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Challenges associated with operational modeling of low-oxygen water in Chesapeake Bay: results from a multiple modeling effort

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INTRODUCTION

Over the last half century, anthropogenic impacts have dramatically decreased water quality throughout the Chesapeake Bay. Improving the health of the Bay has become a priority for the U.S. federal government and the six states that make up the Bay watershed, and together they have committed to utilize a regulatory model to inform their management decisions. As ecosystem and water quality models are becoming increasingly used for operational forecasts as well as scenario-based management decisions, it is important to understand the strengths and limitations of existing models of varying complexity. The utilization of multiple models can also inform projections by providing independent confidence bounds for management decisions based on a regulatory model.

OBJECTIVE

Assess the viability of using models of varying complexity in operational and scenario-based water quality forecasting for the Chesapeake Bay.

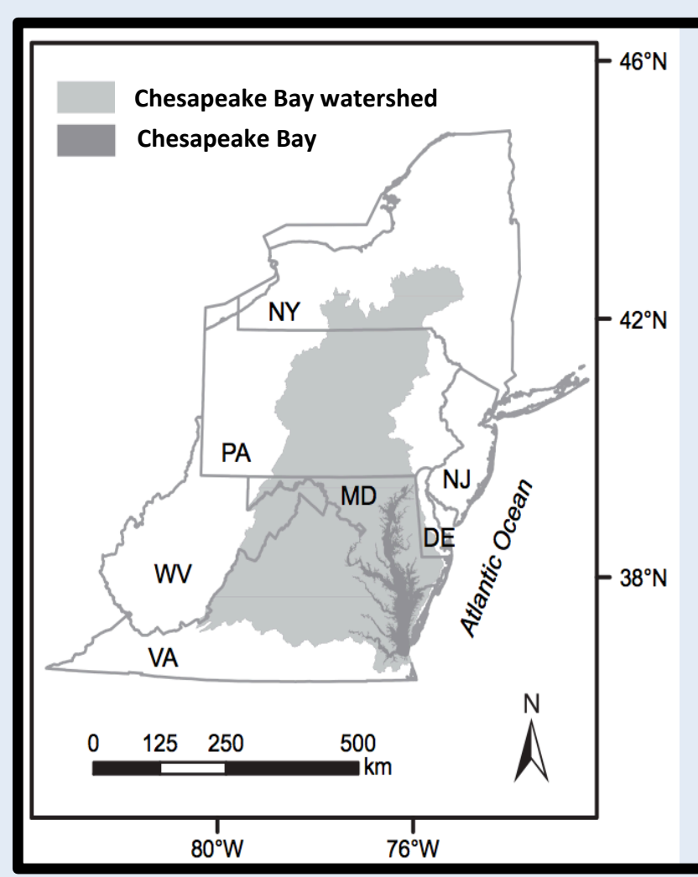

Figure 1. Map of the Chesapeake Bay and its watershed. (Najjar et al., 2010).

METHODS

Simulations of the Chesapeake Bay from six 3-D coupled hydrodynamic-oxygen models of varying complexity (Table 1) were statistically compared to each other and to historical monitoring data using root-mean squared differences (RMSD), bias, standard deviations, and correlation coefficients as illustrated on target and Taylor diagrams (*Joliff et al, 2009; Taylor, 2001*). Model skill for temperature, salinity, dissolved oxygen (DO), nitrate, and chlorophyll was assessed based on cruise data from the EPA's Chesapeake Bay Program for 2004 and 2005 from 13 stations along the main stem of the Bay (Fig. 2). Stations were sampled on 34 cruises: twice a month from April to August and once a month for the remainder of the year. The focus on DO concentrations in this research is because DO is the primary indicator used by regulatory agencies in assessing the health of the Chesapeake Bay.

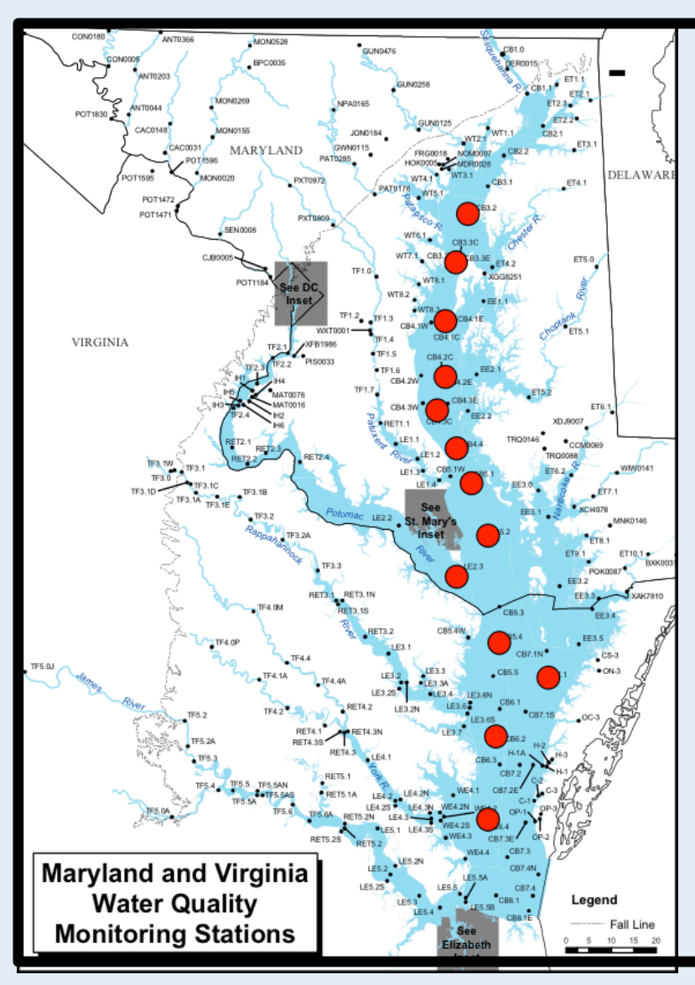

Figure 2. Location of the 13 Chesapeake Bay Program monitoring stations utilized in the study.

MODELS

Six models were used in this study that all couple a hydrodynamic component to a biogeochemical (BGC) component of varying degrees of complexity or to a single, 1-term oxygen variable. CH3D-ICM is the regulatory water quality model used by the EPA's Chesapeake Bay Program. The other five models, including CBOFS (Chesapeake Bay Operational Forecasting System, NOAA-CSDL), have hydrodynamic components built upon the community-based Regional Ocean Modeling System (ROMS). ChesROMS-ECB, ROMS-RCA, and ChesROMS-BGC include a full suit of biogeochemical interactions throughout the water column. CBOFS and ChesROMS-1term both only include dissolved oxygen as a tracer based on a constant respiration rate. CBOFS has higher horizontal resolution than the other ROMS models.

	CH3D-ICM	ChesROMS-ECB	ChesROMS-BGC	ROMS-RCA	CBOFS-1term	ChesROMS-1term
Institute	EPA	VIMS	UMCES	UMCES	NOAA	WHOI
BGC?	Yes	Yes	Yes	Yes	No	No
XY - Grid	0.25 - 1km^2	~ 1km^2	~1km^2	~ 1km^2	~ 0.3km^2	~ 1km^2
Z - Grid	z: ~ 5ft	σ: 20 layers	σ: 20 layers	σ: 20 layers	σ: 20 layers	σ: 20 layers

Table 1. Characteristics of the individual models.

ANALYSIS

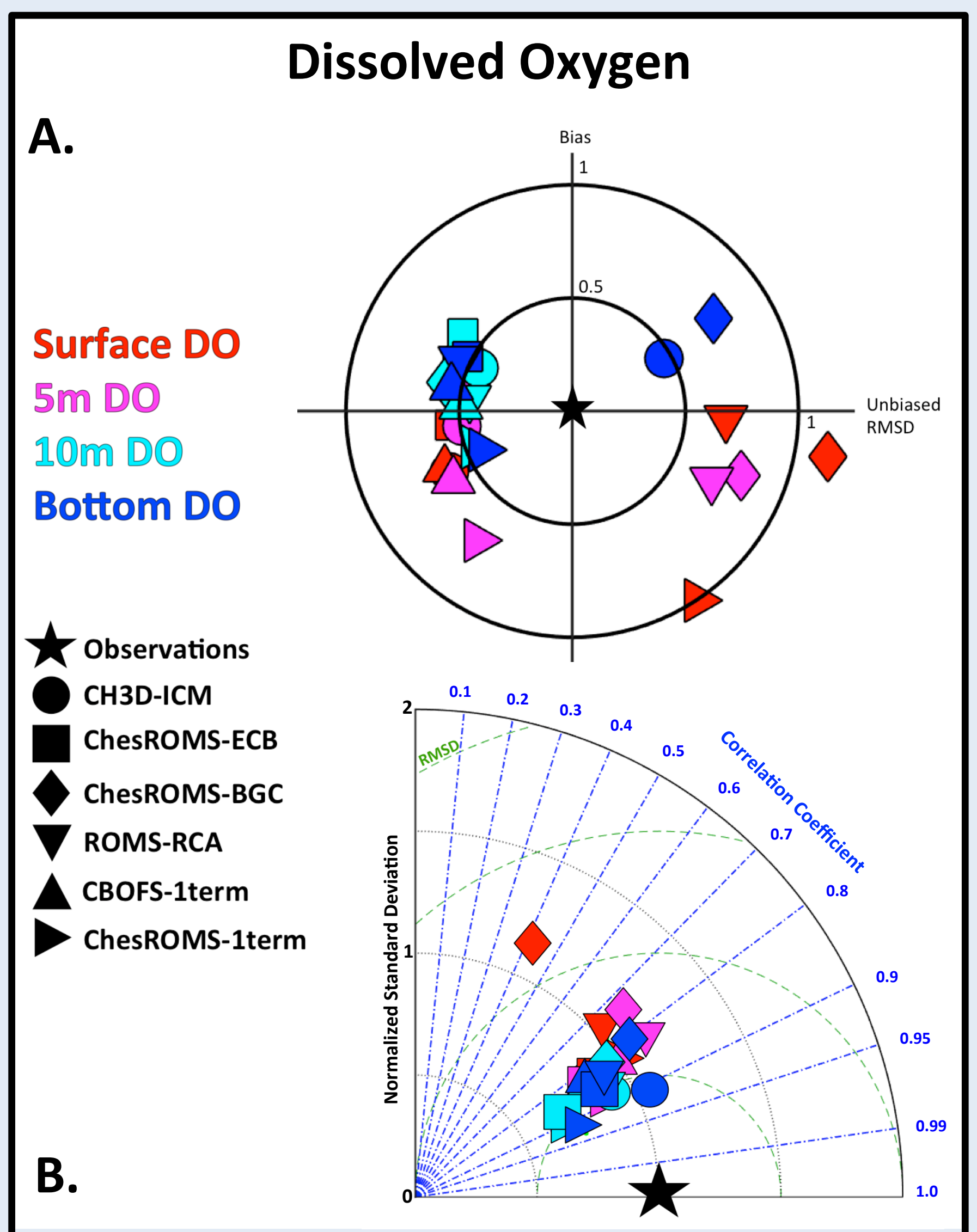

Figure 3. Normalized (A) target diagram and (B) Taylor diagram demonstrating how well the models resolve the mean spatial and temporal variability of DO at the surface, 5m depth, 10m depth, and bottom.

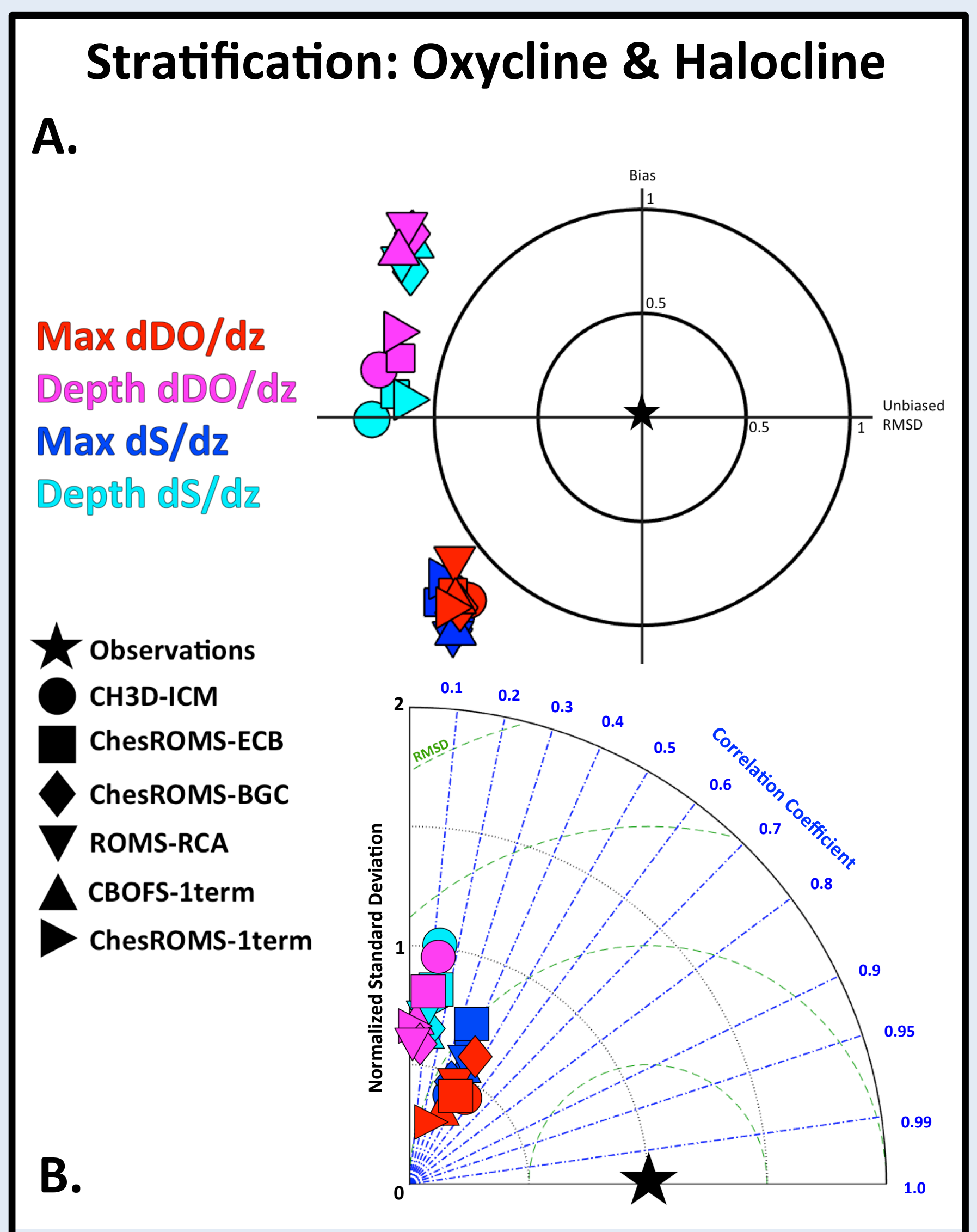

Figure 5. Normalized (A) target diagram and (B) Taylor diagram demonstrating how well the models resolve the mean spatial and temporal variability of maximum stratification (halocline and oxycline) and depth of stratification.

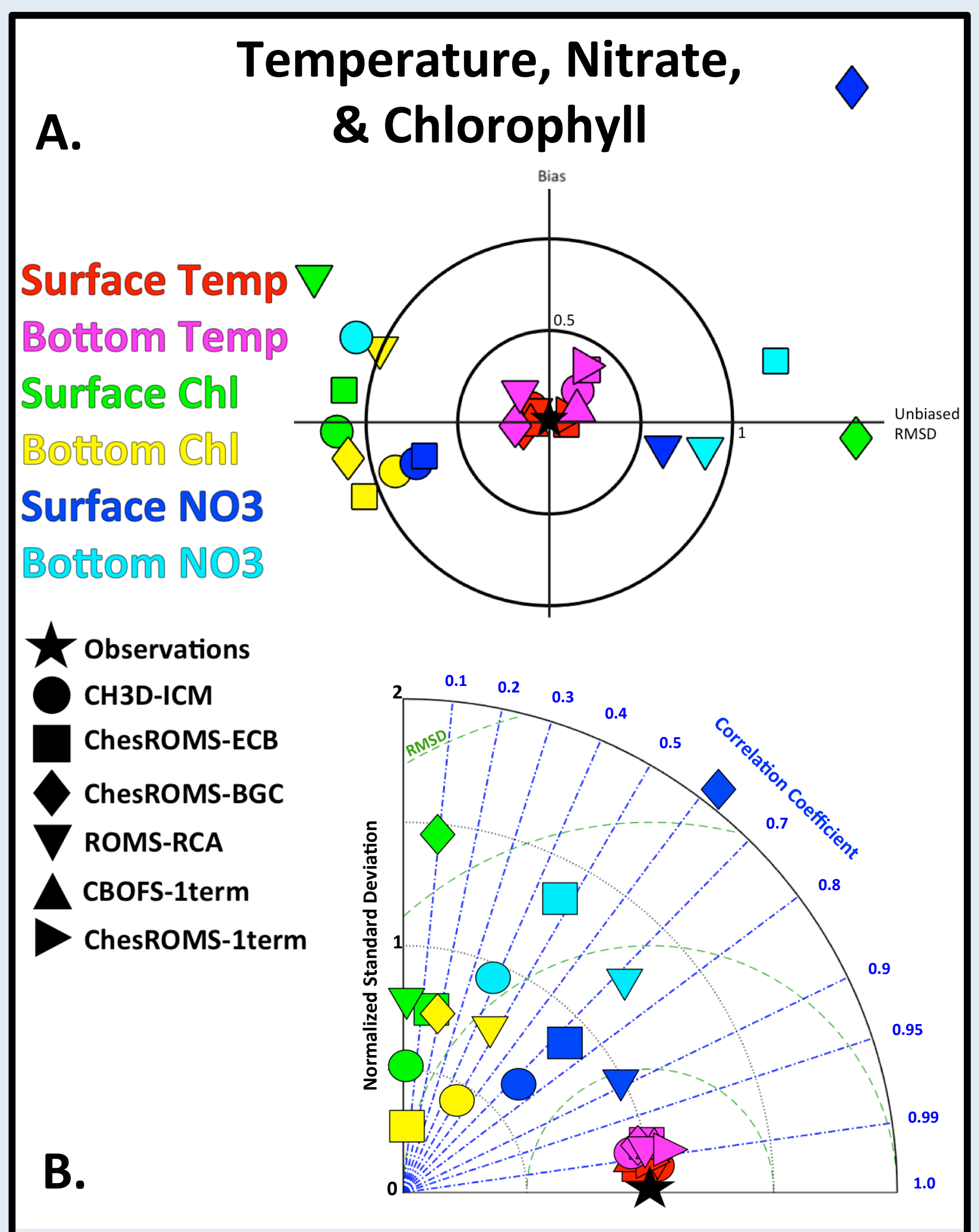

Figure 7. Normalized (A) target diagram and (B) Taylor diagram demonstrating how well the models resolve the mean spatial and temporal variability of surface and bottom temperature, nitrate (BGC models), and chlorophyll (BGC models)

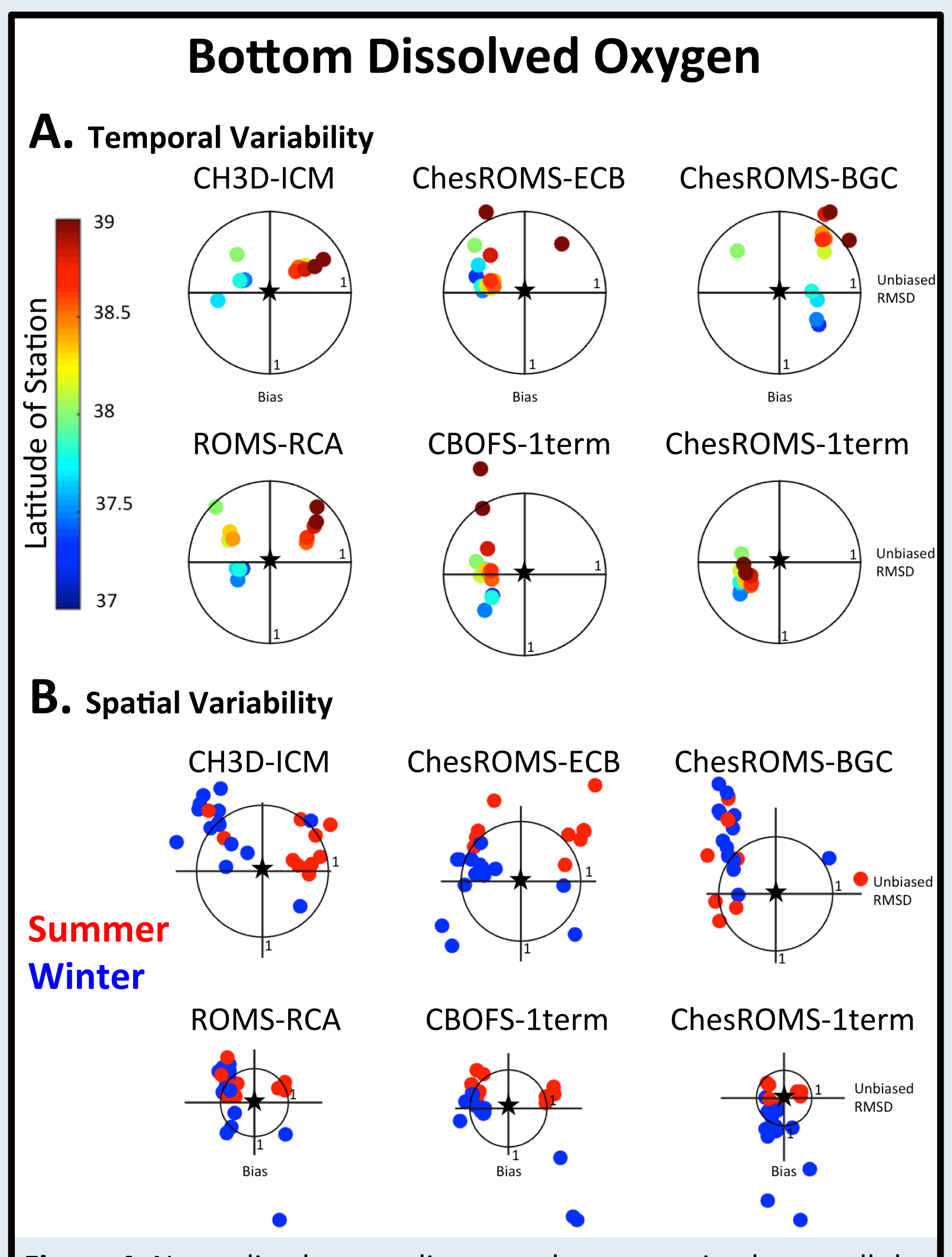

Figure 4. Normalized target diagrams demonstrating how well the models resolve the (A) temporal and (B) spatial variability of bottom DO. Dots in (A) represent observation stations. Dots in (B) represent the month. Red: May-Sept. Blue: Oct-April.

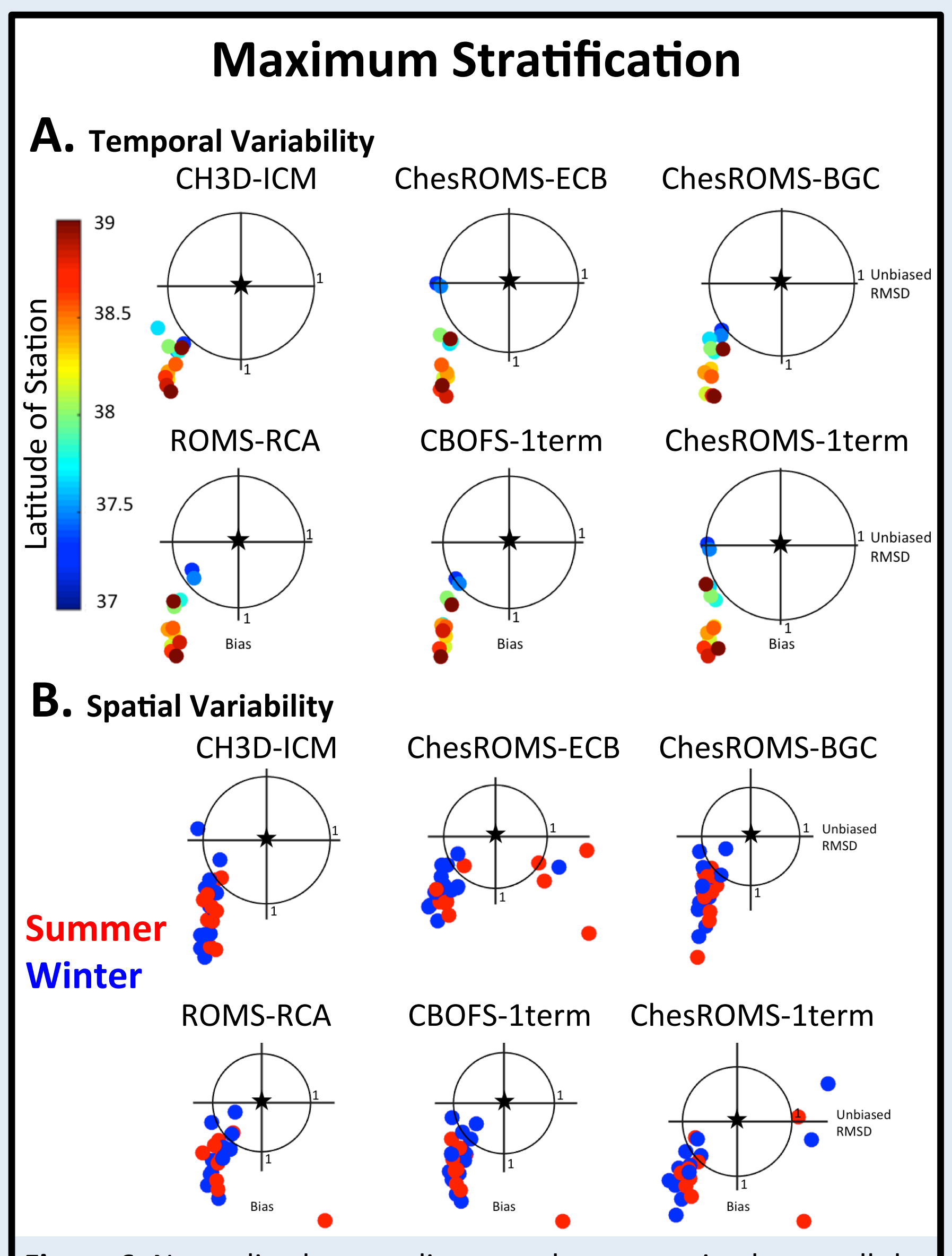

Figure 6. Normalized target diagrams demonstrating how well the models resolve the (A) temporal and (B) spatial variability of stratification. Dots in (A) represent observation stations. Dots in (B) represent the month. Red: May-Sept. Blue: Oct-April.

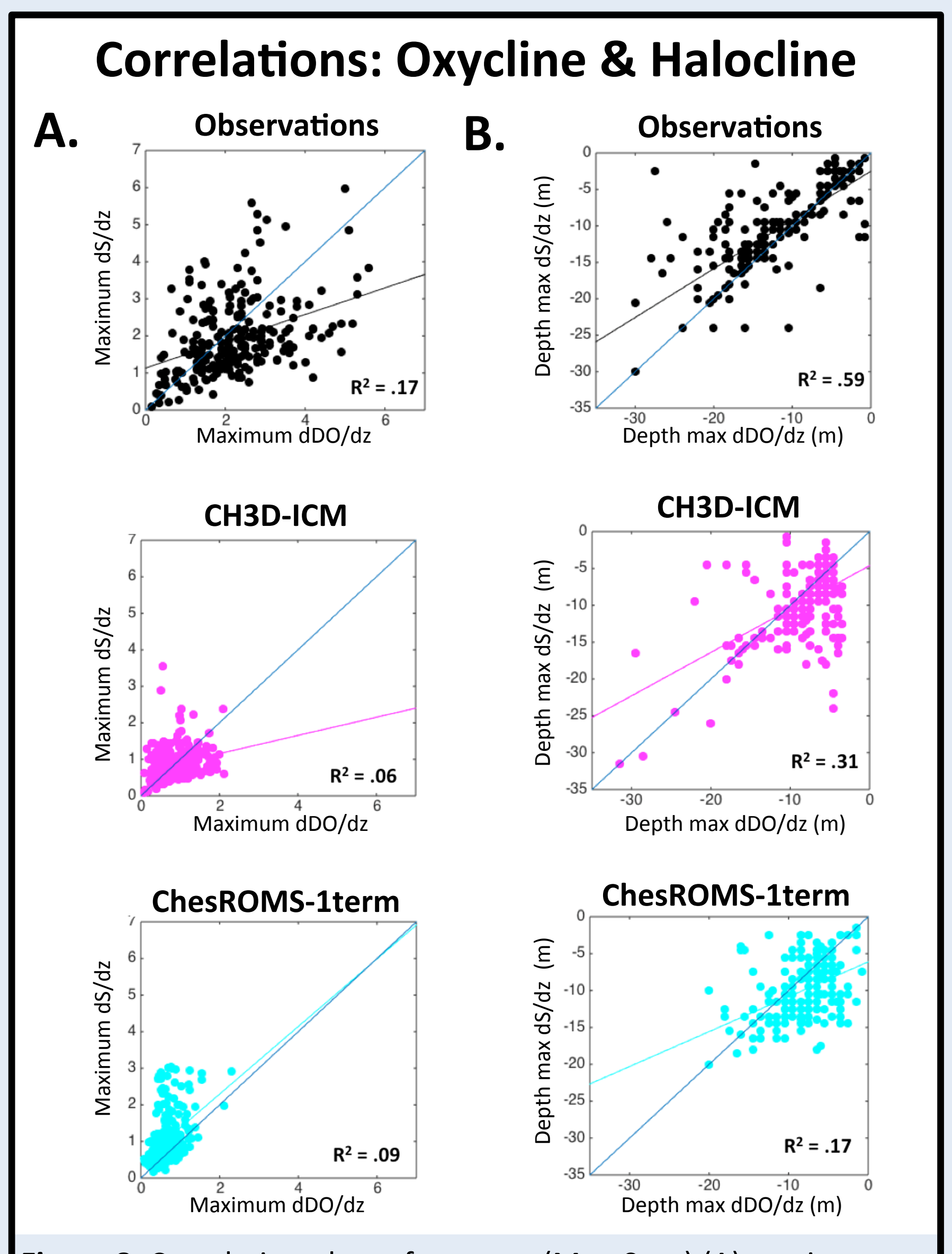

Figure 8. Correlation plots of summer (May-Sept) (A) maximum dDO/dz vs maximum dS/dz and (B) depth of maximum dDO/dz vs depth of maximum dS/dz for observations (black), CH3D-ICM (magenta), and ChesROMS-1term (cyan). All p-values << 0.05.

RESULTS

- All models have significant skill in reproducing bottom DO (Fig. 3), and specifically resolve the mean and seasonal variability of bottom DO well (Fig. 4a), but have difficulty resolving spatial variability (Fig. 4b).

  → ***Simple constant-biology models reproduce bottom DO as well as models that include complex biogeochemical processes.***

- All models underestimate the maximum strength of the oxycline and halocline and place the depth of stratification too high in the water column (Figs. 5 & 6). Stratification too high in the water column results in DO being underestimated relatively near the surface (Fig. 3a).
- All models successfully reproduce temperature, but have difficulty resolving the variables typically thought to be the main drivers of DO variability, e.g. stratification, nitrate, and chlorophyll (Fig. 7).
- Observations demonstrate a stronger correlation between the depths of the oxycline and halocline than between their magnitudes (Fig. 8).

  → ***To adequately model hypoxia throughout the water column, it is more important for models to successfully simulate the depth of stratification than the magnitude of stratification.***

CONCLUSIONS

These findings have significant ramifications for short-term bottom DO forecasts, which may be successful with very simple oxygen parameterizations. On the contrary, scenario-based water quality forecasts are likely to benefit from more complex models, which must adequately reproduce the correct response of the oxygen field to changes in nutrients and organic matter. This study suggests that a key factor for resolving hypoxic conditions throughout the water column is the ability of models to adequately resolve the depth of stratification, rather than the absolute strength of stratification (as long as modeled dS/dz is strong enough to limit vertical mixing). This is critical because the observations show that during hypoxic events, low dissolved oxygen water will fill the water column up to where stratification limits further mixing. This effectively cuts off waters below the depth of maximum stratification for use by the majority of Bay main stem living resources during the summer months. This study also helps to demonstrate how multiple community models can be used together to provide independent confidence bounds for management decisions based on regulatory model results.

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