Seasonal Prediction of Bottom Temperature on the Northeast U.S. Continental Shelf

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I. Motivation

During the recent decades, the northeast US continental shelf (NES) ecosystem has experienced significant changes as a result of climate-scale changes in the physical environment. Shifts in fish stock distribution and production in the Gulf of Maine have been directly linked to changes in water temperature. A reliable prediction of NES environmental variables, particularly ocean bottom temperature, could lead to a significant improvement in demersal fisheries management.

However, the current generation of climate model-based predictions of ocean temperature have realized only limited prediction skill in the coastal shelf regions, especially in NES. There is therefore a need for skillful predictions of ocean bottom temperature using an alternative approach, e.g., statistical models, along with improved understanding of the causes of its variability, to potentially inform fisheries stock assessment and management strategies.

II. Data & Study region

The data used in the statistical prediction of the NES bottom temperature in this study is based on the GLORYS12v1 product [*Lellouche et al.*, 2018], which is a global ocean eddy-resolving (1/12° horizontal resolution and 50 vertical levels) data assimilated hindcast from Mercator Ocean, covering the altimetry era (1993-2018). This reanalysis dataset has been validated through multiple comparisons with obs.

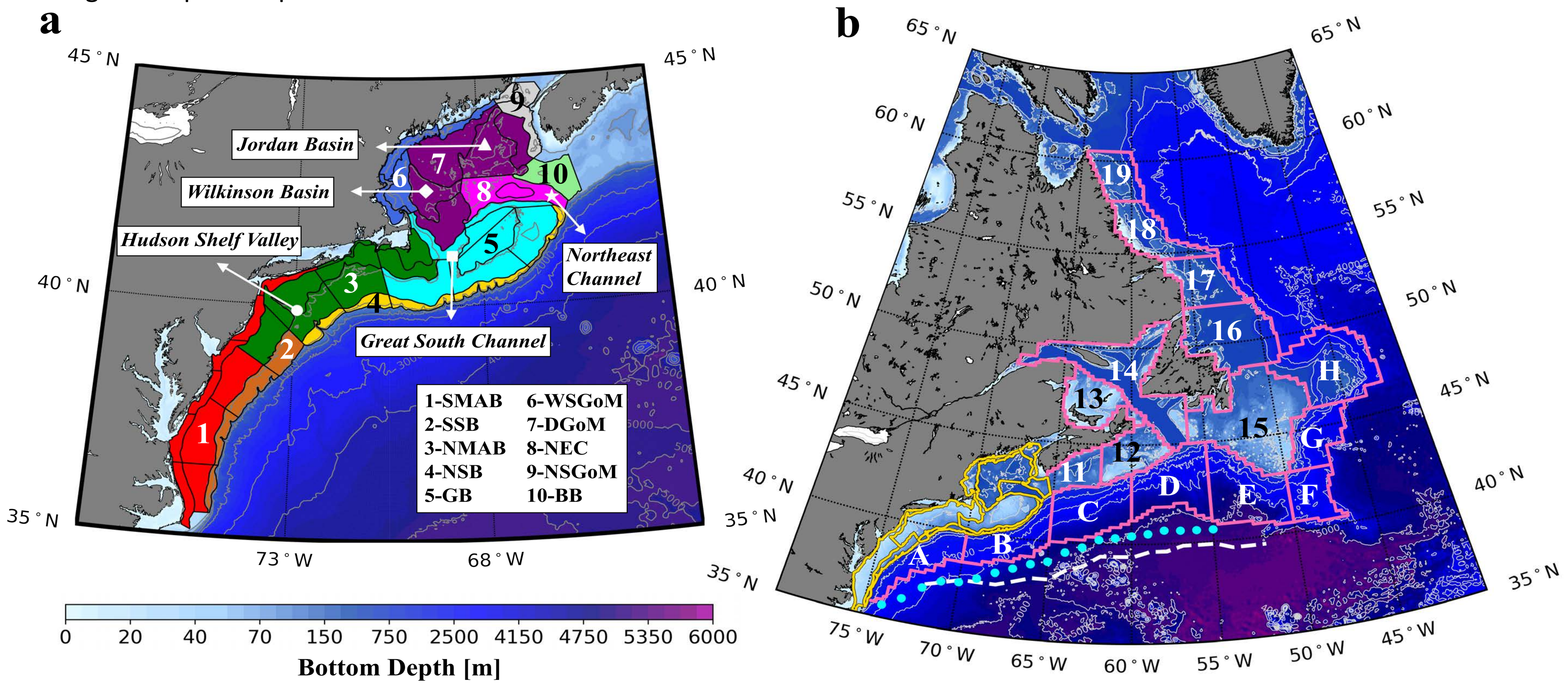

Figure 1. The Northeast U.S. continental shelf (NES; **a**) and the Northwest Atlantic (NWA) continental shelf and slope (**b**).

Here, 47 EcoMon strata are grouped into 10 subregions to be used for statistical prediction:

Box01 - Southern MAB (SMAB); Box02 - Southern shelfbreak (SSB); ***Box03 - Northern MAB (NMAB);*** Box04 - Northern shelfbreak (NSB); Box05 - Georges Bank (GB); Box06 - Western Shallow GoM (WSGoM); ***Box07 - deep GoM (DGoM); Box08 - Northeast Channel (NEC);*** Box09 - Northern Shallow GoM (NSGoM); Box10 - Browns Bank (BB).

Bottom Temperature Anomaly (BTA) of these subregions as well as the following broader subregions are used as the predictors:

Slope Boxes A, B, C, D, E, F, G, and H; Box11 - Western Scotian Shelf (WSS); Box12 - Eastern Scotian Shelf (ESS); Box13 - Southern Gulf of St. Lawrence (SGSL); Box14 - Northern Gulf of St. Lawrence (NGSL); Box15 - Newfoundland Shelf (NFL); Box16 - Northern Newfoundland Shelf (NNFL); Box17-19 - Labrador Shelf (LS);

Model Validation Processes & Prediction Skill Assessment:

To avoid overfitting the statistical models, we performed a 12-fold cross-validation. Prediction skill is accessed between the cross-validated forecast and original BTA time series for the target region and forecast month.

- *Anomaly Correlation Correlation (**ACC**)*
- *Root Mean Square Error (**RMSE**)*
- *Brier Skill Score (**BSS**; relative to the base model)*

III. Results and Discussions

A. The Local Persistence Model (*Predictor - **Local Persistence of BTA***):

$$\widehat{BTA}_i(t) = \alpha \cdot BTA_i(t-\tau) + c$$

i = subregion number, e.g., box03 - NMAB; t = forecast month from Jan to Dec; τ = lead months from 1 to 12; α, c are coefficients.

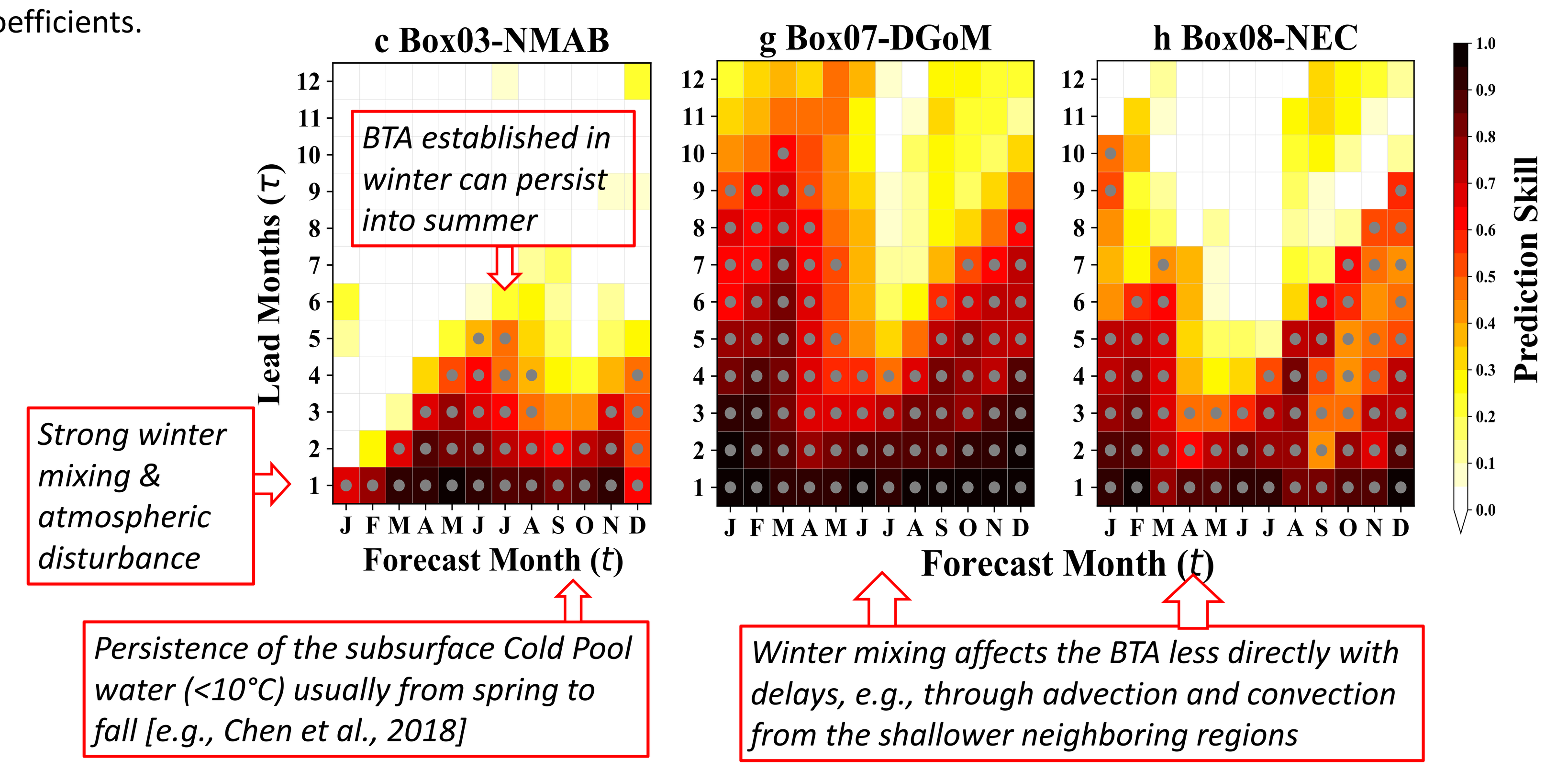

Figure 2. ***Local Persistence yields significant prediction skills for lead time up to several months.*** The prediction skill indicated by the anomaly correlation coefficient (ACC). The x-axis represents target forecast month (t), and y-axis represents lead months (τ). The grey dots in each panel indicate that the ACC is significant at the 95% confidence level.

B. The Persistence-Advection Model (*Predictor - **Local or Nonlocal BTA***): $\widehat{BTA}_i(t) = \alpha \cdot BTA_j(t-\tau) + c$

i, j = subregion number, e.g., box03 - NMAB; when $j = i$, it equals the local persistence model; t = forecast month from Jan to Dec; τ = lead months from 1 to 12; α, c are coefficients.

- ***Markers***: prediction skill > 95% confidence level;
- ***Gray dots***: local persistence dominates;
- ***Triangles***: prediction skill is higher than the local persistence model;
- ***Black triangles***: significantly (>95% confidence level) higher than the local persistence model;
- ***Numbers and alphabets***: the best nonlocal predictor's locations.

- Significant improvements have been achieved using this model in all subregions;
- On average, the **NMAB** shows the most improvement among the subregions;
- While the **DGoM** shows the least improvement, as its local persistence model already showed strong performance;
- Most of significant improved skills in **NEC** are for summer forecast months at a lead time of 3-12 months from slope regions;
- Most of those best nonlocal predictors are located along the **upstream advective paths and/or within neighboring sub-regions**, indicating the advective pathways of subsurface temperature anomalies

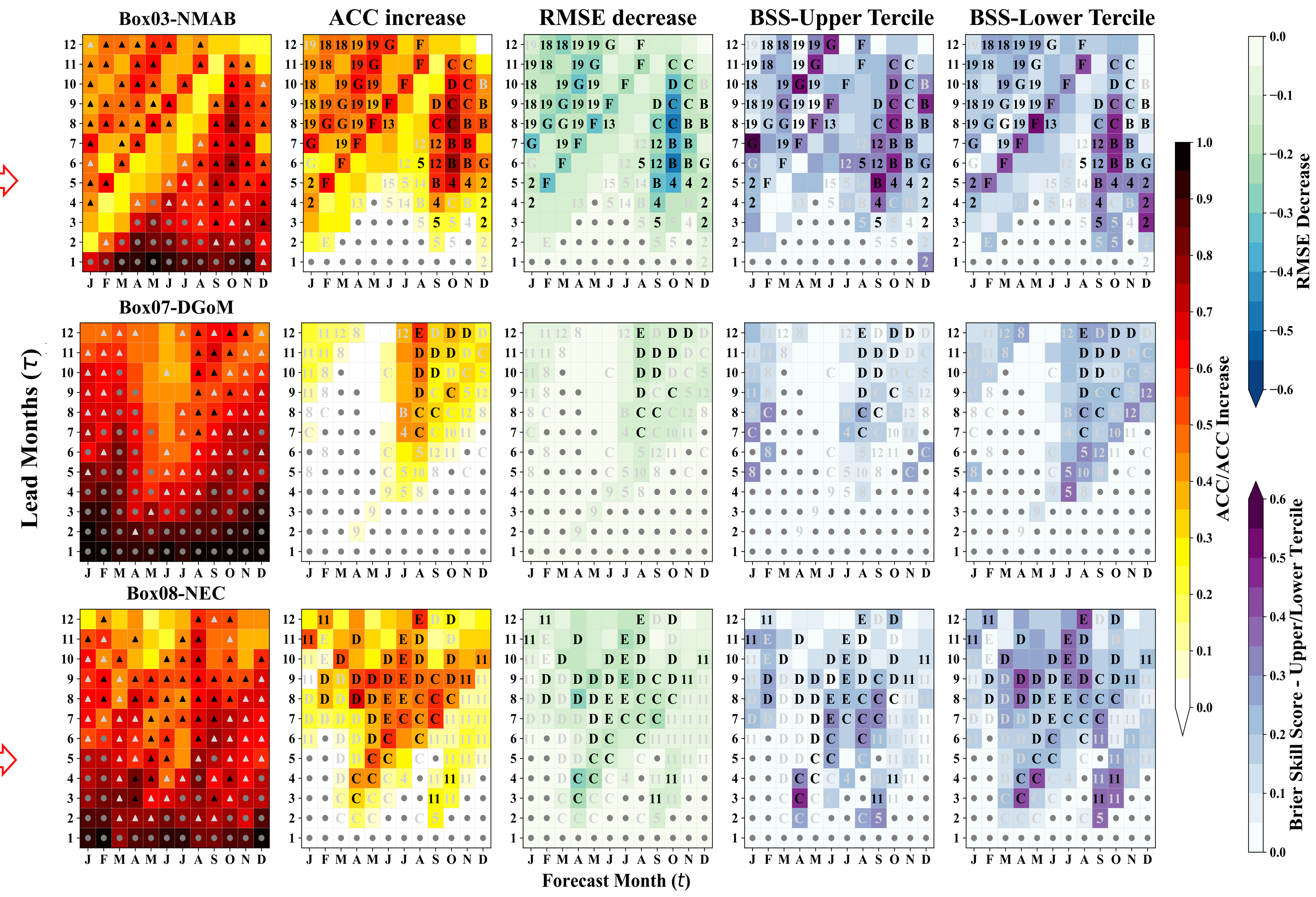

Figure 3. ***Nonlocal predictors largely improves the prediction skills.*** The prediction skill for three subregions, i.e. (top row) box03-NMAB, (middle row) box07-DGoM, and (bottom row) box08-NEC, represented by the ACC prediction skill of the persistence-advection model, as well as the skill improvement relative to the local persistence model based on the ACC (i.e., persistence-advection minus local persistence), RMSE, and the Brier Skill Score for upper and lower terciles.

C. The Gulf Stream Index Model and NAO Index Model (*Predictor - **GSI or NAOI***): $\widehat{BTA}_i(t) = \alpha \cdot X(t-\tau) + c; X = GSI \text{ or } NAOI$

- **SSH-based GSI** (1993-2018) *Pérez-Hernández & Joyce (2014);*
- **T200-based GSI** (1954-2018; Gulf Stream North Wall Index) *Joyce et al. (2009); EN4 Dataset;*
- **NAO Index** (1950-2018) *Barnston and Livezey (1987);*

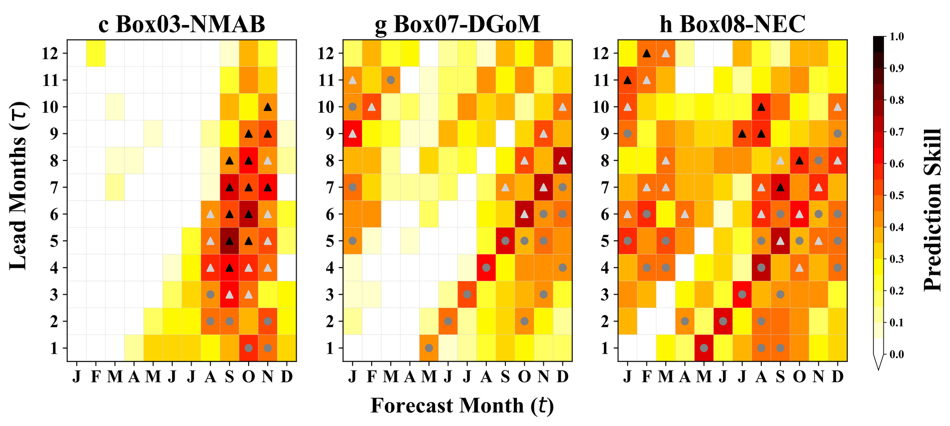

Figure 4. The prediction skill of the 200-m temperature-based GSI model in subregions.

- BT of NMAB has a seasonally dependent relationship to the GSNW position (T200-GSI);
- T200-GSI signal initiating in April is identified as a significant predictor in DGoM and NEC;
- SSH-based GSI and NAOI show very limited skill for all forecast months on lead months within a year, as T200-based GSI reflects the meridional variability of the GSNW that contains the effects from warm core rings and GS meanders; while SSH-based GSI mainly captures the variability of GS main axis.

D. The Persistence-Advection Model with GSI or NAOI (*Predictor - **Local or Nonlocal BTA or GSI or NAOI***):

$$\widehat{BTA}_i(t) = \alpha \cdot X(t-\tau) + c; X = BTA_j, GSIs, \text{or } NAOI$$

- This further generalized model results in limited improvement relative to the original persistence-advection model, and improved skills are not significantly different at 95% confidence level.

E. Spatial Persistence-Advection Model (*Use each grid points as a predictor*)

$$\widehat{BTA}_i(t) = \alpha \cdot BTA_{x,y}(t-\tau) + c$$

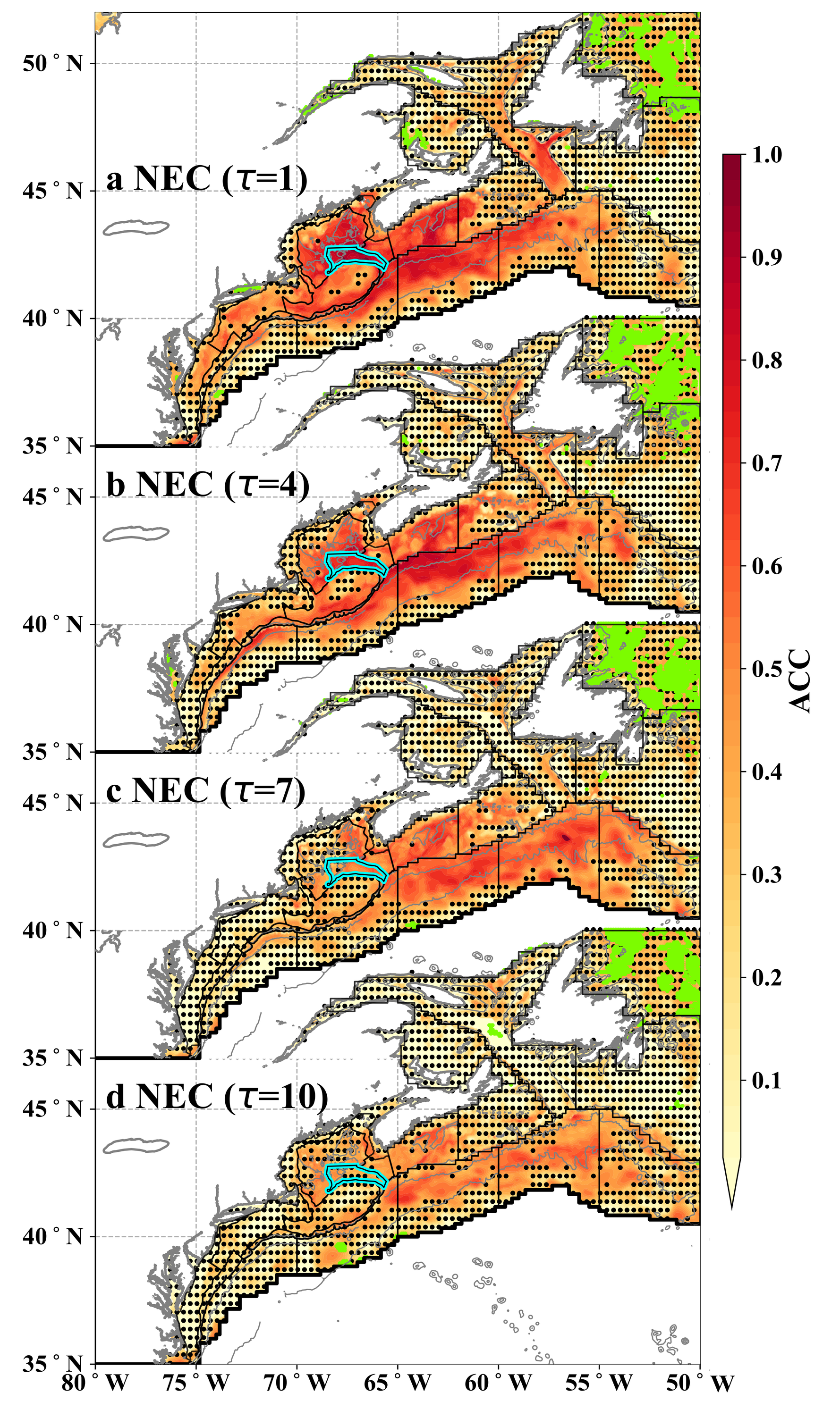

Figure 5. Spatial patterns of the maximum prediction skill when each grid point is used as a predictor ***to illustrate advective signal*** in the persistence-advection model for the target box 08-NEC at a lead time of (**a**) 1 month, (**b**) 4 months, (**c**) 7 months, and (**d**) 10 months.

IV. Conclusions

- *Local Persistence Model:* $\hat{T}_i(t) = \alpha \cdot T_i(t-\tau) + c$
- *Persis.-Advection Model:* $\hat{T}_i(t) = \alpha \cdot T_j(t-\tau) + c$ ♥
- *T200-GSI Model:* $\hat{T}_i(t) = \alpha \cdot GSI_{T200}(t-\tau) + c$
- *SSH-GSI Model:* $\hat{T}_i(t) = \alpha \cdot GSI_{SSH}(t-\tau) + c$
- *NAO Index Model:* $\hat{T}_i(t) = \alpha \cdot NAO(t-\tau) + c$

- Overall, the combination of **local** and **nonlocal** bottom temperatures lead to significant improvements in prediction skill of bottom temperature anomaly in NES;
- The best nonlocal predictors are mainly located in the **neighboring** or **upstream** regions, which indicates the subsurface temperature advection;
- The use of T200-based GSI also improved the skill, but the improvements were confined to **fall** forecast months and were **not** significantly better than those nonlocal BT predictors.

References

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