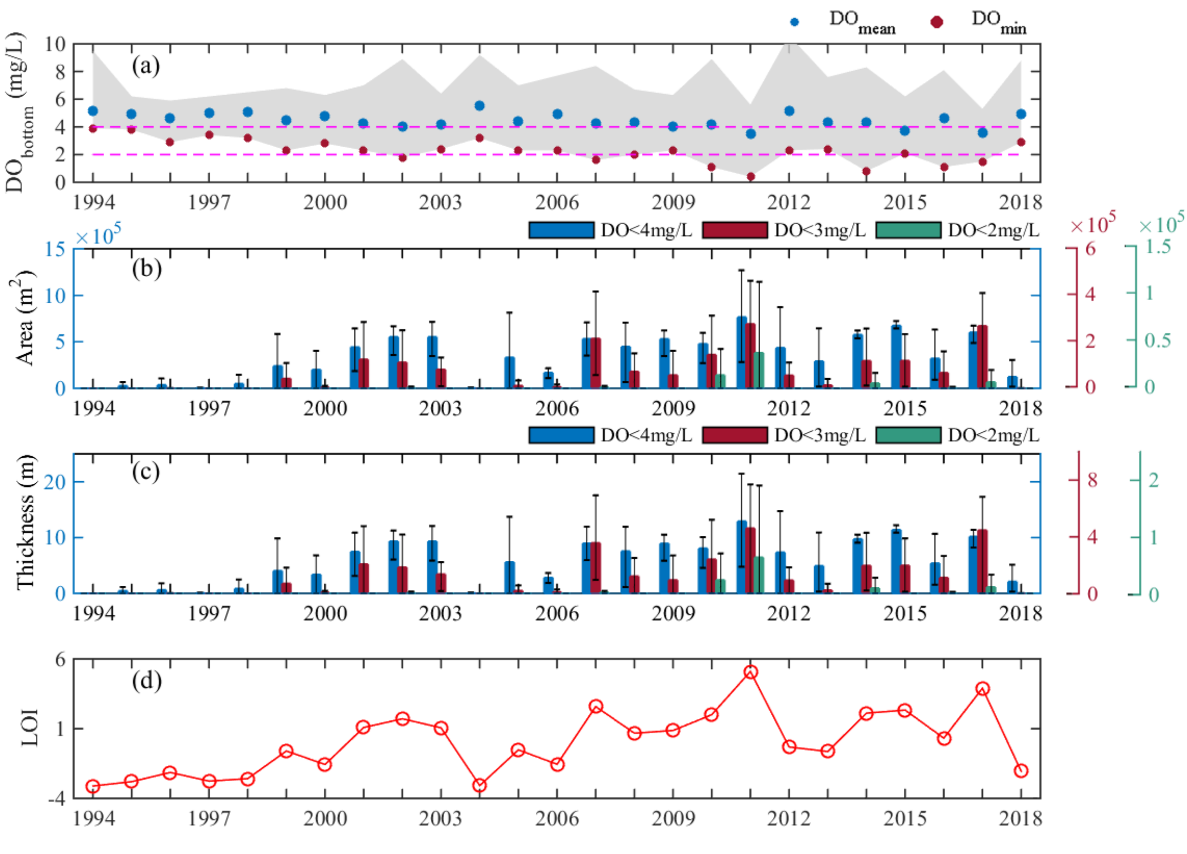

Figure r2. Interannual variations in the spatiotemporally (10 stations in June, July and August) mean and minimum concentrations of observed DO at the bottom (a), the cross-sectional areas (b) and layer thicknesses (c) of low-oxygen conditions, and LOI (e) in summer during 1994-2018. For (b) and (c), note that the color bars represent the mean value of three summer months, while black thin bar represent the range across three summer months.

7. **Figure A2:** Similarly to Figure 4, specify which month of the summer these plots are for. If

they are average of all the summer cruises, please justify that approach.

Response: As for the vertical DO distributions in Figure A2, they are averages of all the summer cruises. Specifically, we first averaged the observational data in the three summer months to obtain the summer means at the surface, middle, and bottom, respectively, and then interpolated them onto the profile grids to get the summertime vertical DO distributions (results shown in Figure A2). We will clarify this in the revised manuscript.

8. **Figure 5:** The min and mean DO symbols in legend seem switched.

Response: Thank you for the suggestion. We will correct this mistake.

9. **Figure 5:** I'd like to see the surface and bottom graphs with the same vertical scale (0 to 10).It can be confusing to have them different when they are right next to each other.

Response: As suggested, we will use the same vertical scale (0 to 10) in the surface and bottom graphs.

10. **Figure 5:** I'm unsure from the descriptions as to how the mean and minimum were calculated with multiple stations and months of the summer. Is the minimum the absolute minimum observed in that region in the summer, or an average of the lowest value across the stations? Also is the mean a spatial and temporal mean across the summer?

Response: As mentioned earlier (please see our response to Comment 6), the mean and minimum DO values shown in Figure 5 are the spatiotemporally average and minimum DO concentrations for the bottom observations (using all the data from 10 stations in June, July, and August, i.e. 30 data points in total for each year). Indeed, the minimum is the absolute DO minimum observed in the region in three summer months, and the mean is the spatiotemporal mean across the summer. We will revise the caption of Figure 5 to make it clear as follows:

"Figure 5. Long-term trends of the spatiotemporally mean and minimum values of observed DO at the surface and bottom waters in three summer months for all the stations (a-b) and for the northwestern (c-d), southern (e-f), and eastern (g-h) subregions, and long-term trends of the cross-sectional areas of low oxygen (i) and oxygen deficiency (j)."

11. **Figure 6:** The really high values in the range in recent years in July are worth mentioning. Is that just one location that is causing that range to increase, or is it some indication of increased variability?

Response: For the larger range of DO in July after 2012, it exhibited increased spatial variability. As shown in Figure r3, in July after 2012, high DO was constantly observed at the bottom of stations NM6, NM8 and SM20, while low DO was observed at the bottom of SM18 and SM19. We could find some explanations from the vertical distributions of Chl *a* concentrations (please see Figure r3 below). The high Chl *a* in NM6, NM8 and SM20 revealed that phytoplankton flourished within the region. Due to shallow depth of these stations, high DO resulted from photosynthesis was observed at surface and bottom. However, stations located in the downstream (e.g. SM18 and SM19) would receive much organic matter transported by hydrodynamic processes. Driven by stronger water-column stratification therein, low-oxygen conditions often occurred at bottom in SM stations. After 2012, high Chl *a* occurred in July with more frequency and larger intensity, which could be main reason for larger range of DO at bottom. We will provide some discussion on this issue in our revised manuscript.

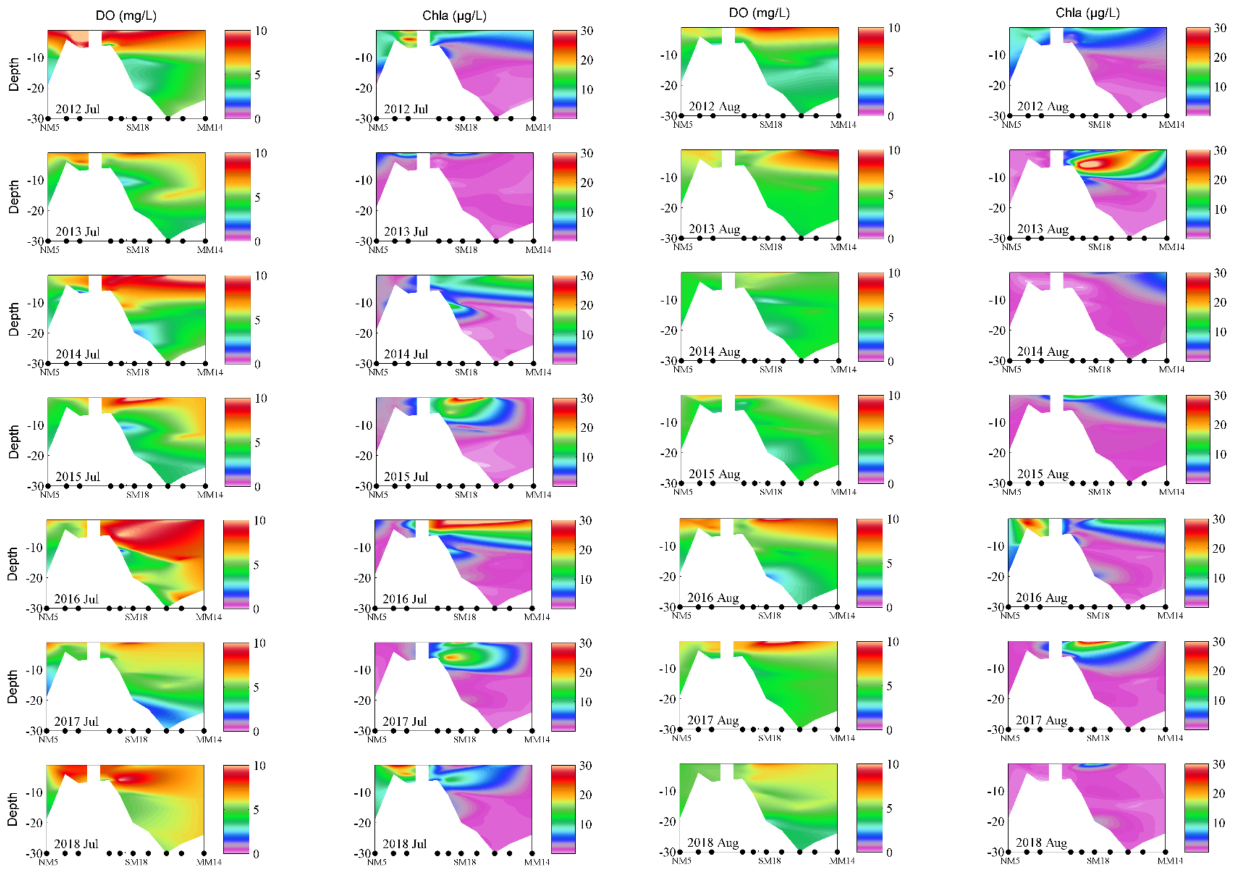

Figure r3. vertical distributions of DO and Chl *a* in July and August during 2012-2018.

12. **Line 233:** A diagram or flow-chart that describes the sampling and cases used in the regression analysis to get to the results would help my understanding (and probably other readers) of the methods. This could go in the Appendix.

Response: Thank you for the comment. We will add a flow-chart to describe the sampling and cases selection processes.

13. **Figure 9:** The wind speed decrease over time seems very large. Because the results indicate this is an important variable, this deserves more discussion or investigation. If the authors

already know other work that has investigated decreasing wind speeds, please cite it and describe briefly. But if there is no other research explaining this wind decrease, it would be a good idea to double-check the data and be sure that it is not an artifact of sampling dates or density shifting or sensor height changing.

Response: We totally understood the concern of the reviewer. In fact, we could find supports on the decrease of wind speed both in the Pearl River Basin (Zhang et al., 2019) and the northern South China Sea (Gao et al., 2020). Previous studies suggested that due to the weakening of atmospheric cycle activities and the East Asian monsoon (Xu et al., 2006; Zhang et al., 2009), the annual average wind speed in the Pearl River Basin exhibited a significant declining trend (at a rate of -0.003 m/s per year) during 1960-2016 (Zhang et al., 2019). In addition, previous studies showed that the long-term increase of air temperature in the Pearl River Delta region contributed to air stability and weakened the intensity of tropical cyclone (Chen et al., 2020a), which would lead to a decline of summertime wind speed in the PRE. In the northern South China sea, the summer average wind speed decreased at a rate of 0.05 m/s per year during 2004-2020 (Gao et al., 2020), which was close to that in the eastern PRE (-0.03 m/s per year). We will add more description on the decrease in wind speed in our revised manuscript (section 4.2).

14. **Appendix Figure A1:** is important b/c it doesn't suffer from any possible aggregation or averaging bias. It might be useful to make an addition panel that shows how the bottom summer counts have changed over time – maybe make one for the first half and one for the 2nd half of the record. This could also show if there's a spatial shift.

Response: Thank you for the comment. Based on the reviewer's suggestion, we have investigated changes in the occurrence of bottom low-oxygen conditions in summer during two different periods (please see Figure r4 below) to examine if there is a spatial shift. As shown, the low-oxygen and hypoxic conditions were more severe during 2006-2018 when compared to those during 1994-2005, implying a deoxygenation pattern over time. However, there is no spatial shift found between the two periods. Stations NM5 and SM18 had the highest intensity of low-oxygen events in both periods.

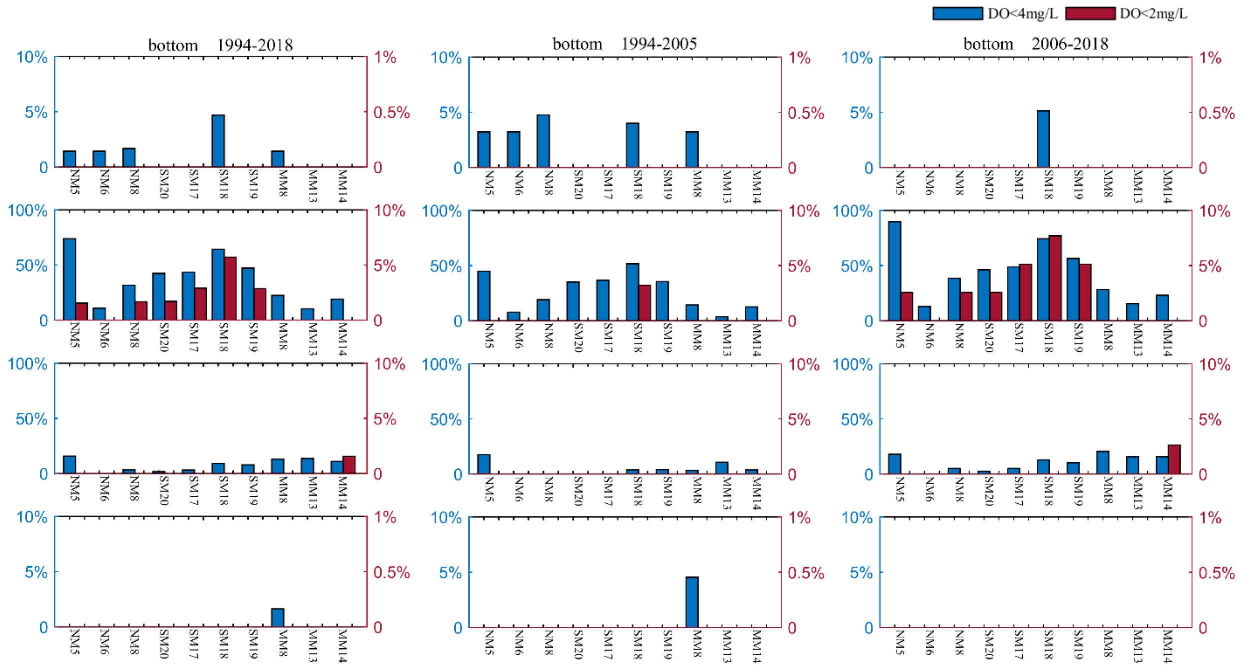

Figure r4. Frequencies of occurrence of low-oxygen and hypoxic events in four seasons at the bottom (1994-2018, 1994-2005, 2006-2018) layer.

Technical Corrections:

(1) **Abstract, Line 15** – change "was" to "were"

Response: We will correct it as suggested.

(2) **Abstract, line 17** – suggest changing "through the principal component analysis" to something else. Maybe "as a result of a principal component analysis"

Response: We will revise it as suggested.

(3) **Abstract, line 25** – It is unclear what "It" refers to in this sentence. Please re-write.

Response: We will revise it as follows:

"The deteriorating eutrophication has driven a shift in the dominant source of organic matter from terrestrial inputs to in situ primary production, which has probably led to an earlier onset of hypoxia in summer."

(4) **Abstract, last sentence** – the phrase "in the context of" is fairly awkward. Consider re-wording this sentence to make your summary stronger.

Response: We will revise it as follows:

"In summary, the eastern PRE has undergone considerable deterioration of low-oxygen conditions driven by substantial changes in anthropogenic eutrophication and external physical factors."

(5) **Intro, Line 33** – suggestion you use "organisms" instead of "creature"

Response: We will revise it as suggested.

(6) **Intro, Line 43-45** – Simplify (or remove) this sentence since the next few sentences cover a lot about oxygen depletion. I'd suggest just "Terrestrial organic matter discharged to estuaries can lead to intense microbial respiration."

Response: We will revise it as suggested.

(7) **Intro, Line 54:** For the Ni et al. 2020 paper, it is important to change "ocean" to "estuary." They did not study the external impact of the Atlantic Ocean warming on the Chesapeake Bay.

Response: We will revise it as suggested.

(8) **Methods, Lines 84-93** – Who collected this data?

Response: The data were provided by the Environmental Protection Department of Hong Kong. We will make it clear in the Materials and Methods section.

(9) **Results, Line 144** – I do not think the word "varied" is correct here.

Response: We will revise the sentence to *"The summertime temperature fluctuated between 28.21 ±1.19 °C…"* . All the relevant phrases in the manuscript will be revised accordingly.

(10) **Results, Line 168** – wording like this sentence can be simplified. You could just start with "DO concentrations exhibited significant…"

Response: We will revise it as suggested.

(11) **Results, Line 192, and other places** – The phrase "DO content" is not something I've seen very much before in the hypoxia literature. I'd suggest using "DO concentrations" or just "DO".

Response: We will revise it as suggested.

(12) **Figure 6** – It would be helpful to use the same open circles for the blue symbols as in Figure 5.

Response: As suggested, we will change the legends of DO_{mean} and DO_{min} in Figure 6 and make them consistent with those in Figure 5.

(13) **Discussion, Lines 297-298:** Please revise the sentence that starts with "As quantified by statistic methods…" to work on the wording. Maybe "Our analysis showed that increasing DIN…"

Response: We will revise it as suggested.

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