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Spatial and temporal variability of chlorophyll-a and its relation to physical and biological parameters: a case study for the European Arctic Corridor

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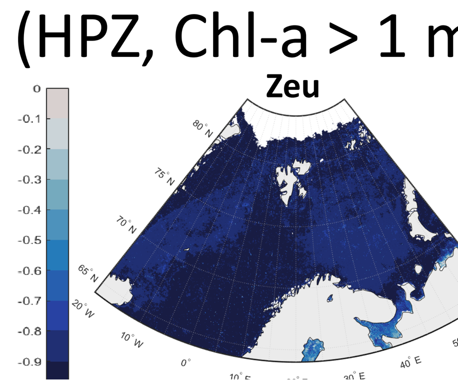
INTRODUCTION

This study focuses on analyzing the **spatial and temporal variability of chlorophyll-a** (Chl-a) **concentration** as an indicator of **ocean productivity** in the European Arctic Corridor (**the Barents, Norwegian and Greenland Seas**), and its **dependence** on the following environmental **parameters**: **euphotic layer depth** (Zeu), **Photosynthetically Active Radiation** (PAR), **Sea Surface Temperature** (SST), **Mixed Layer Depth** (MLD) and Sea Surface **Salinity** (SSS).

METHODS

- we analyzed **monthly 4x4 km remote sensing** data for **2010-2019 years** from:
  - Ocean Colour Climate Change Initiative (OC CCI) database, v5.0 (Chl-a and Zeu)
  - NASA's Ocean Biology Processing Group's MODIS images (PAR)
  - MUR SST database (SST)
  - ESA's SMOS images (SSS)
  - MLD was calculated from in situ EN4 Hadley Center and ARMOR data
- we used the **Random Forest Machine Learning** algorithm in the Classifier modification to create **models** to retrieve the **position of high-productivity waters** (HPZ, Chl-a > 1 mg m^{-3}) on the basis of the data above

1. Chl-a and connected factors' variability (Fig. 1)



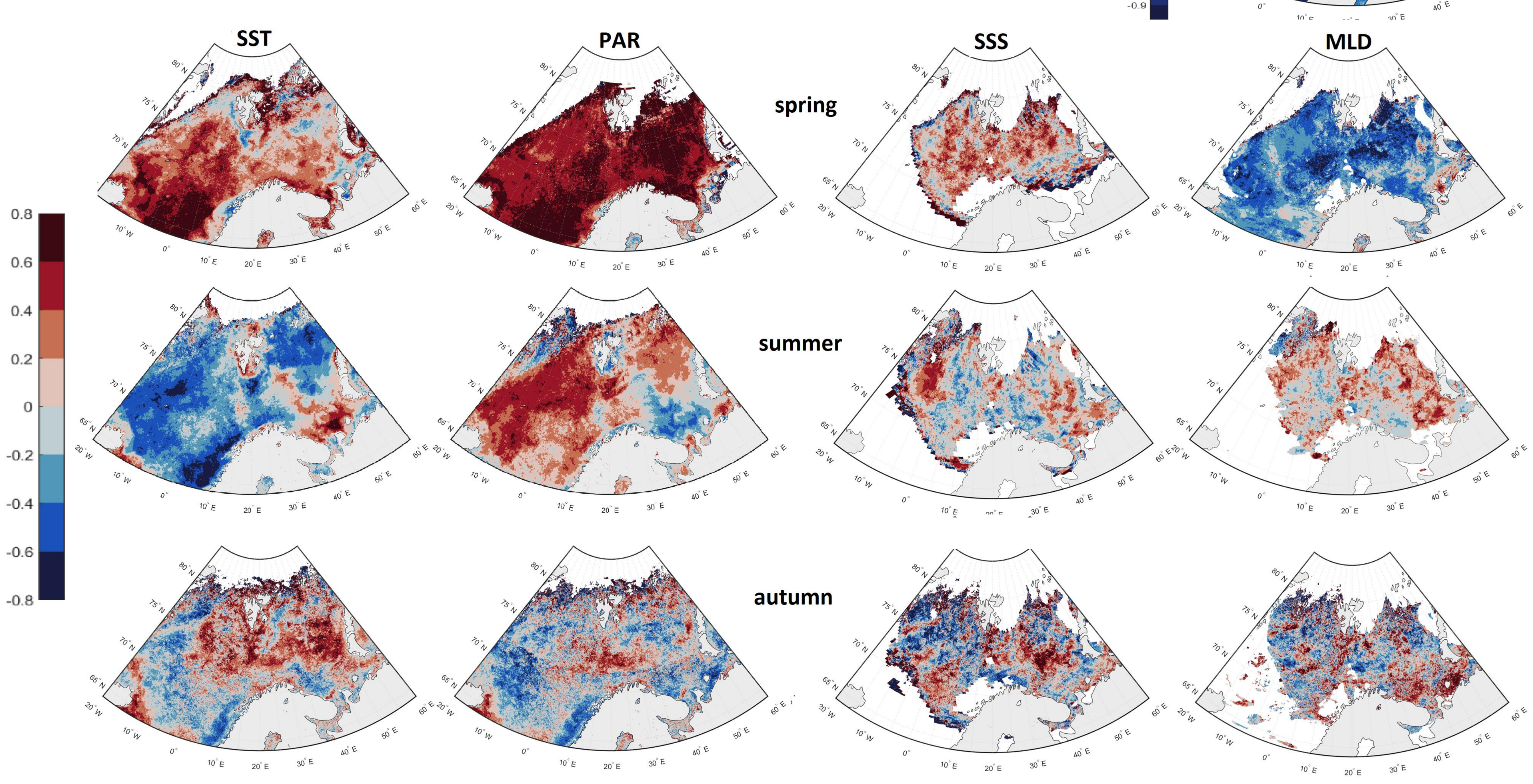


Fig. 1. Spatial and temporal variability of the correlation coefficient (R) between the concentration of chlorophyll-a (Chl-a) [mg m^{-3}] and environmental parameters: sea surface temperature (SST) [°C], photosynthetically active radiation (PAR) [mol quant m^{-2} day^{-1}], sea surface salinity (SSS) [psu] and mixed layer depth (MLD) [m] in 2010-2019. R is averaged by seasons.

We found that the **Chl-a and Zeu connection** is **the strongest** of all factors, with the correlation coefficient (**R**) being **above 0.8** during the whole year.

Meanwhile, the connection between **Chl-a and SST and PAR** is the most uniform during the spring bloom: **R** during that period is the highest (**0.4 – 0.6**) and **mostly positive**. That correlation fades somewhat during summer, and the connection turns opposite for Chl-a and SST. During the **autumnal bloom** the connection is the **most chaotic**, **R** is mainly **negative**, |R|> 0.4.

For **Chl-a and SSS and MLD**, these factors have the most **uniform** correlation distribution **during spring**, R is **positive** for Chl-a and **SSS** correlation, **negative** – for the Chl-a and **MLD** one, **|R|= 0.4 – 0.6**; **correlation** once again becomes **less uniform** during **summer** and **autumn** seasons.

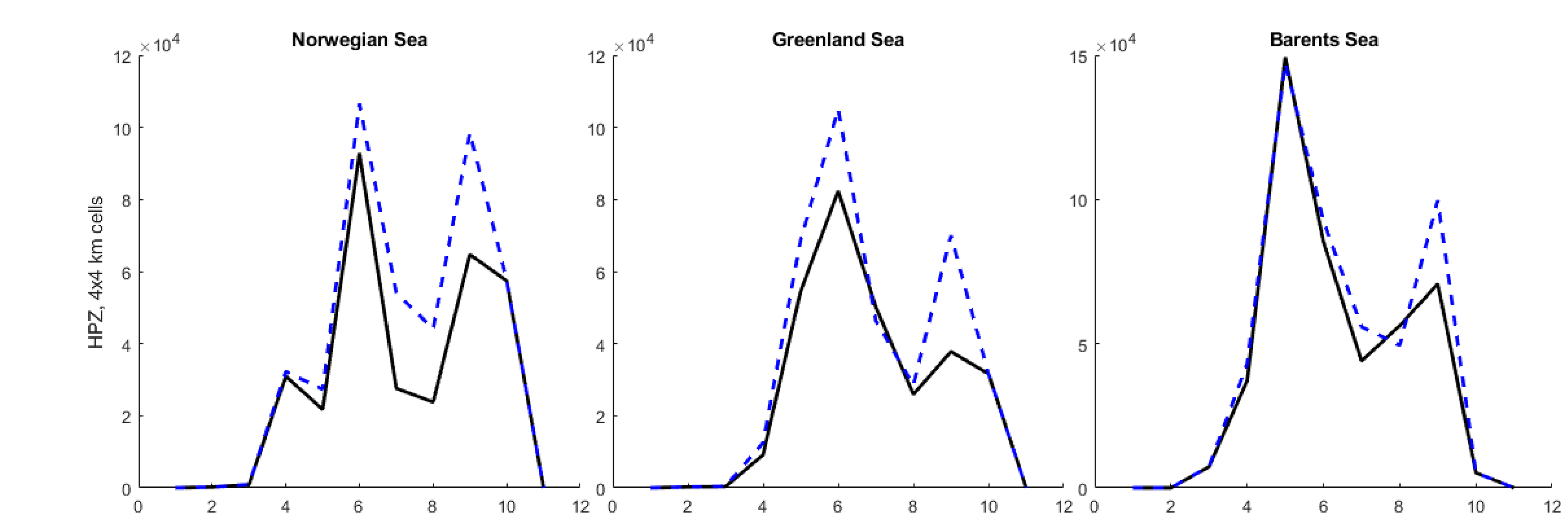


Fig. 2. Estimation of the total area of high-productivity waters (HPZ) (based on chlorophyll-a concentration) for the Barents, Greenland and Norwegian Seas based on modelling results. The area is given in cells of 4x4 km.

2. Machine Learning results: algorithms, metrics and results

a) *Overall numeric results*

Our **models performed fairly well**: they **correctly** estimated **over *90%*** of **all results** for the whole sample, and **over *70%*** for **only 2019** as validation. The summed up HPZ area (***Fig. 2***) is mostly estimated correctly, however the **models underestimate the summary area during bloom** months (may-jun, sep-oct).

b) *Spatial distribution of modelled HPZ*

All **models performed** (***Fig. 3***) **best** (meaning they correctly predicted not only the overall spread of HPZ, but their exact location) **during summer**, when there is a gap in productivity; **during** the spring and autumn **blooms** the models correctly predict the overall location of HPZ, but they often **underestimate the spread of the bloom**.

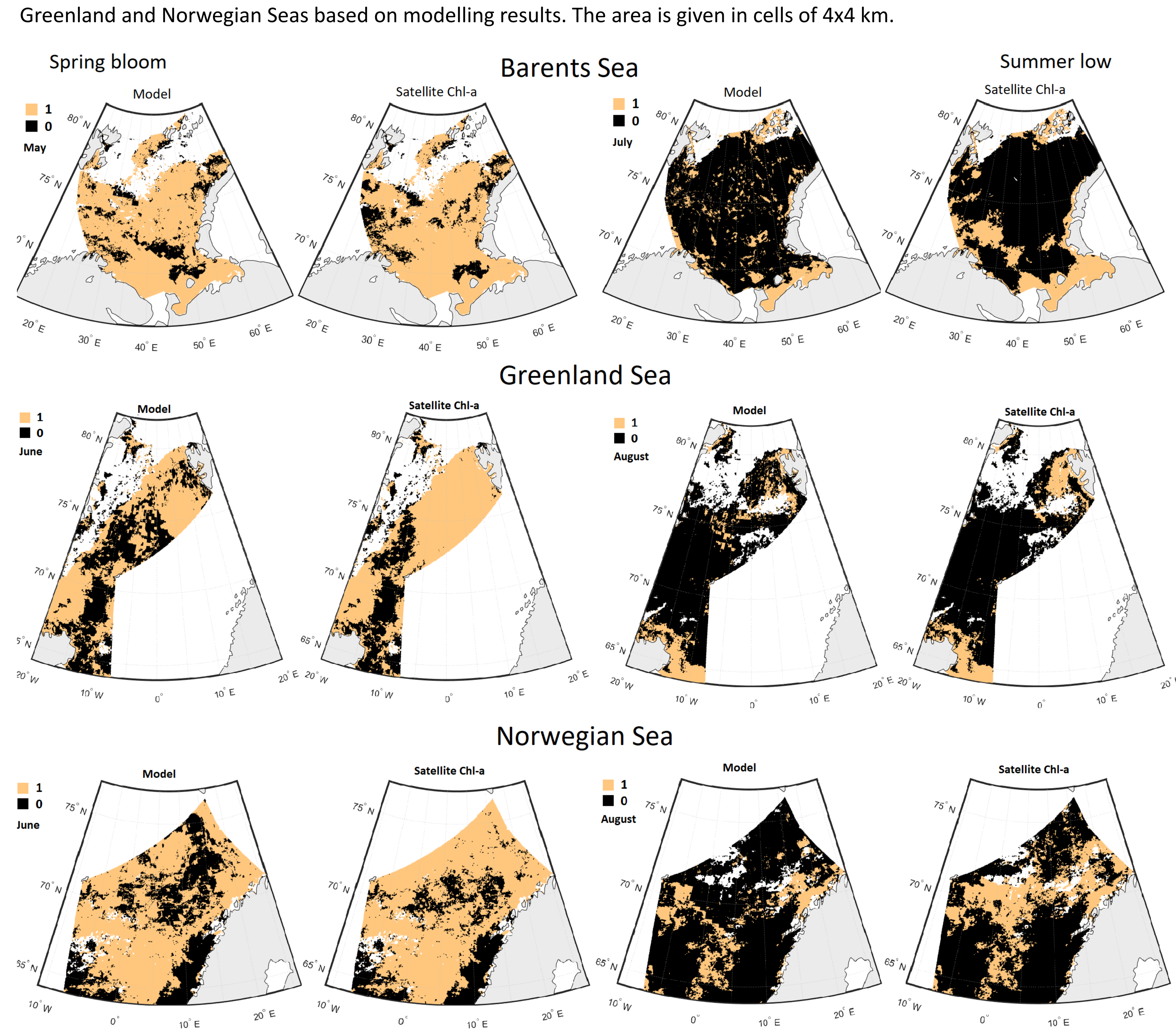


Fig. 3. The position of high-productivity zones (HPZ) during spring bloom and summer low months for all seas in 2019. Here "1" is a HPZ with a concentration of chlorophyll-a greater than 1 mg m^{-3}, "0" is low-productivity waters with a concentration of chlorophyll-a less than 1 mg m^{-3}.

CONCLUSIONS

This study shows that **Chl-a variability** (***Fig. 4***) is mostly determined by **light availability** (PAR and Zeu) and intrusions of **dynamically active warm, saline Atlantic waters** and **low-salinity river output and melting ice** (SST and SSS as indicators).

Our **models** show **good performance scores** and could be used to determine **high-productivity zones** in the **Arctic seas** in the future.

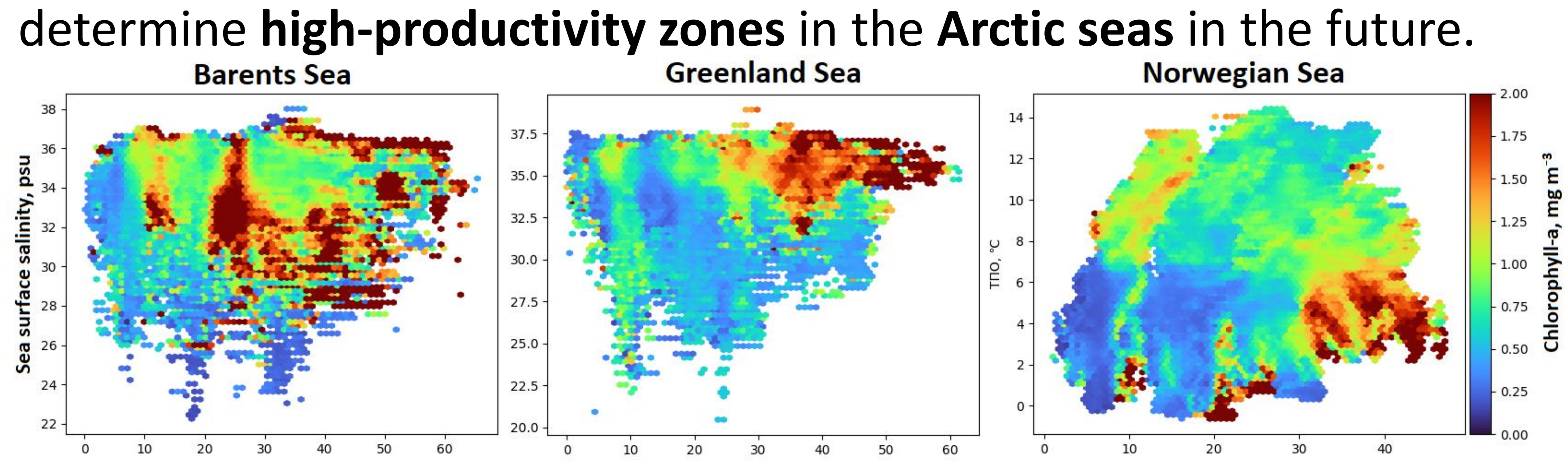


Fig. 4. Hexagonal scatterplots for the Greenland, Norwegian and Barents Seas for chlorophyll-a (colored) [mg m^{-3}] and sea surface salinity (SSS) [psu] and photosynthetically active radiation (PAR) [mol quant m^{-2} day^{-1}].