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Probabilistic bias adjustment of seasonal predictions of Arctic Sea Ice Concentration*

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MOTIVATION

- **Seasonal predictions** of Arctic sea ice concentration (SIC) are key to **mitigate** the negative impact and **assess** potential opportunities posed by the **rapid decline** of Arctic sea ice coverage.
- Seasonal predictions produced with **climate models** have **systematic biases** and complex spatio-temporal errors that grow with forecast **lead time**.
- **Operational** forecast are routinely **bias corrected** and **calibrated**.
- Arctic sea ice predictions are mainly corrected based on **one-to-one deterministic post-processing** methods.
- **Decision-making** requires proper **quantification of uncertainty** and **likelihood of events**, particularly of extremes.

MOTIVATION

- Seasonal predictions of Arctic sea ice concentration (SIC) is key to mitigate the negative impact and assess potential opportunities posed by the rapid decline of sea ice coverage.
- Seasonal predictions are based on statistical models, which are highly sensitive to model errors and uncertainties.
- Operational forecasting requires a reliable and robust model.
- Arctic sea ice predictions are mainly corrected based on one-to-one deterministic post-processing methods.
- Decision-making requires proper quantification of uncertainty and likelihood of events, particularly of extremes.

We introduce a probabilistic bias correction scheme based on a conditional Variational Autoencoder (cVAE).

PROBLEM STATEMENT

t : initialization time, l : lead time

- **Goal:**

Learn probabilistic mapping from biased *ensemble mean predictions* $\bar{x}_{tl}$ to an *observational distribution* $p(y|\bar{x}_{tl})$ conditioned on $\bar{x}_{tl}$

- **Learning objective:**

Maximize the likelihood of the observation y_{tl} in the distribution $p(y|\bar{x}_{tl})$: $(\text{Max log } p(y = y_{tl}|\bar{x}_{tl}))$

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- **Generative Framework:**

- cVAE learns the conditional distribution of data using latent variable z with prior distribution $p_{\omega}(z|\bar{x}_{tl})$:
 $N(\mu_{\text{NN}_{\omega}}(\bar{x}_{tl}), \sigma_{\text{NN}_{\omega}}(\bar{x}_{tl}))$

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- Optimizes the **Evidence Lower Bound** as the surrogate objective (ELBO):

$$\log p(y = y_{tl}|\bar{x}_{tl}) \geq -KL(q_{\phi}(z|y_{tl}, \bar{x}_{tl}) || p_{\omega}(z|\bar{x}_{tl})) + \mathbb{E}_{q_{\phi}(z|y_{tl}, \bar{x}_{tl})}[\log p_{\theta}(y = y_{tl}|z, \bar{x}_{tl})]$$

- KL is the Kullback–Leibler Divergence regularizing the latent space and the expectation term is the reconstruction loss being proportional to Mean Square Error (MSE) for a Gaussian Distribution
- Distributions are parametrized as Gaussians distributions using neural networks with parameters θ, ϕ and ω .

DATA

Model:

- Retrospective **12-months forecasts** of Arctic SIC from CanSIPS^{*} v3's **CanESM5** during 1980 to 2021.
- Each forecast consists of **10 ensemble members**
- predictions remapped to the standard 1×1 grid on latitudes above 50° North.
- 1980- 2015 used for training, 2015-2018 for validation, and 2019-2020 as test sample

Observation:

- **Satellite-based NOAA/NSIDC** Climate Data Record of passive microwave SIC v4 during 1980 to 2021.
- Remapped and sampled at the same locations and times instances

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RESULTS

nadj : bias adjusted outputs from cVAE (**100 members**)

badj : benchmark lead time dependent climatological mean adjustment (**10 members**)

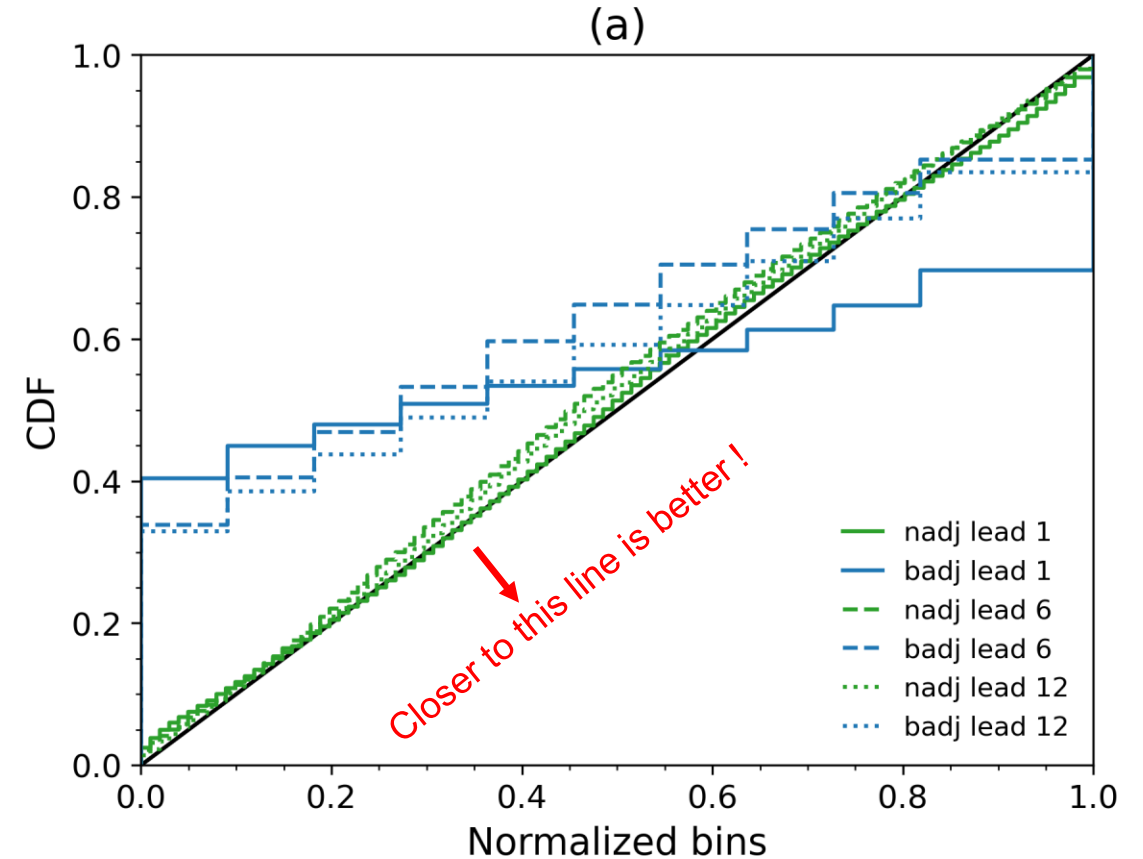
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Probabilistic metrics:

1. Cumulative Distribution Functions (CDF) of rank histograms
 - In a **well-calibrated forecast ensemble**, the verification data should be indistinguishable from any member of the ensemble.
 - This corresponds to **a flat rank histogram** and **a 1:1 CDF**
 - reported at critical marginal ice grid cells ($0.15 \leq \text{SIC} \leq 0.90$) to avoid heavily weighting for fully covered or open ocean regions.



(a) CDF of rank histograms of the nadj/badj versus lead times measured at marginal ice grid cells. Only three lead times are plotted for visibility.

RESULTS

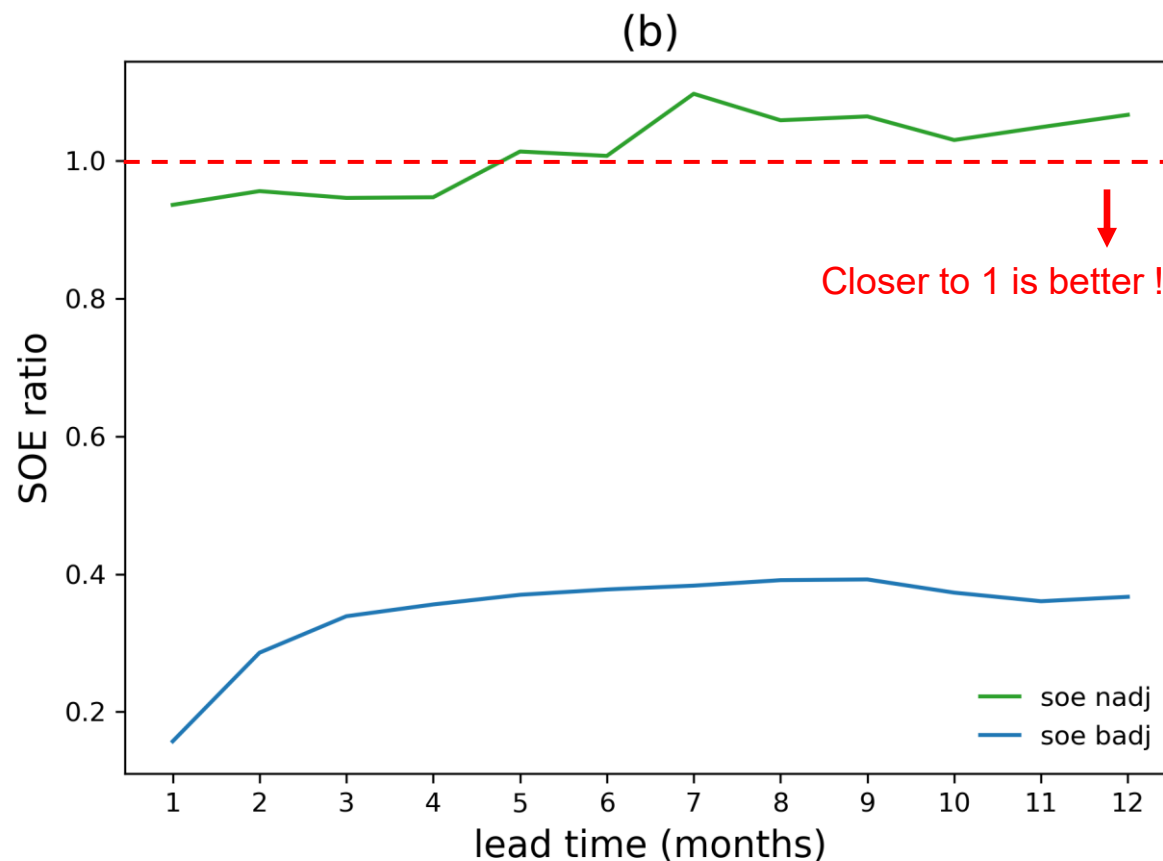
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Probabilistic metrics:

2. Spread-over-Error (**SOE**) ratio

- The noise variance and mean square error (MSE) define the SOE, which measures the **reliability of the ensemble**
- **SOE = 1** indicates that the **ensemble members and observations are statistically indistinguishable** [Ho et al. 2013]
- $\text{SOE} < 1$ ($\text{SOE} > 1$) indicates potential over(under) confidence. F



(b) SOE versus lead time showing reliability.

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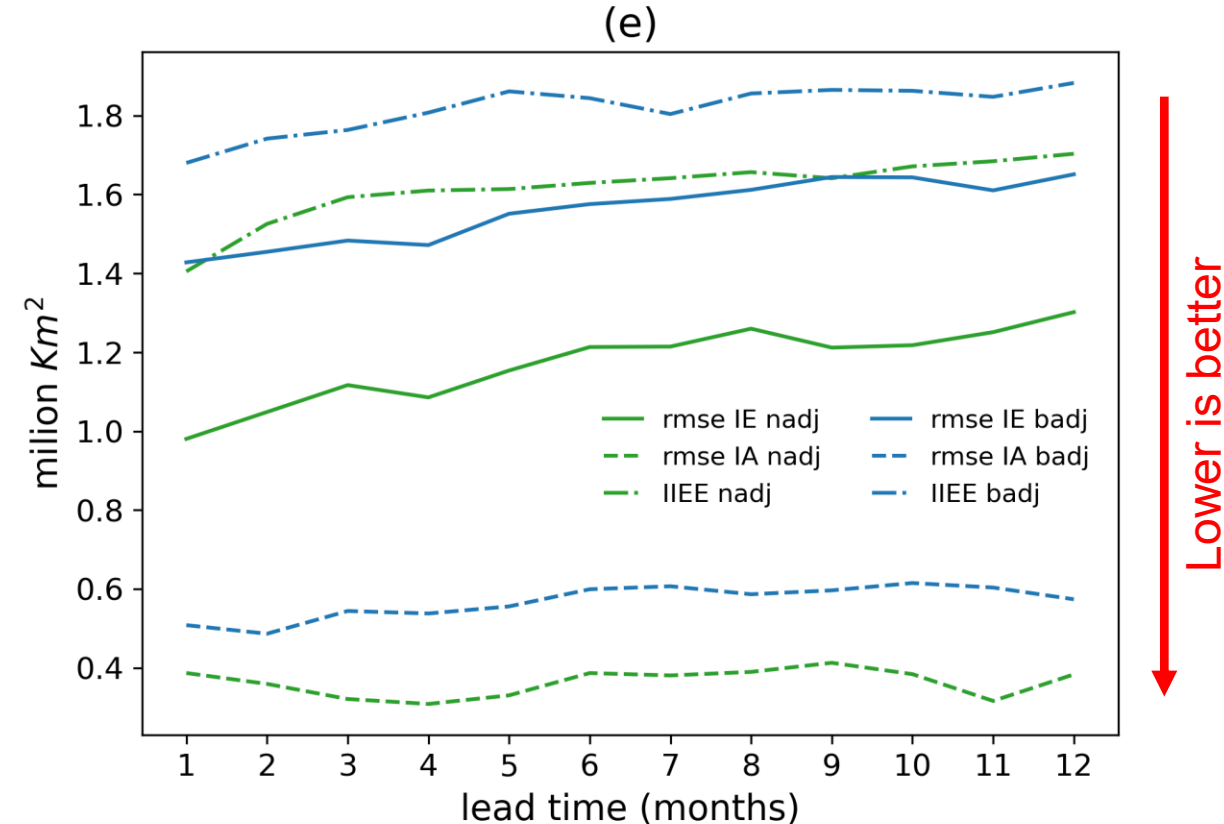
Deterministic metrics:

- Measured using ensemble mean of forecast ensemble against observation

4. **IA**: Integrated Ice Area (total ice area)

5. **IE**: Integrated Ice Extent (total ice area where $0.15 \leq \text{SIC} \leq 0.90$)

6. **IIEE**: Integrated Ice Edge Error (error in predicting edge of ice)



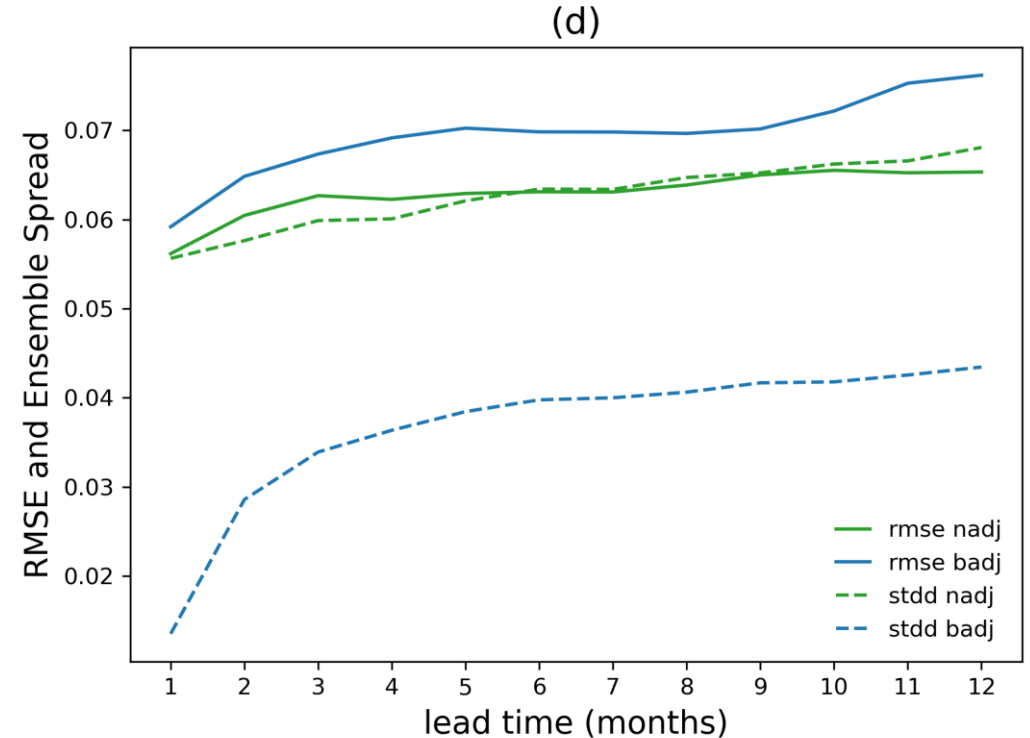
(e) For each lead time, RMSE of SIA (solid line) and SIE (dashed line) over initialization time, and average IIEE (dotted line) over initialization time is compared between ensemble mean nadj/badj and obs.

CONCLUSIONS

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- **cVAE adjusted forecasts outperforms benchmark for all metrics.**
- **Errors increase with lead time as uncertainty grows expectedly.**
- **cVAE adjusted SOE ratio remains close to 1 for all lead times.**



(d) RMSE (solid) over initialization time between the ensemble mean nadj/badj compared to obs at grid cells level averaged over the entire region. The dashed line shows the global mean ensemble spread averaged over initialization time.

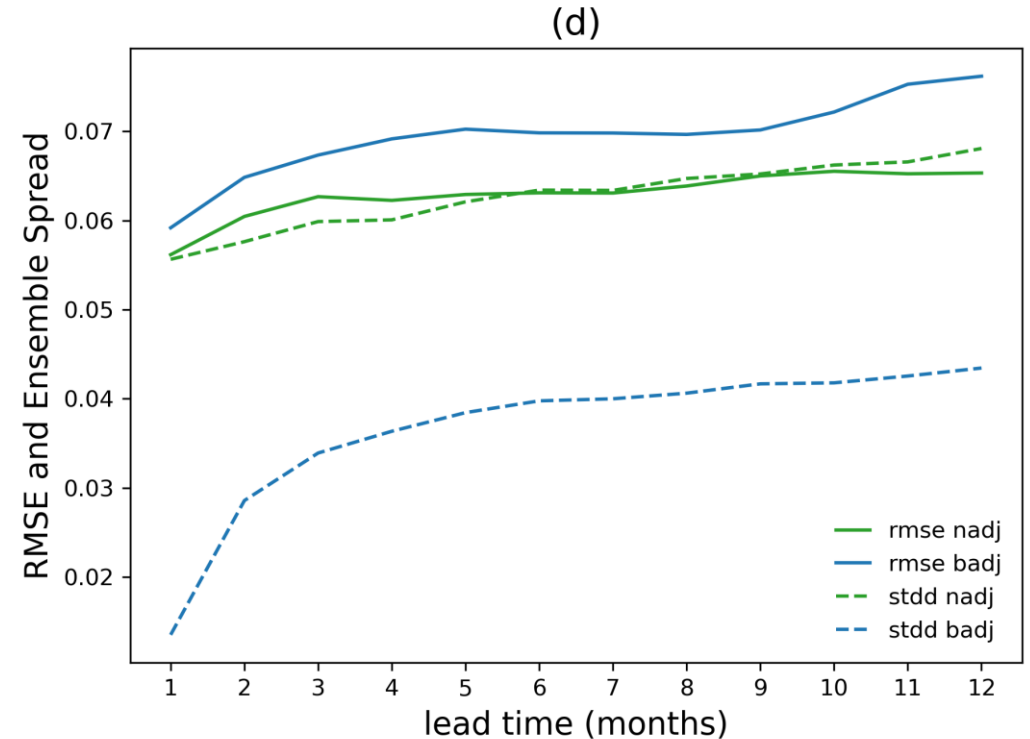
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cVAE maps raw biased predictions into skillful, reliable, well-calibrated forecasts.



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THANK YOU!

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Questions and Feedback are welcome:

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