Dear Reviewers,

We deeply appreciate your comments and effort towards improving our manuscript. We have taken your constructive comments carefully in the revision of our manuscript. For the revision, please kindly refer to the point-to-point responses as followings and the revised manuscript. The changes we made have been noted in the blue color for highlighting.

Response to Reviewer

The spectral-based model proposed by Wang et al. (2014) was modified in this study for retrieving PSC in the East China Sea from MODIS data. Internal relationship between PSC and the spectral variability of phytoplankton absorption is the key point for this model. In order to minimize the effect of high noise and low accuracy at shore wavelengths, the authors reconstructed the R_{rs} spectra by using the multivariate linear relationships at different wavelengths. Based on in situ match-up data analyses, satellite derived PSC compared well with those derived from HPLC pigment composition. Seasonal variability of PSC in the three sub-regions were discussed by considering different environmental factors, which gave us a better understanding of PSC distribution in ECS at synoptic scales. We can see obvious improvement in the revised manuscript.

Response: Thank you for your positive comment.

I suggest minor revision considering the following points:

1. Detailed information for estimating PSC from the DPA approach are required. In this study, Chlorophyll-b was one of the diagnostic pigments of nano-phytoplankton, which is different from that method used by Brewin et al. (2010) for open ocean. More explanations are needed.

Response: Thank you for your suggestion. In our study, the diagnostic pigment analysis (DPA) was applied to compute the PSC from HPLC pigment data (hereafter called the HPLC-derived PSC). The DPA approach was originally proposed by Vidussi et al. (2001), and subsequently improved by Uitz et al. (2006). In addition, Hirata et al. (2008) used the improved DPA approach to account for the occurrence of Chlorophyll-b in nano-phytoplankton class size, because it was most abundant at high

Chla (> 0.25 mg m^{-3}) and was a minor pigment at lower Chla (Hirata et al., 2008). Subsequently, Hirata et al. (2011) and Brewin et al. (2010) further refined the DPA approach to account for ambiguity of C_f signal in diatoms and the occurrence of C_h signal in picophytoplankton. In this study, the HPLC-derived PSC results were then given by:

$$f_{micro} = \left(1.41C_f + 1.41C_p\right) / \sum W_i P_i \quad (1)$$

$$f_{nano} = \left(0.60C_a + 0.35C_b + 1.01C_{Cb} + x \times 1.27C_h\right) / \sum W_i P_i \quad (2)$$

$$f_{pico} = \left(0.86C_z + y \times 1.27C_h\right) / \sum W_i P_i \quad (3)$$

where x and y are the proportions of nano- and pico-phytoplankton in Hex, respectively. When Chla >0.08 mg m^{-3}, x=1 and y=0; when Chla are between 0.001 and 0.08 mg m^{-3}, x=12.5Chla and y=1-12.5Chla. $\sum W_i P_i$ is the weighted sum of the seven diagnostic pigments (Uitz et al., 2006), according to the formula:

$$\sum W_i P_i = 1.41C_f + 1.41C_p + 0.60C_a + 0.35C_b + 1.27C_h + 0.86C_z + 1.01C_{Cb} \quad (4)$$

In the revised manuscript, we have added these explanations in Section 2.2.1.

2. It's not surprising to see the poor performance of the model by Brewin et al. (2015) or Sun et al. (2017). There are several points we have to consider. Different criteria for estimating the PSC from the diagnostic pigments were used which may result in large differences in the basic dataset. We also have to consider the regional differences. Did the authors use the model directly? Maybe the coefficients for these models could be locally modified before comparison.

Response: Thank you for your valuable comments and suggestions. Indeed, we directly used the Brewin et al. (2015) and Sun et al. (2017) models with their original coefficients in the manuscript. The regional differences may affect and result in the poor performance of these models. Thus, in the revised manuscript, in order to better assess the performance of these models in the ECS, as you suggested, we regionally tuned these published models before comparison. The fitting produce was applied to our field dataset collected in the ECS using a standard nonlinear least-squares method. Fig. R1 and Fig. R2 show the comparison between the HPLC-derived PSC and modeled PSC values using the retuned Brewin et al. (2015) model and the retuned Sun et al. (2017) model, respectively. However, it can be clearly seen from Fig. R1 (top row) that the data were quite scattered, and the fractional variation of each population in the ECS as a function of Chla didn't strictly agree with the results of Brewin et al. (2015). Meanwhile, the scatter plots of Fig. R1 (bottom row) and Fig. R2 show the poor fitting results of the regionally tuned model development with low *R* values and high RMSE values, especially for nano-phytoplankton. These results indicated that the two "abundance-based" models may not perform well in the East China Sea as suggested by Wang et al. (2014). Therefore, it should be noted here that the two retuned models were used to better assess the performance of our refined PSC model only, although the Brewin et al. (2015) model and Sun et al. (2017) model may not necessarily applicable in the ECS (Wang et al., 2014).

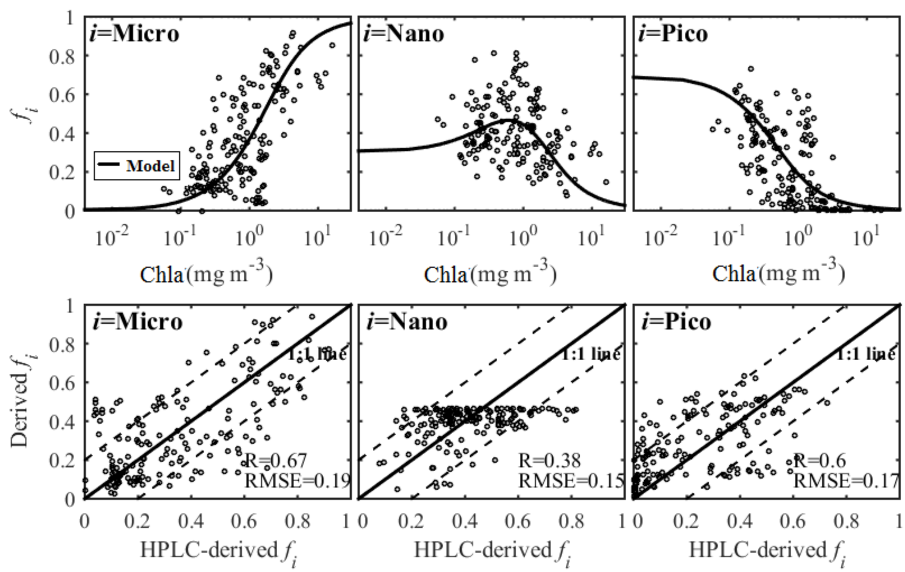

Fig. R1 The top row shows the size fractions of phytoplankton (f_i) as a function of chlorophyll-a concentration, and the bottom row shows the comparison results between the HPLC-derived PSC and modeled PSC values using the retuned Brewin et al. (2015) model.

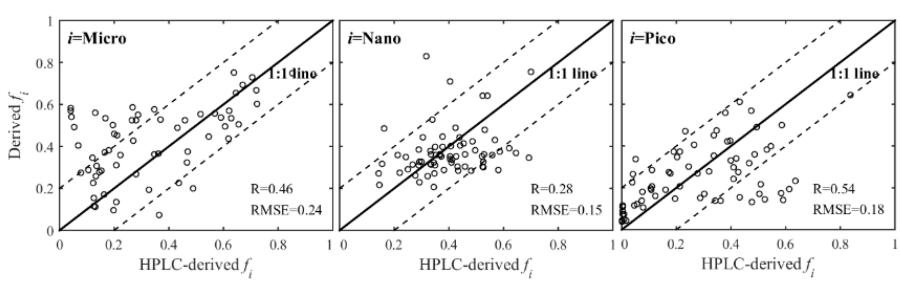

Fig. R2 The comparison results between the HPLC-derived PSC and modeled PSC values using the retuned Sun et al. (2017) model.

In this study, the retuned Brewin et al. (2015) model for the ECS was expressed as:

$$\begin{aligned} f_{pico} &= 0.19\left[1-exp\left(-3.6Chla\right)\right]/Chla \\ f_{p,n} &= 1.0\left[1-exp\left(-1.0Chla\right)\right]/Chla \\ f_{nano} &= f_{p,n} - f_{pico} \\ f_{micro} &= 1 - f_{p,n} \end{aligned} \quad (1)$$

where f_{micro}, f_{nano}, f_{pico}, and $f_{\text{p,n}}$ are the size fractions of micro-, nano-, pico-phytoplankton, and the sum of nano- and pico-phytoplankton, respectively. Chla is the chlorophyll a concentration. And, the retuned Sun et al. (2017) model for the ECS was expressed as:

$$\begin{aligned} f_{pico} &= 0.66Chla^{-1}\left[1-exp\left(-Chla^{2}\times R_{rs}\left(680\right)\right)\right]^{0.16} \\ f_{nano} &= 4.17Chla^{-1}\left[1-exp\left(-Chla^{2}\times R_{rs}\left(680\right)\right)\right]^{0.32} \\ f_{micro} &= 1 - f_{nano} - f_{pico} \end{aligned} \quad (2)$$

where R_{rs} (680) is the remote sensing reflectance at 680 nm.

Our refined PSC model was compared with the retuned Brewin et al. (2015) model and the retuned Sun et al. (2017) model (Fig. R3, i.e., Fig. 7 in the revised manuscript). The scatter distributions of the satellite-derived PSC using our refined PSC model were closer to the 1:1 line than those of the other two models. According to the statistical indicators, our refined PSC model had the best performance, with higher R values and lower RMSE values (Fig. R3b). For the retuned Brewin et al. (2015) model, the R values of 0.58, 0.066, and 0.53 and RMSE values of 0.2, 0.14, and 0.18 were observed for micro-, nano-, and pico-phytoplankton, respectively (Fig. R3c). For the retuned Sun et al. (2017) model, the R values were 0.36, -0.042, 0.5 for micro-, nano-, and pico-phytoplankton, when the corresponding RMSE values were 0.25, 0.17, and 0.18, respectively (Fig. R3d). The retuned Brewin et al. (2015) model and the retuned Sun et al. (2017) model had relatively poor performance in the ECS. These comparison results indicated that the performance of our refined PSC model using the reconstructed satellite data was better than those of the retuned Brewin et al. (2015) model and the retuned Sun et al. (2017) model in our study region.

In the revised manuscript, we have added these explanations about this issue in Section 3.4.

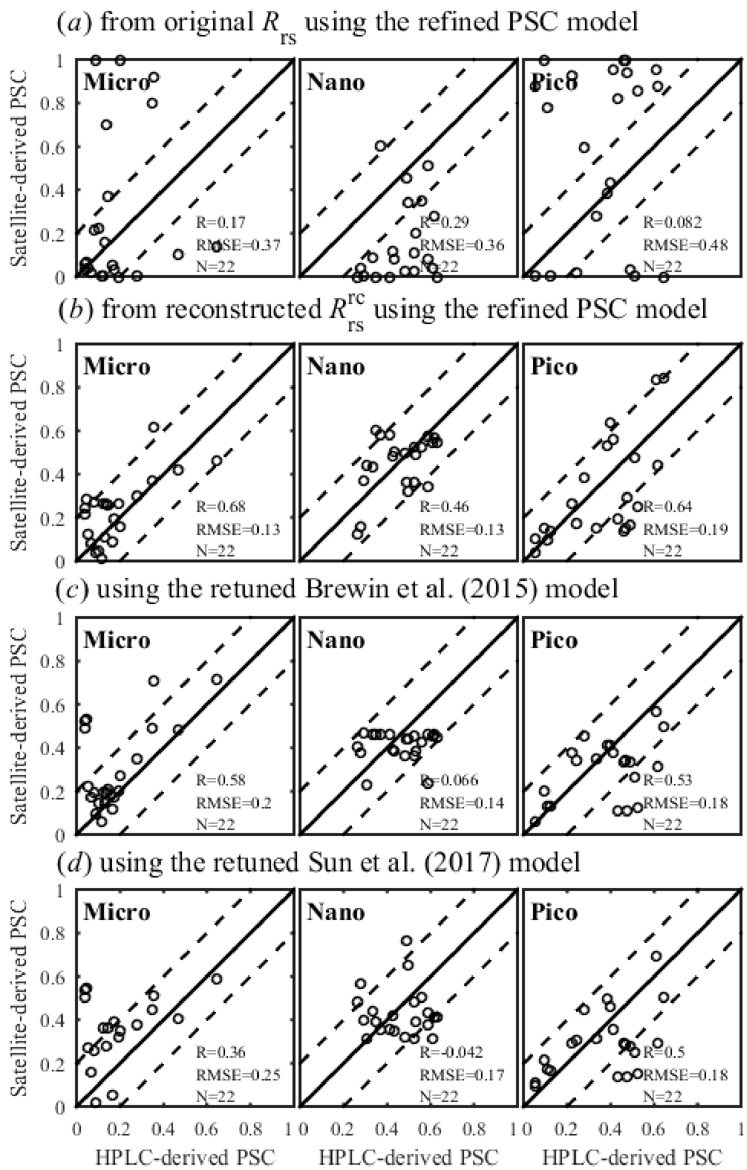

Fig. R3. Comparison of the HPLC-derived and satellite-derived PSC values from the original satellite R_{rs} (a) and the reconstructed satellite R_{rs}^{rc} (b) using the refined PSC model in this study; using the retuned Brewin et al. (2015) model (c); using the retuned Sun et al. (2017) model (d). Solid lines denote the 1:1 lines.

3. General spatial distribution of PSCs seems reasonable. Obvious differences about the seasonal variability of PSCs in three sub-regions were shown in Fig.8 and Fig.9. We can see clear shift of the dominant phytoplankton size class, especially in MSR and KR regions. More explanations about these

variabilities with referred to previous work (two of them are listed below) could be very helpful for confirming these results. I think these results could also be highlighted in the abstract.

Some references:

Guo, S.J., Y.Y. Feng, L. Wang, M.H. Dai, Z.L. Liu, Y. Bai, and J. Sun, 2014. Seasonal variation in the phytoplankton community of a continental-shelf sea: the East China Sea. Marine Ecology Progress Series, 516 103-126. Liu, X., Xiao, W., Landry, M.R. et al.， 2016. Responses of Phytoplankton Communities to Environmental Variability in the East China Sea. Ecosystems , 19: 832-849. https://doi.org/10.1007/s10021-016-9970-5.

Response: Thank you for your comments and the valuable references. In the revised manuscript, we have added more detailed explanations and discussion of the seasonal distributions of the PSC in the ECS (see Section 4.2), and also added the related previous studies to support the findings of our study. Meanwhile, these references have been cited in our work accordingly. Furthermore, in the revised manuscript, the main results about the spatiotemporal variations of the PSC in the ECS have been highlighted in the Abstract. Thank you.

4. The exact size and location of three sub-regions could be specified by giving the longitude and latitude range, rather than the pixel numbers.

Response: Thank you for your suggestion. In the revised manuscript, we have given the longitude and latitude range of three subareas (see the last paragraph of Section 2.1).

References used in this response:

Brewin, R. J., Sathyendranath, S., Hirata, T., Lavender, S. J., Barciela, R. M., and Hardman-Mountford, N. J.: A three-component model of phytoplankton size class for the Atlantic Ocean, Ecological Modelling, 221, 1472-1483, 2010.

Brewin, R. J. W., Sathyendranath, S., Jackson, T., Barlow, R., Brotas, V., Airs, R., and Lamont, T.: Influence of light in the mixed-layer on the parameters of a three-component model of phytoplankton size class, Remote Sensing of Environment, 168, 437-450, 10.1016/j.rse.2015.07.004, 2015.

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Sun, D., Huan, Y., Qiu, Z., Hu, C., Wang, S., and He, Y.: Remote‐Sensing Estimation of Phytoplankton Size Classes From GOCI Satellite Measurements in Bohai Sea and Yellow Sea, Journal of Geophysical Research: Oceans, 122, 8309-8325, 2017.

Uitz, J., Claustre, H., Morel, A., and Hooker, S. B.: Vertical distribution of phytoplankton communities in open ocean: An assessment based on surface chlorophyll, Journal of Geophysical Research: Oceans, 111, 2006.

Vidussi, F., Claustre, H., Manca, B. B., Luchetta, A., and Marty, J. C.: Phytoplankton pigment distribution in relation to upper thermocline circulation in the eastern Mediterranean Sea during winter, Journal of Geophysical Research: Oceans, 106, 19939-19956, 2001.

Wang, S. Q., Ishizaka, J., Yamaguchi, H., Tripathy, S. C., Hayashi, M., Xu, Y. J., Mino, Y., Matsuno, T., Watanabe, Y., and Yoo, S. J.: Influence of the Changjiang River on the light absorption properties of phytoplankton from the East China Sea, Biogeosciences, 11, 1759-1773, 2014.