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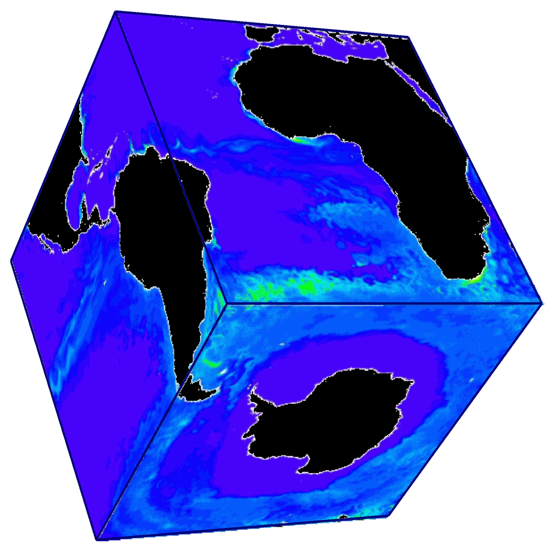
On the drivers of phytoplankton blooms in the Antarctic seasonal ice zone: a GCM approach



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Introduction

- The Antarctic seasonal ice zone (SIZ) has been found to support spring phytoplankton blooms on orders of magnitude greater than in neighboring open ocean waters.
- Hypothesis - Melting sea ice creates a shallow, stable pycnocline where phytoplankton communities can develop in the high-light, high-nutrient conditions.
- Approach – Ocean modeling may help elucidate the drivers of bloom dynamics due to difficulties of remote and *in situ* observation in the SIZ (Fig. 1).

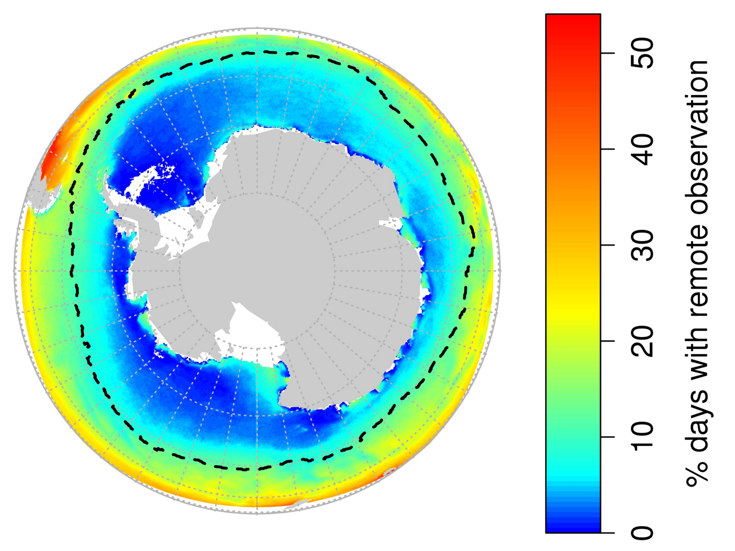

Figure 1. Fraction of days with remote estimates of Chl α from 1997-2007. Black dashed isocline indicates maximum extent of the SIZ for the entire period.

Methods

- Simulations - Conducted with the Massachusetts Institute of Technology Global Circulation Model (MITgcm) coupled with the Carbon and Nitrogen Regulated Ecosystem Model (CN-REcoM).
- Focus areas - Well correlated SIZ sub-areas to remotely-sensed estimates (Fig. 2).
- Analysis – Variable fields were subjected to an Empirical Orthogonal Function analysis (EOF) to extract the dominant temporal signal. Signals were then analyzed with a Generalized Additive Model (GAM) to assess their importance on phytoplankton dynamics (Fig. 3).

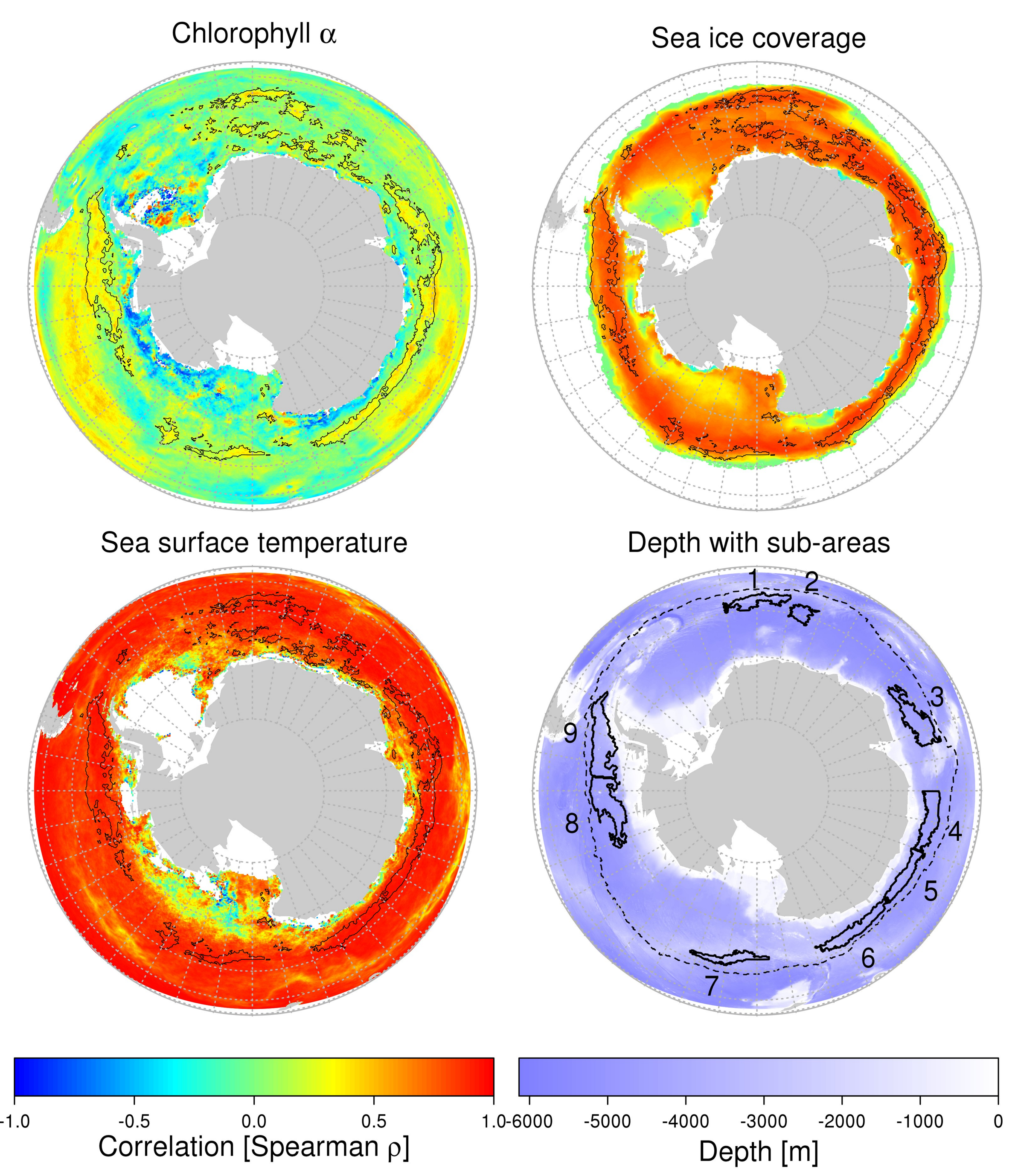

Figure 2. Correlation of simulated vs. remote sensing estimates for Chl α, SST, and sea ice coverage. Isoclines indicate areas of strong correlation among all three fields.

Nine sub-areas were selected for further statistical analysis (bottom right). Black dashed isocline shows the maximum extent of the SIZ.

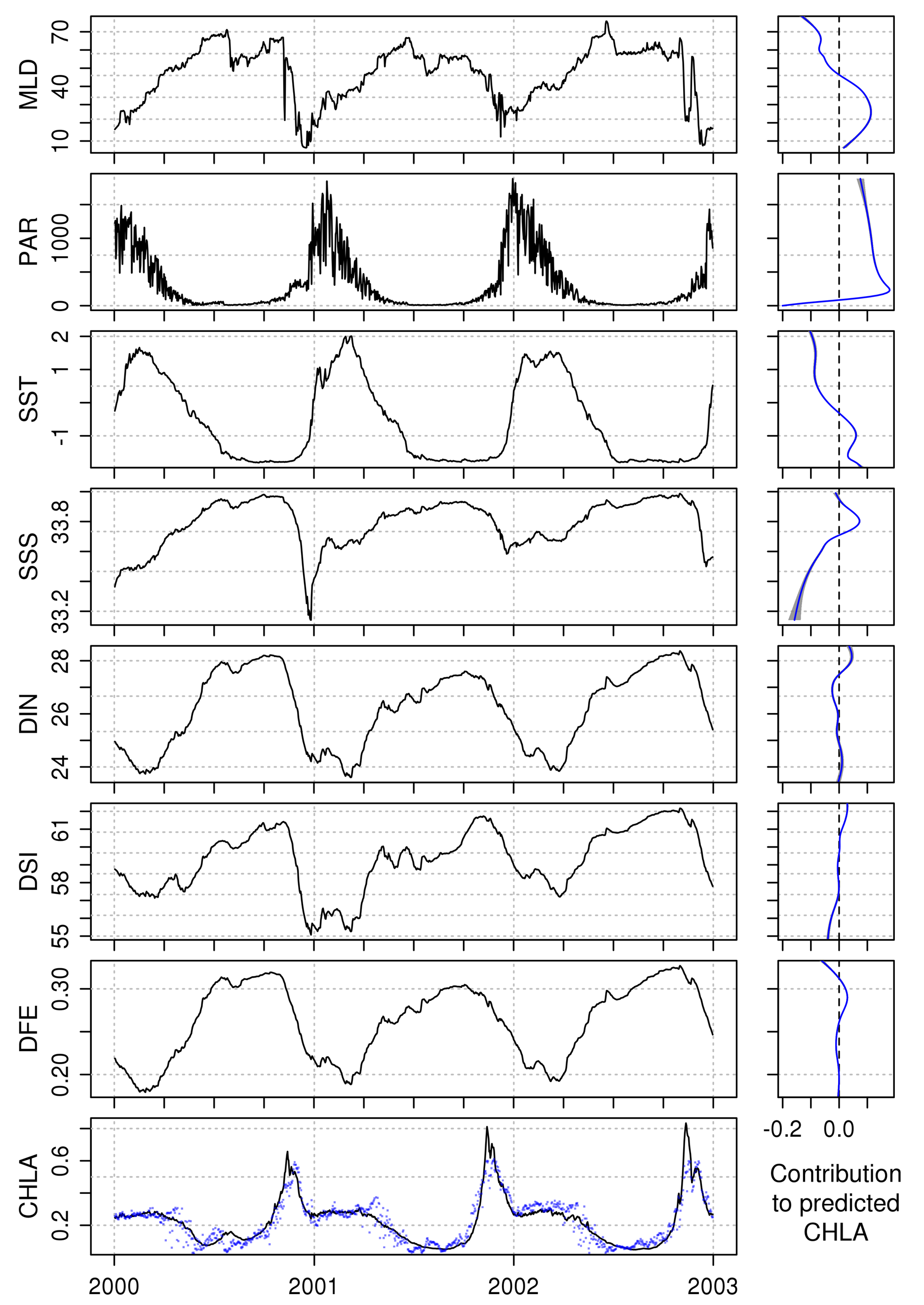

Figure 3. Example of fitted smooth terms predicting the CHLA time series from other covariates at a single grid location. GAM prediction shown as blue dots in CHLA time series.

Table 1. MITgcm variable descriptions

Abbreviation	Variable	Units
CHLA	Surface Chlorophyll α	mg m^{-3}
MLD	Mixed layer depth	meters
PAR	Integrated photosythetically active radiation (<MLD)	mol photons m^{-2} sec^{-1}
SST	Sea surface temperature	°C
SSS	Sea surface salinity	psu
DIN	Surface dissolved inorganic nitrogen	mmol m^{-3}
DSI	Surface dissolved silicate	mmol m^{-3}
DFE	Surface dissolved iron	μmol m^{-3}

Table 2. Significance of smooth terms

Term	df	ΔAIC	L-ratio	p-value
s(MLD)	8.15	942	946	<0.001
s(PAR)	7.16	4994	4998	<0.001
s(SST)	7.24	491	495	<0.001
s(SSS)	8.03	643	647	<0.001
s(DIN)	8.20	98	102	<0.001
s(DSI)	7.49	92	96	<0.001
s(DFE)	7.91	113	117	<0.001
R-sq.(adj) = 0.817 ; n = 5478				

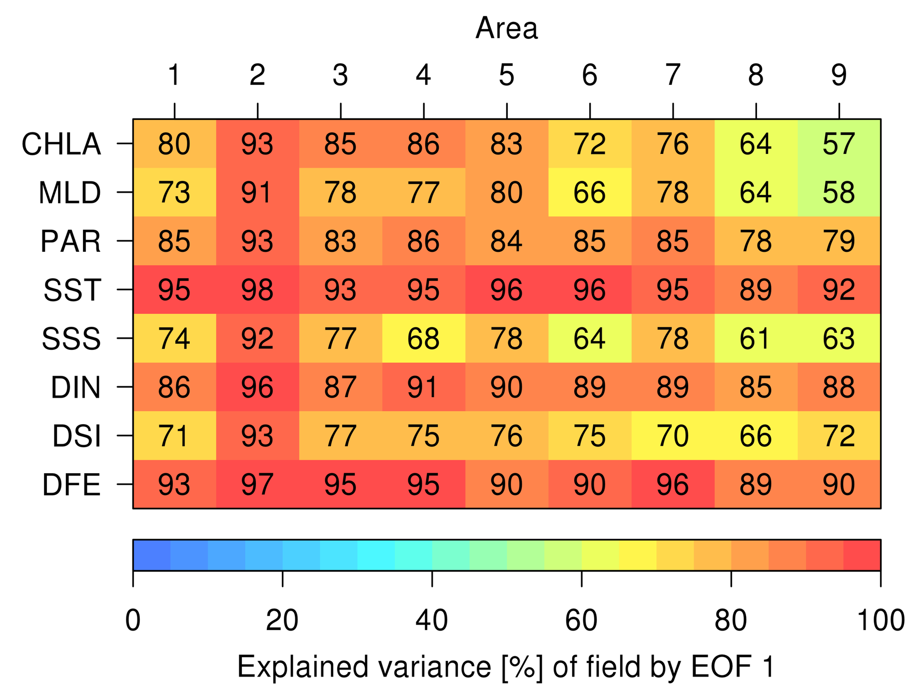

Figure 4. Explained variance of the leading EOF for each variable field.

Results

- Leading EOFs explain a large percent of each variable's spatio-temporal dynamics due to the relatively small spatial extent of sub-areas (Fig. 4).
- GAM results support the hypothesis that physical conditions best explain blooms dynamics (*i.e.* MLD, PAR) while nutrient limitation is of lesser importance (*i.e.* DIN, DSI, DFE) (Fig. 5).

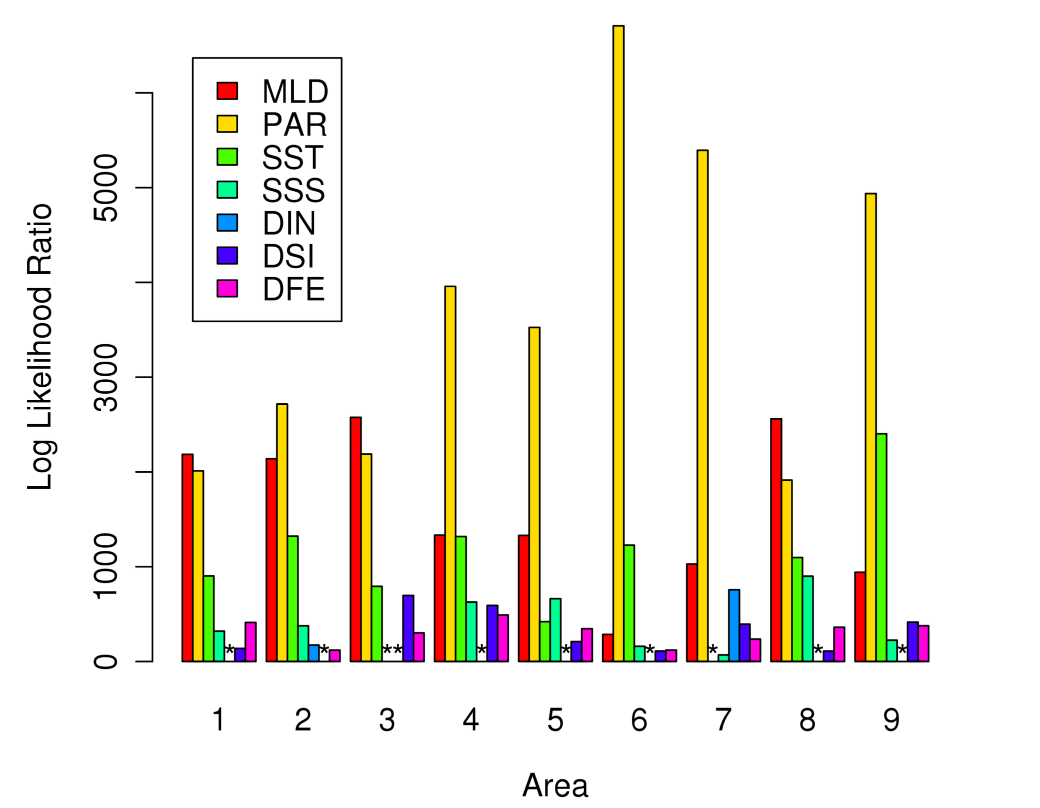

Figure 5. Log likelihood ratios of GAM model term inclusion. All terms are significant at the <<0.001 level.

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