

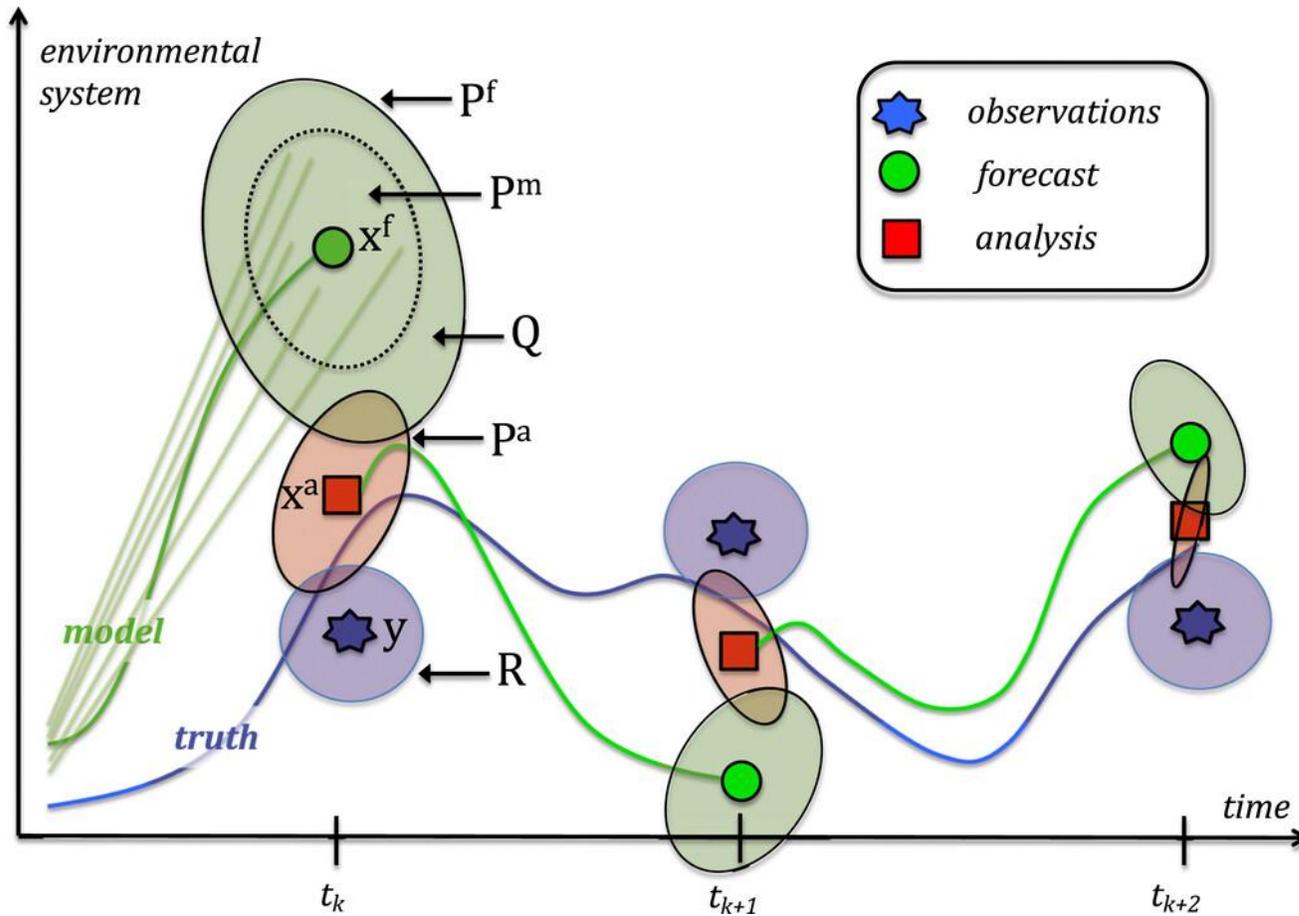
Constraining Atmospheric Forcing Errors for Sea Ice Data Assimilation in Short-Range Forecasts

Hee-Sung Jung¹, Jonathan Poterjoy¹, and Alek Petty²

¹Department of Atmospheric and Oceanic Science, University of Maryland, College Park

²Earth System Science Interdisciplinary Center (ESSIC), University of Maryland, College Park

Why data assimilation?



P^f : Background error covariance

P^a : Analysis error covariance

R : Observation error covariance

Tandeo et al., 2020

Data assimilation (DA) constrains model states with observations

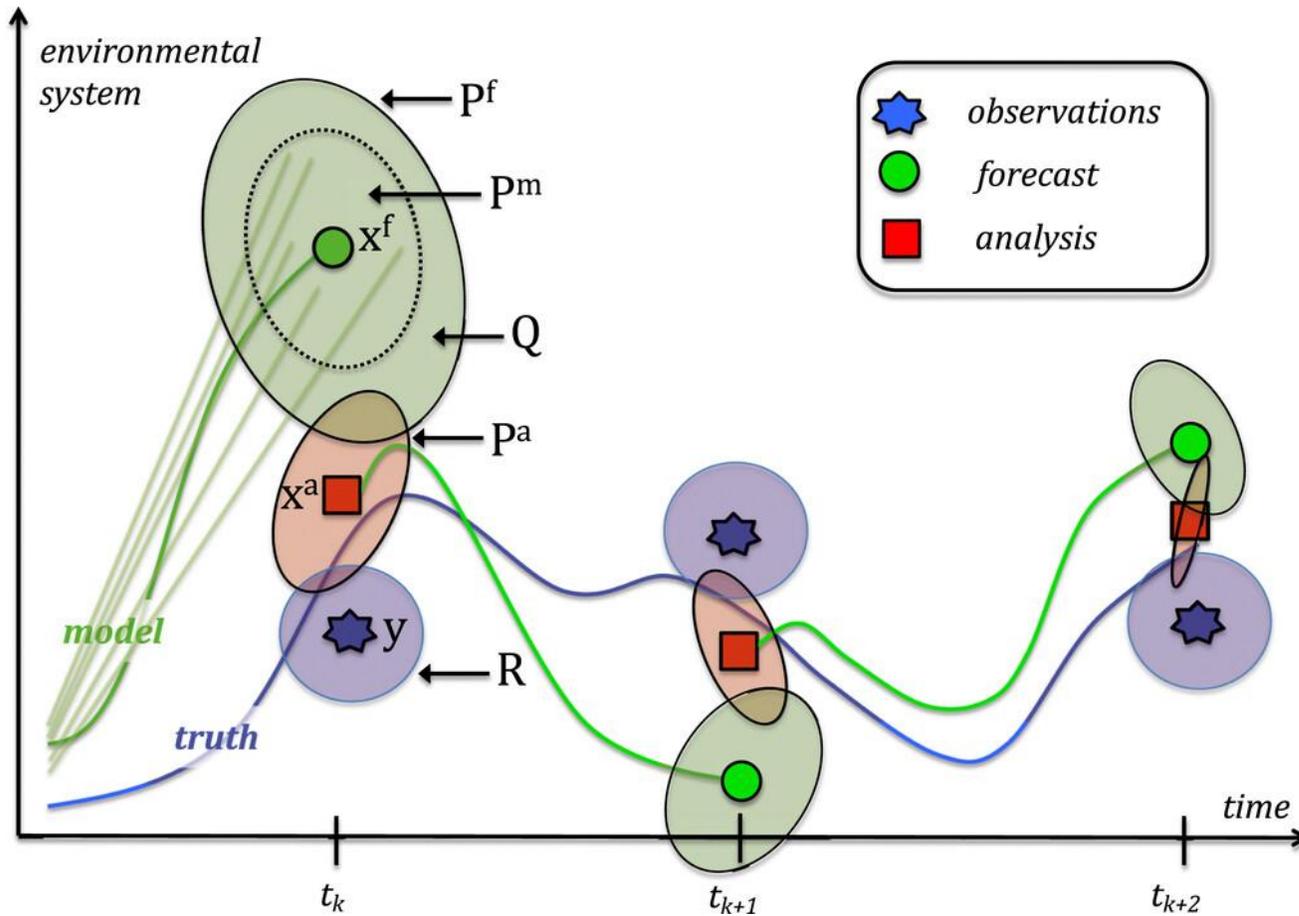
1. When agreement with the truth is needed at finer scales

➔ Numerical weather prediction

2. When observational constraints need to be applied for increased realism

➔ Generating a reanalysis

Why data assimilation?



P^f : Background error covariance

P^a : Analysis error covariance

R: Observation error covariance

Tandeo et al., 2020

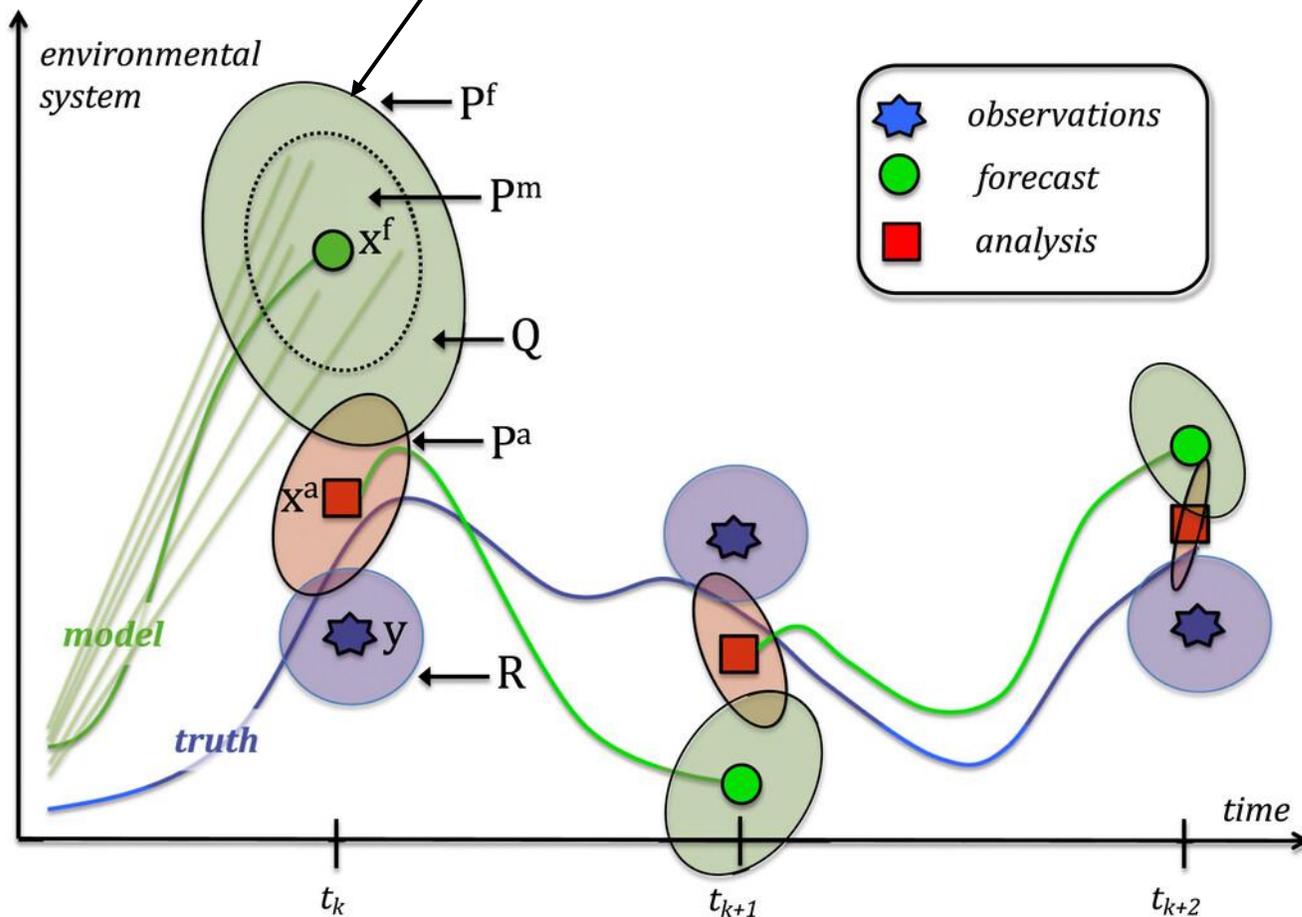
Data assimilation (DA) constrains model states with observations

We need “good” estimates of P^f and R for DA to function properly.

Why data assimilation?

Ensembles are used to estimate P^f

$$\leftarrow e_{model} + e_{ic} + e_{OCN} + e_{ATM}$$

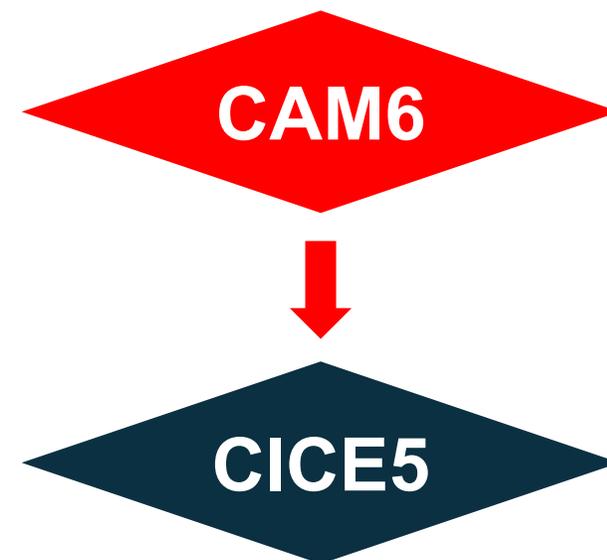


P^f : Background error covariance

P^a : Analysis error covariance

R: Observation error covariance

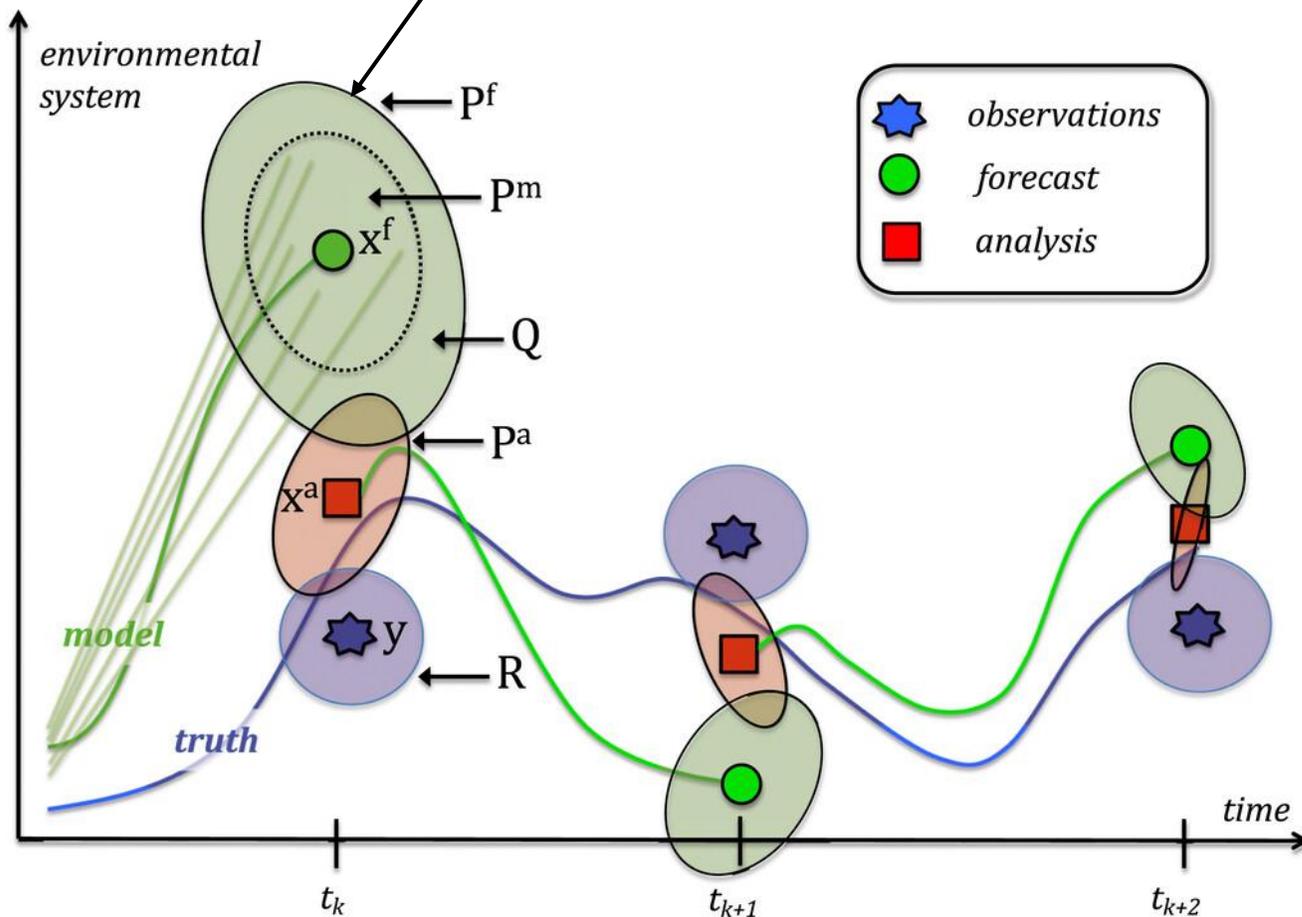
Tandeo et al., 2020



Why data assimilation?

Ensembles are used to estimate P^f

$$\leftarrow e_{model} + e_{ic} + e_{OCN} + e_{ATM}$$



P^f : Background error covariance

P^a : Analysis error covariance

R : Observation error covariance

Tandeo et al., 2020

$$e_{ATM} \sim N(0, P_{ATM})$$



CICE5

Covariance model

$$\mathbf{e}_{\text{ATM}} = \mathbf{Q}\mathbf{G}\mathbf{z} = \mathbf{P}_{\text{ATM}}^{1/2}\mathbf{z}$$

$$\mathbf{z}_t = \mathbf{M}\mathbf{z}_{t-1} + \mathbf{A}\eta_t$$

Training data: Coupler history outputs from 80-member DART+CAM6 reanalysis

➤ Direct compatibility w/ CESM cplhist mode

Q: Inter-variable balance

G: Spatial correlation structure

(M, A): 1st order Markov chain

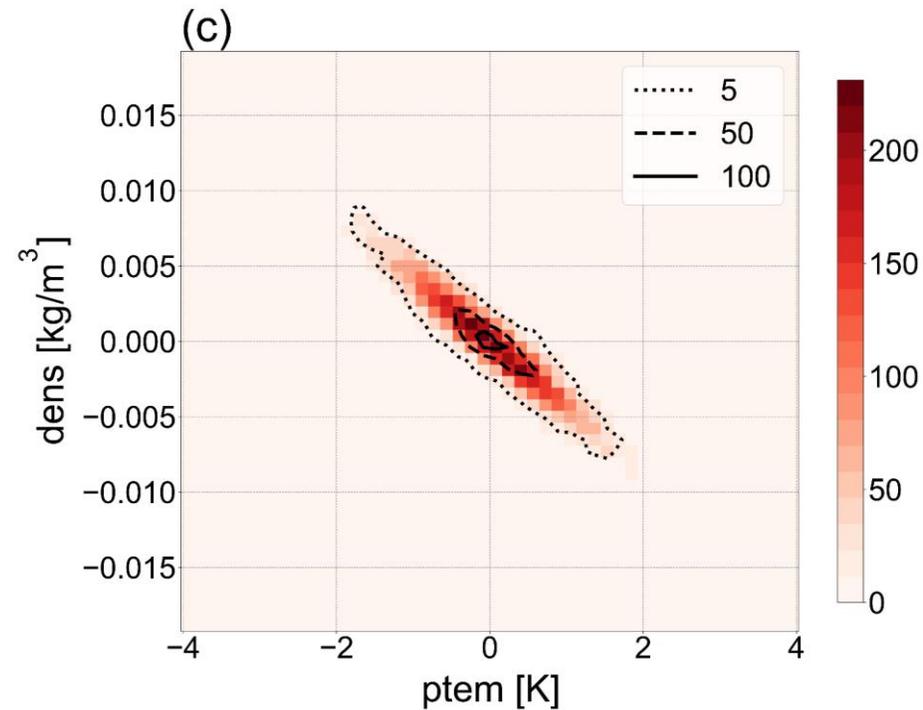
Z: Sample from distribution $\rho\mathbf{N}(\mathbf{0}, \mathbf{I})$

- $\rho > 1$: Inflate atmospheric errors

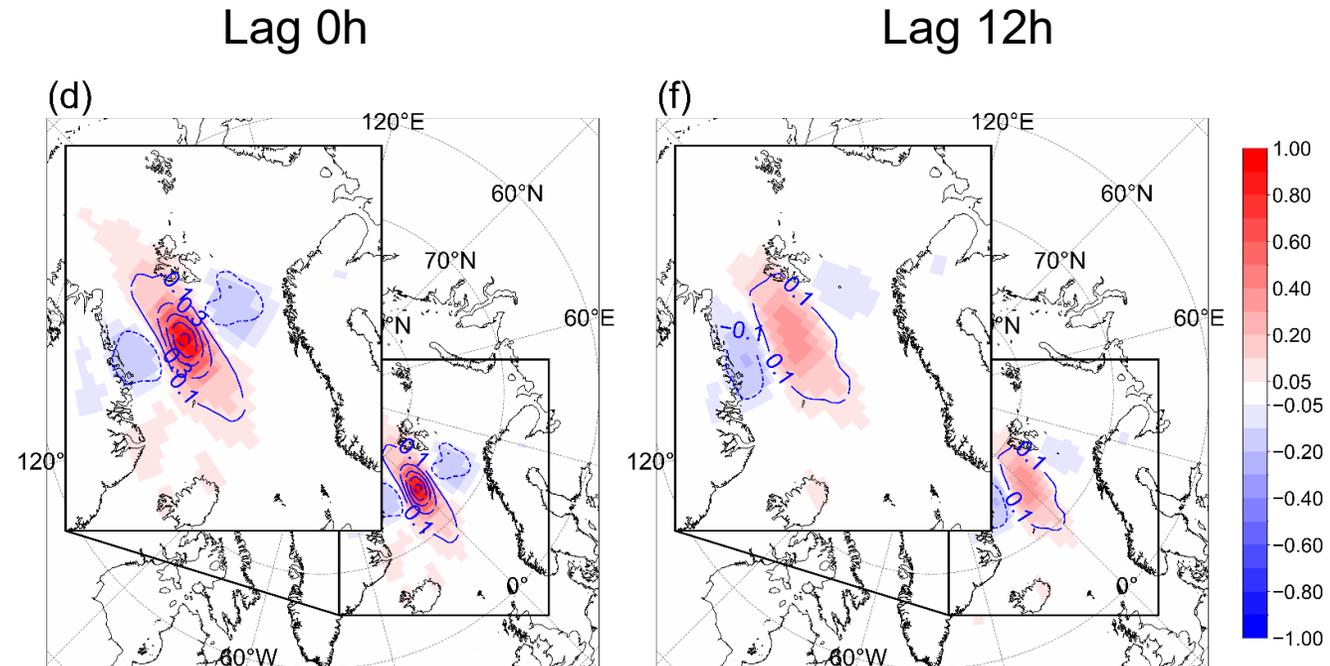
- $\rho < 1$: Deflate atmospheric errors

Covariance model

Modeled intervariable balance



Modeled spatiotemporal correlation

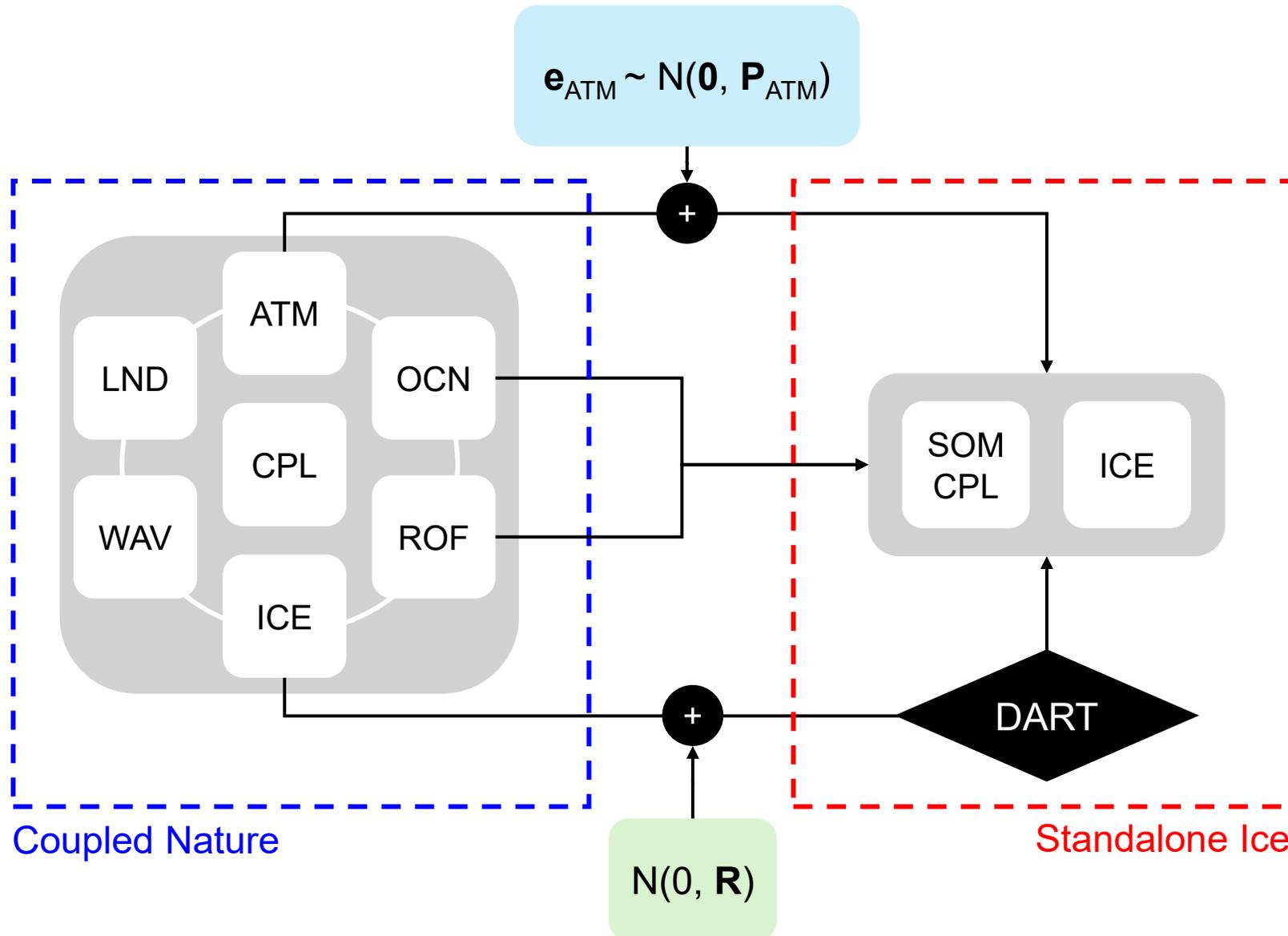


- Contours show errors computed from CAM6 reanalysis
- Colors show errors sampled from our covariance model

Experiment setup

Coupled Nature

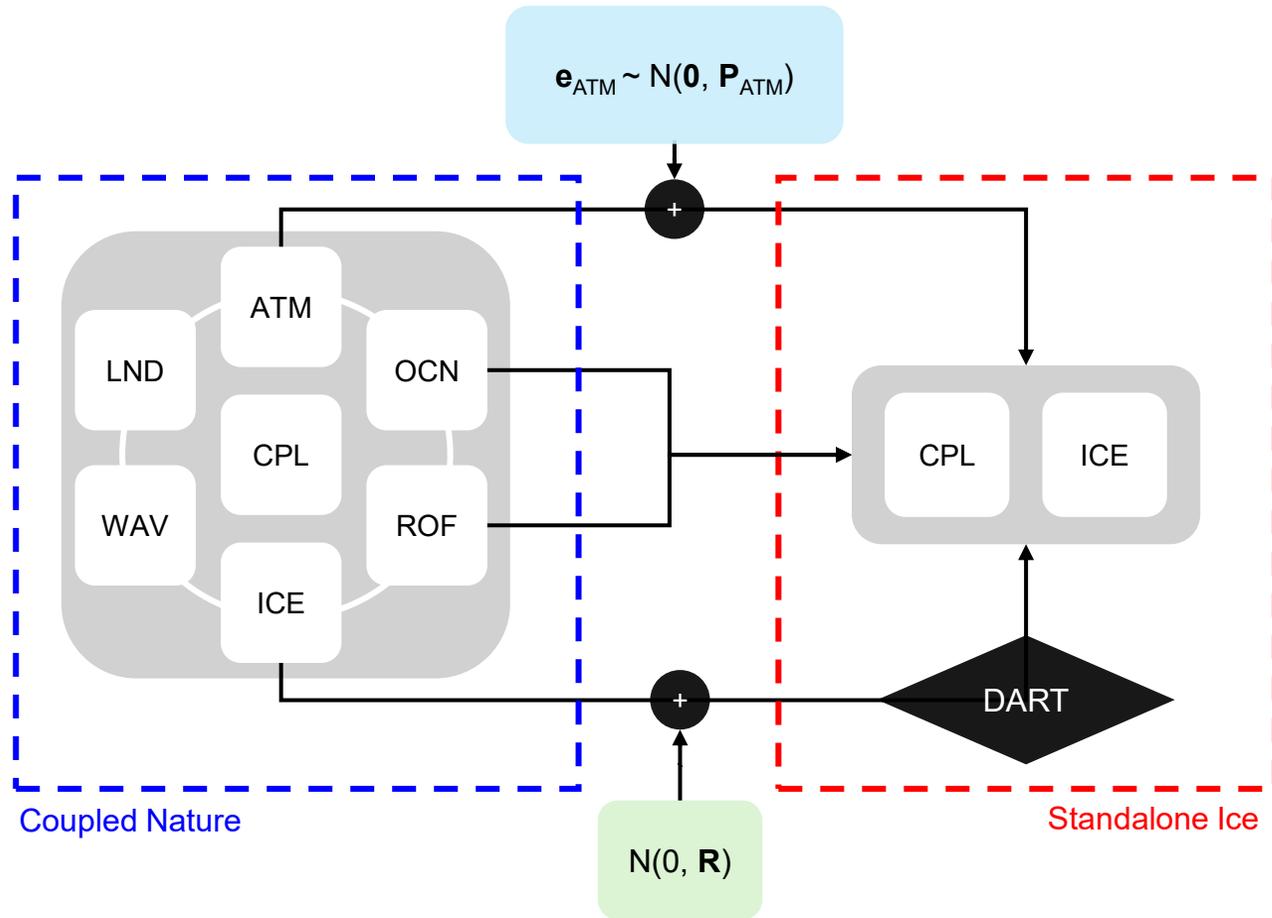
- Branched from CESM2-lessmelt
- Proxy for the real-world



Standalone Ice

- Errors added to ATM forcings
- DA via CESM-DART interface
- Proxy for NWP/reanalysis system

Experiment setup: Model error

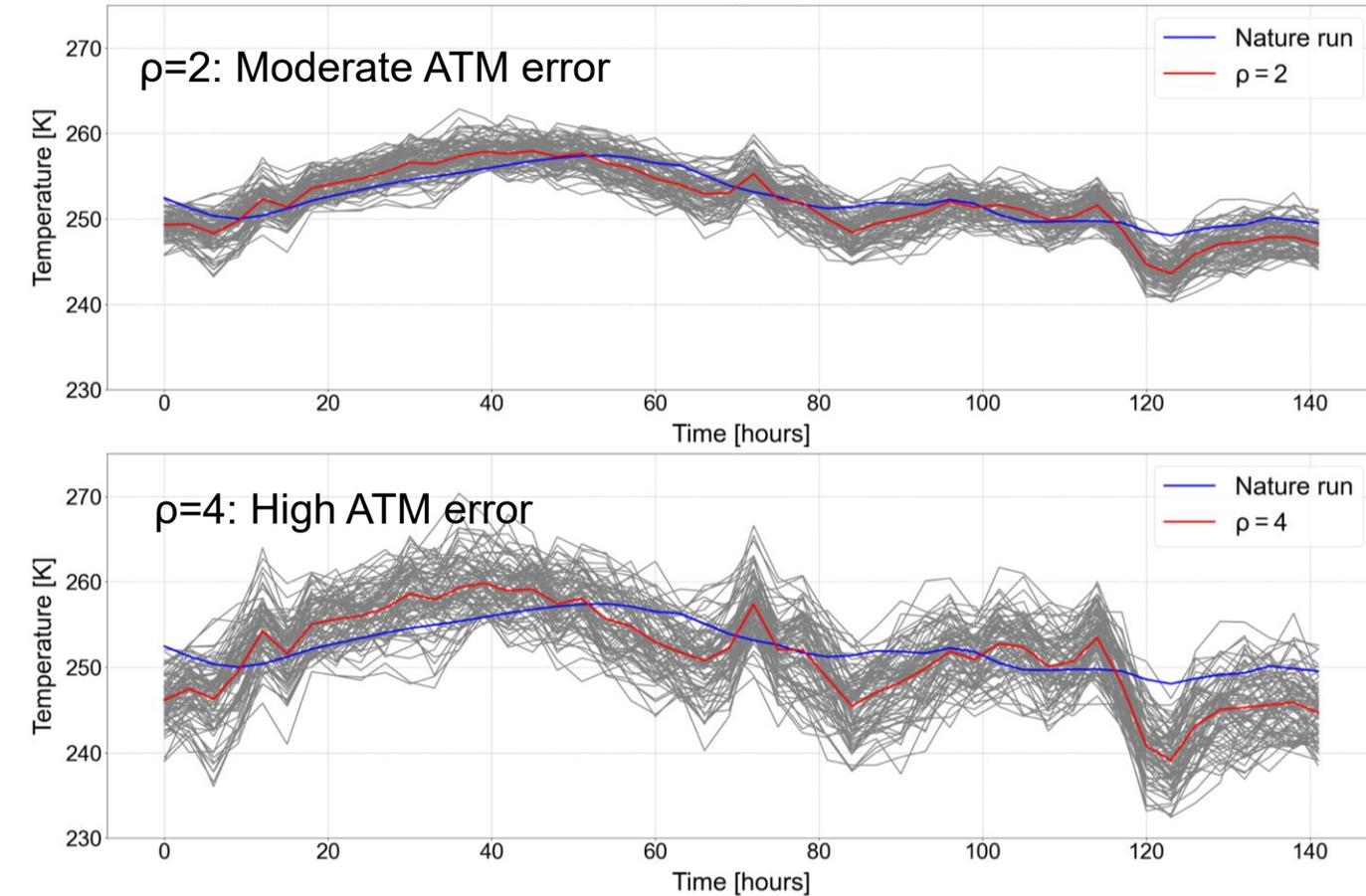


$$\sigma_f = \sigma_{ATM} + \sigma_{Initial\ condition} + \sigma_{Model}$$

$$\hat{\sigma}_f = \hat{\sigma}_{ATM} + \hat{\sigma}_{Initial\ condition}$$

Model error associated missing coupling is represented via the different CESM2 configurations used in for the **nature** and **DA** runs.

Experiment setup: Atmospheric forcing error



$$\bar{\Psi} = \Psi_T + e$$

$$\Psi^i = \bar{\Psi} + e^i, \quad i = 1, \dots, N_{\text{ens}}$$

$$e \sim N(\mathbf{0}, \rho \mathbf{P})$$

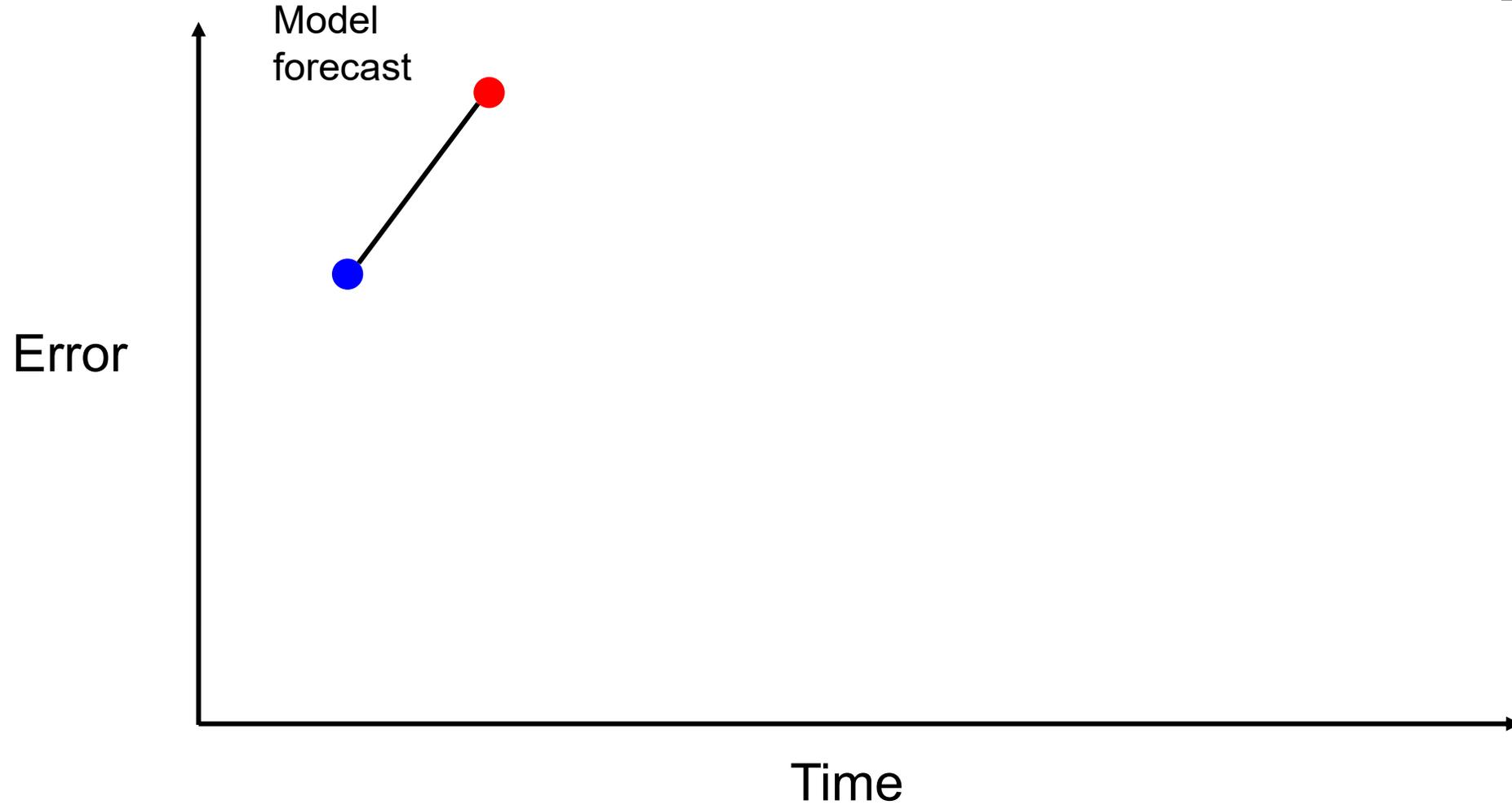
$$\sigma_f = \sigma_{ATM} + \sigma_{Initial\ condition} + \sigma_{Model}$$

$$\hat{\sigma}_f = \hat{\sigma}_{ATM} + \hat{\sigma}_{Initial\ condition}$$

By design the atmospheric ensembles characterize the distribution of the atmospheric background error

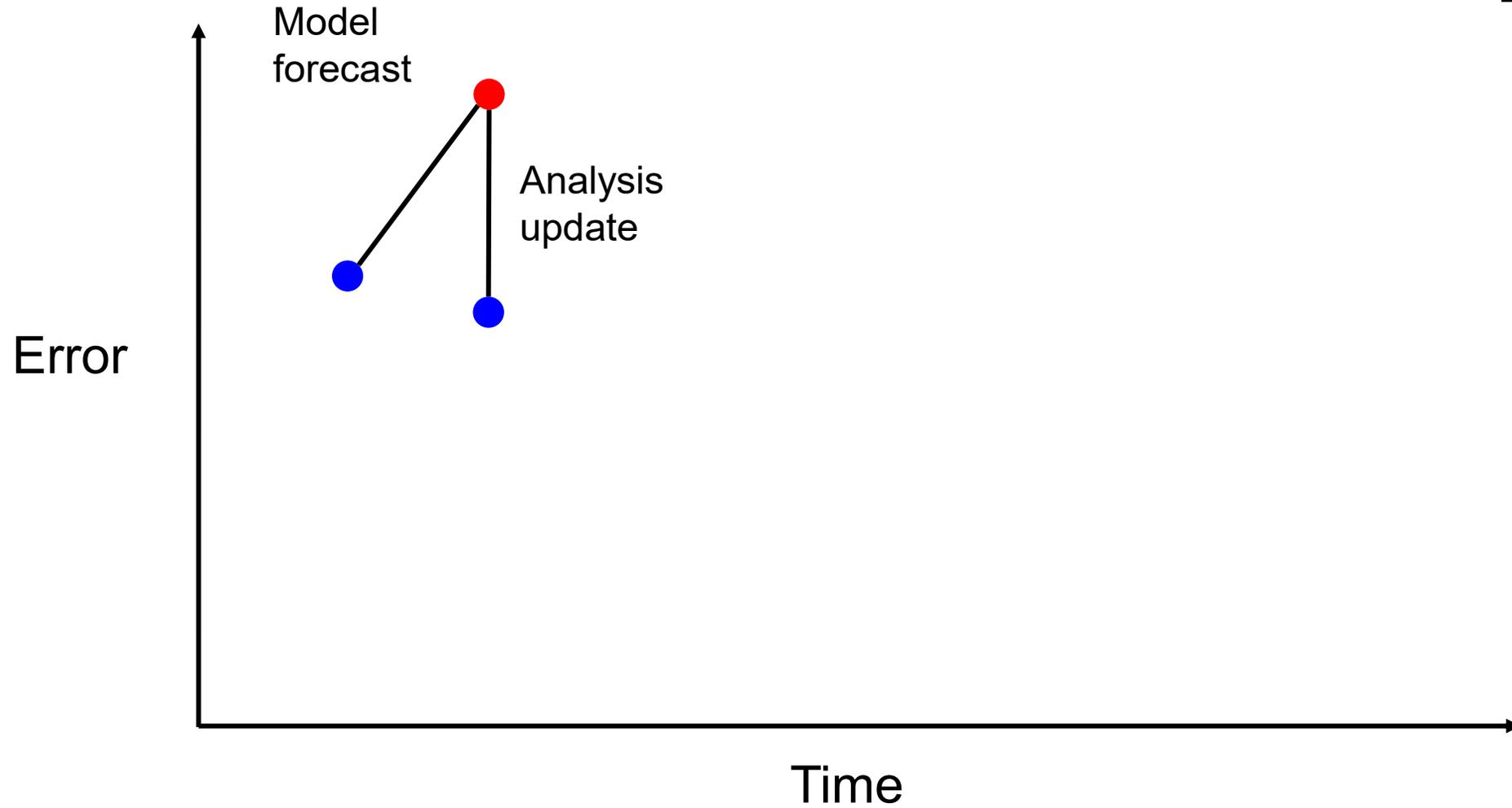
Verification method: Sawtooth plot

- Analysis
- Background



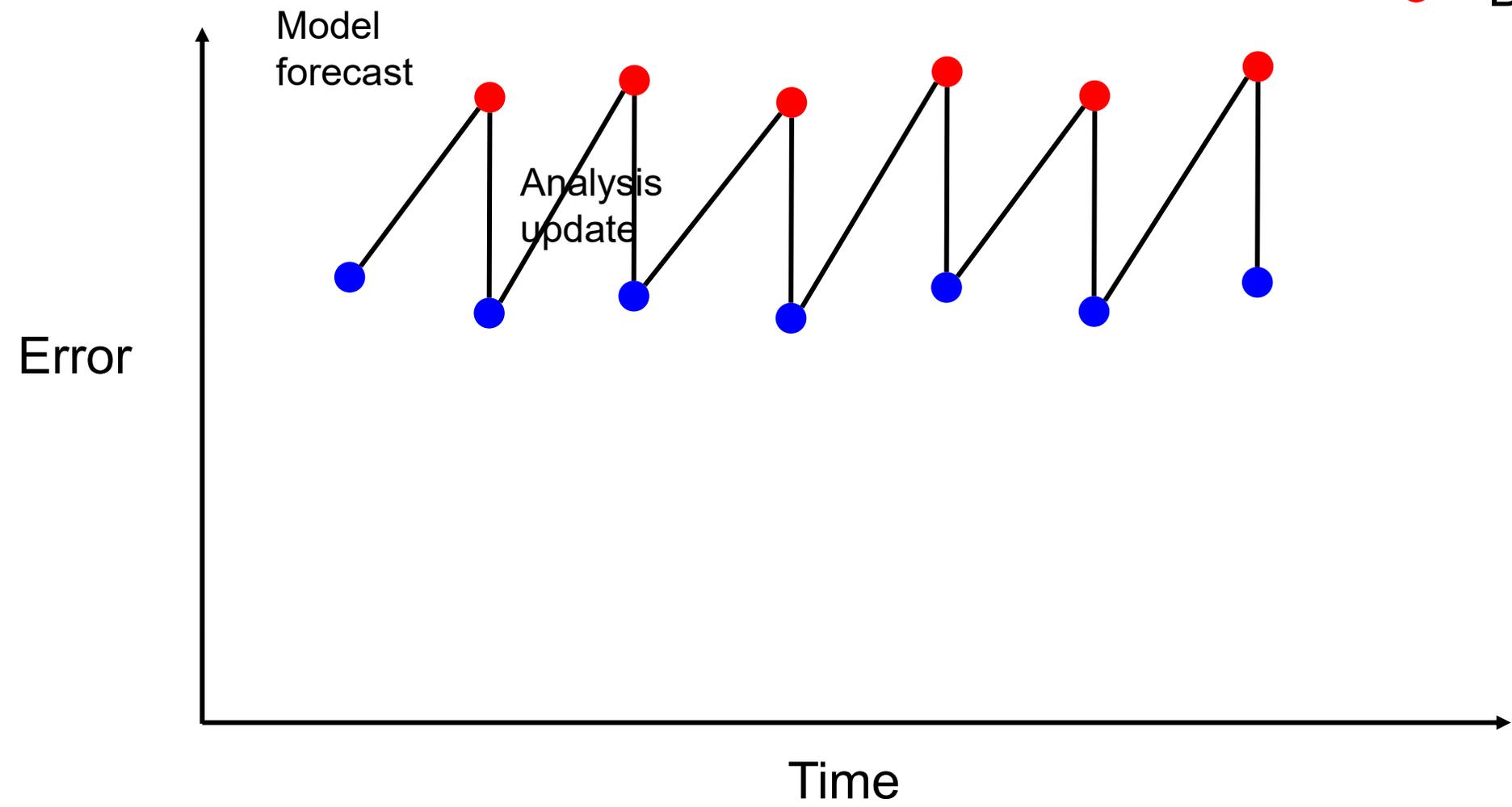
Verification method: Sawtooth plot

- Analysis
- Background



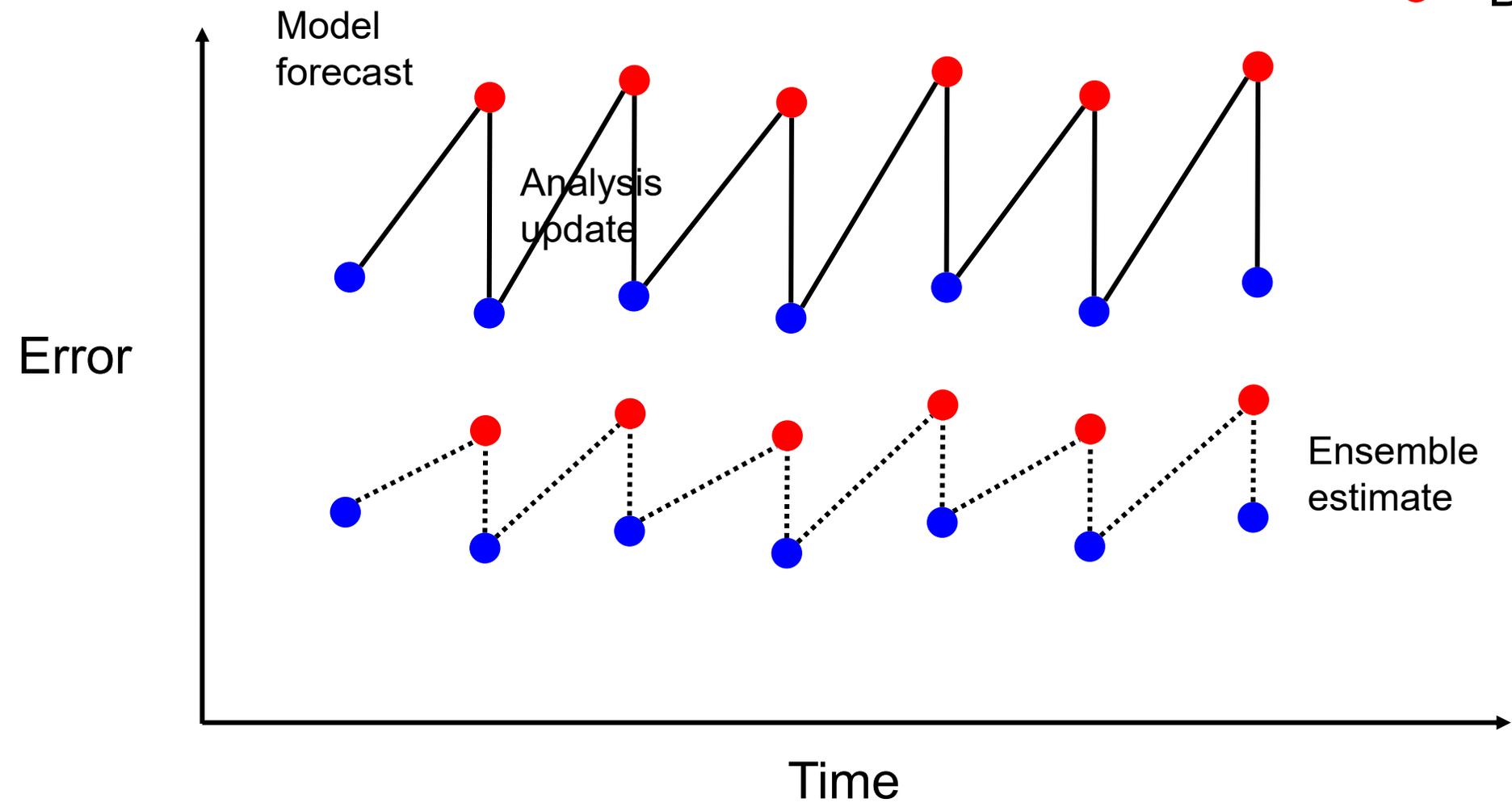
Verification method: Sawtooth plot

- Analysis
- Background

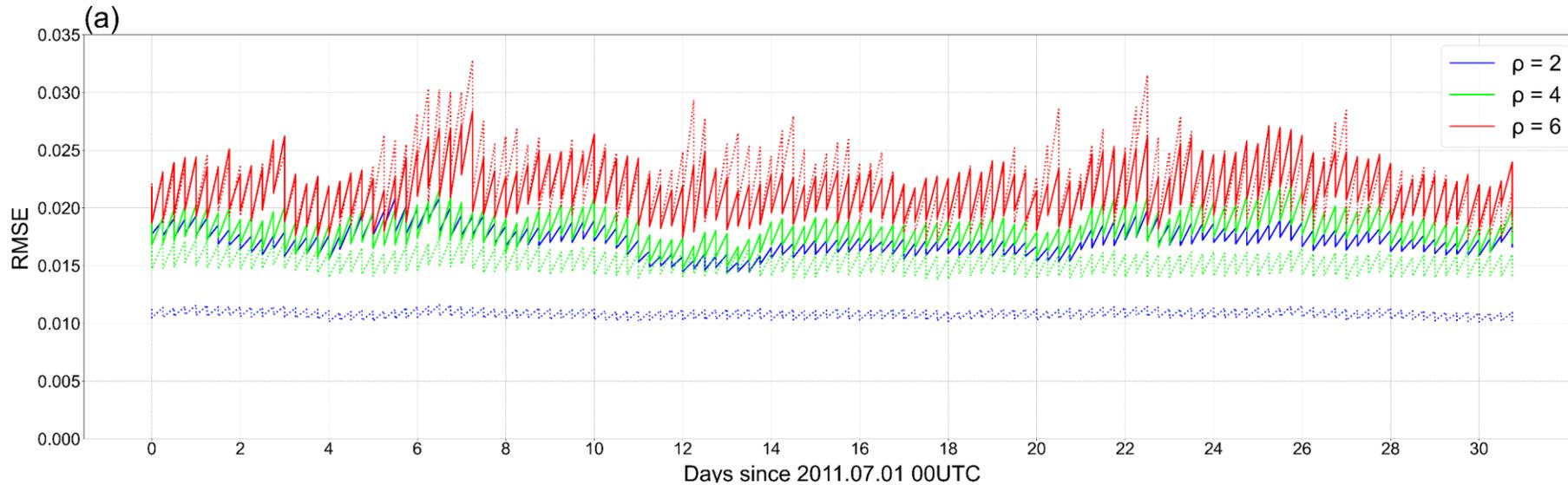


Verification method: Sawtooth plot

- Analysis
- Background



Results: Is our sea ice ensemble also well behaved?



$\rho=2$: Forced w/ low error

$\rho=4$: Forced w/ moderate error

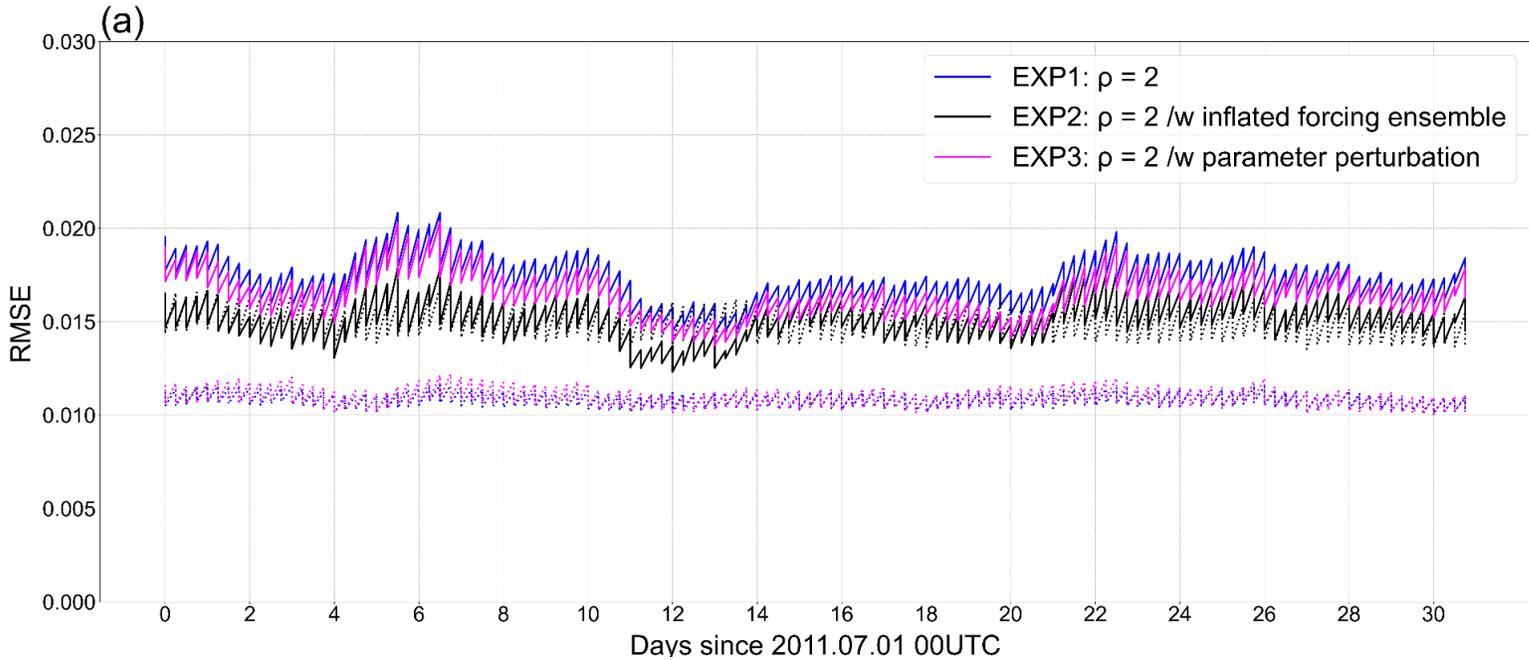
$\rho=6$: Forced w/ high error

Solid lines: $\sigma_f = \sigma_{ATM} + \sigma_{Initial\ condition} + \sigma_{Model}$

Dotted lines: $\hat{\sigma}_f = \hat{\sigma}_{ATM} + \hat{\sigma}_{Initial\ condition}$

- As ρ increases, the ensemble estimated background errors more closely resemble the actual background errors
 - Larger ρ means more dominant contributions from σ_{ATM} , thus better-behaved ensemble
- ➔ Ensembles are **adjustable** to accommodate a range of different background error values!

Results: Can we tune the sea ice ensemble?



- ATM inflation provides better consistency in both magnitude and amount of error growth during the forecast
- Limited control over the ensemble via parameter perturbation

EXP	Background error (Solid line)	Ensemble estimate (Dotted line)
1: Control	$\sigma_f = \sigma_{ATM} + \sigma_{Initial\ condition} + \sigma_{Model}$	$\hat{\sigma}_f = \hat{\sigma}_{ATM} + \hat{\sigma}_{Initial\ condition}$
2: Inflated ATM ensemble	$\sigma_f = \sigma_{ATM} + \sigma_{Initial\ condition} + \sigma_{Model}$	$\hat{\sigma}_f = \hat{\sigma}_{ATM} \uparrow + \hat{\sigma}_{Initial\ condition}$
3: Parameter perturbation	$\sigma_f = \sigma_{ATM} + \sigma_{Initial\ condition} + \sigma'_{Model}$	$\hat{\sigma}_f = \hat{\sigma}_{ATM} + \hat{\sigma}_{Initial\ condition} + \hat{\sigma}_{Model}$

Discussion: For making reanalysis?

ρ can be adjusted to account for (unknown) errors in the reanalysis forcings

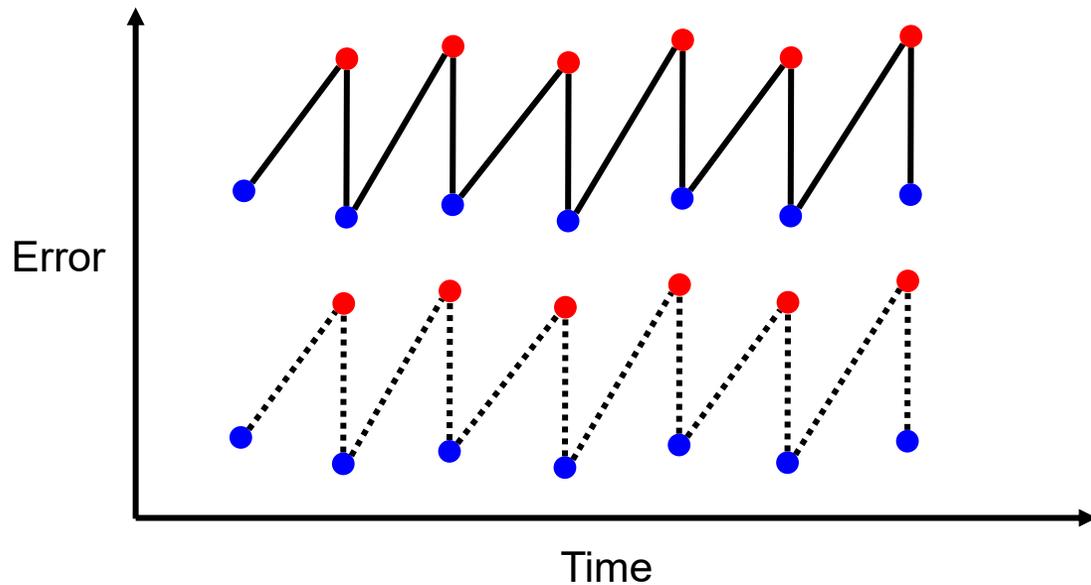
$$\text{RMS}(\mathbf{d}) = \text{RMS}(\mathbf{y} - \mathbf{h}(\mathbf{x})) \approx \sqrt{\sigma_0^2 + \sigma_f^2}$$

→ Unknown individually...

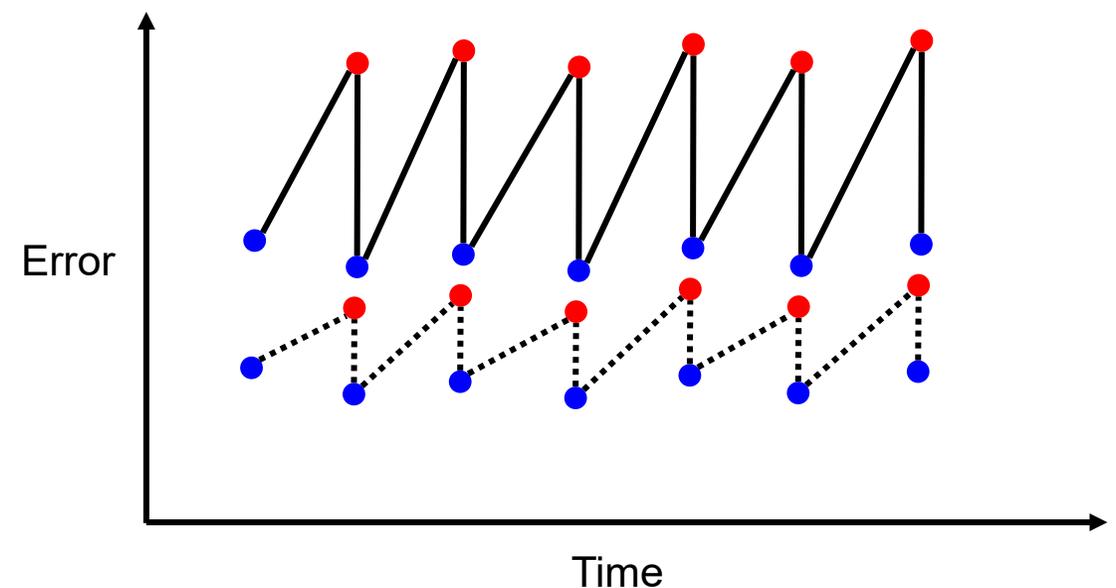
$$\text{RMSD}_{\text{ens}} \approx \sqrt{\hat{\sigma}_0^2 + \hat{\sigma}_f^2}$$

→ Both $\hat{\sigma}_0$ and $\hat{\sigma}_f$ now tunable

$\hat{\sigma}_0$ or inflation



$\hat{\sigma}_f$



Future works

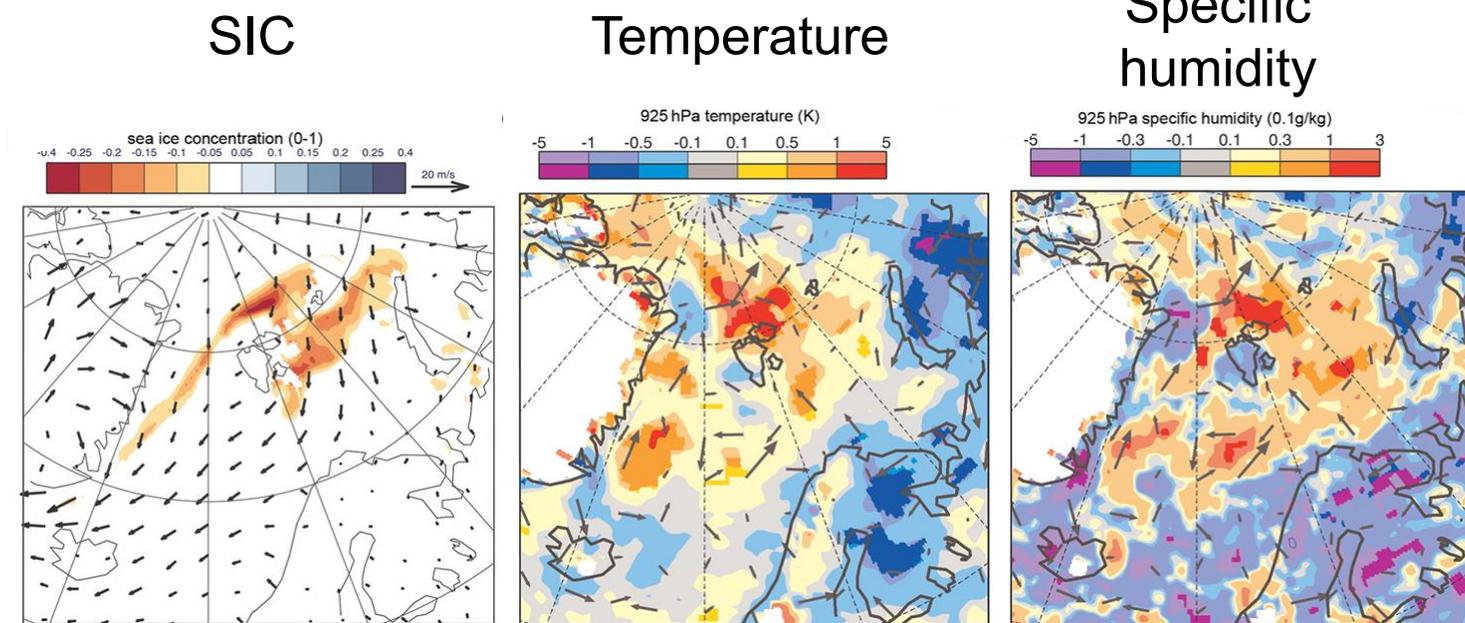
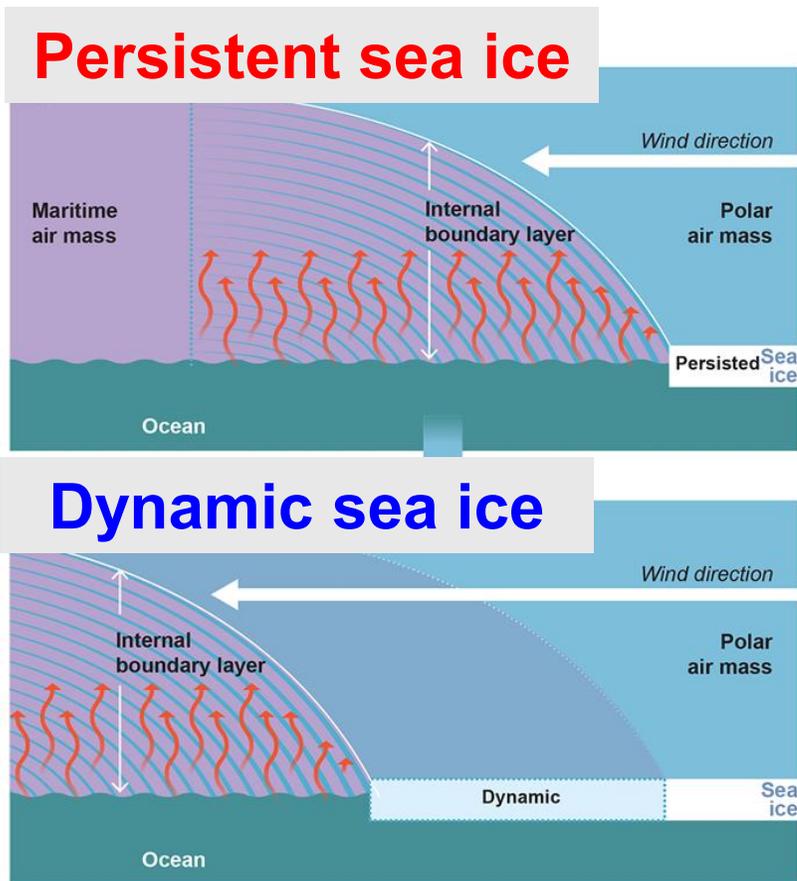
- Determine adequate values of ρ for an actual reanalysis atmosphere for sea ice DA
- Generate forced sea ice reanalysis with the specified ρ assimilating SIC, SIT, snow depth(?) observations
- Evaluate observation influences based on realistic OSSE setup...?

- [1] Croad, H. L., Keeley, S. P., Methven, J., Harvey, B., Volonte, A.: Examining the sensitivity of ECMWF IFS weather forecasts to sea-ice coupling for the summer-time Arctic and cyclones, QJRMS, 2025.
- [2] Day, J. J., Keeley, S., Arduini, G., Magnusson, L., Mogensen, K., Rodwell, M., Sandu, I., and Tietsche, S.: Benefits and challenges of dynamic sea ice for weather forecasts, Weather Clim. Dynam., 2022.
- [3] Kay, J. E., DeRepentigny, P., Holland, M. M., Bailey, D. A., DuVivier, A. K., Blanchard-Wrigglesworth, E., . . . Rosenbloom, N.: Less Surface Sea Ice Melt in the CESM2 Improves Arctic Sea Ice Simulation With Minimal Non-Polar Climate Impacts, Journal of Advances in Modeling Earth Systems, 2022.
- [4] Raeder, K., Hoar, T. J., El Gharamti, M., Johnson, B. K., Collins, N., Anderson, J. L., . . . Coady, M.: A new CAM6 + DART reanalysis with surface forcing from CAM6 to other CESM models. Scientific Reports, 2021.
- [5] Tandeo, P., Ailliot, P., Bocquet, M., Carrassi, A., Miyoshi, T., Pulido, M., Zhen, Y.: A Review of Innovation-Based Methods to Jointly Estimate Model and Observation Error Covariance Matrices in Ensemble Data Assimilation, Monthly Weather Review, 2020.

Extra slides

Why data assimilation?

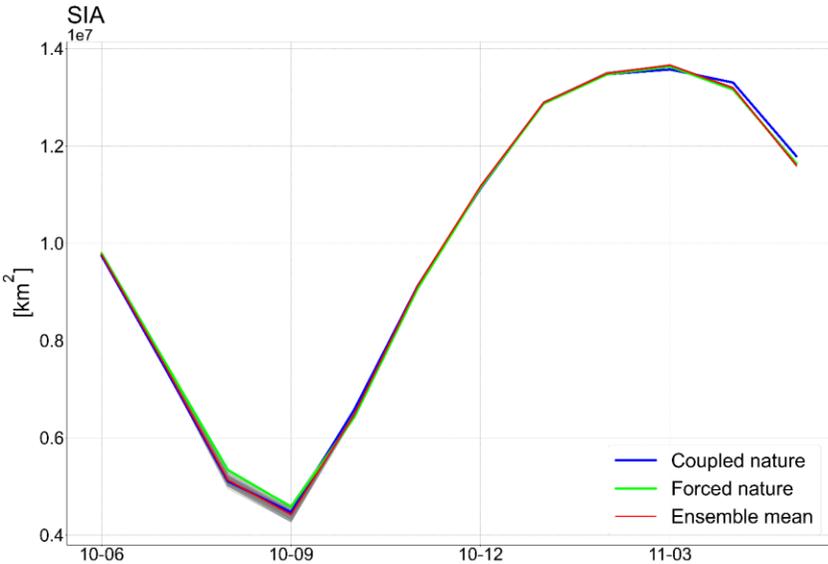
(Persistent) – **(Dynamic)** sea ice



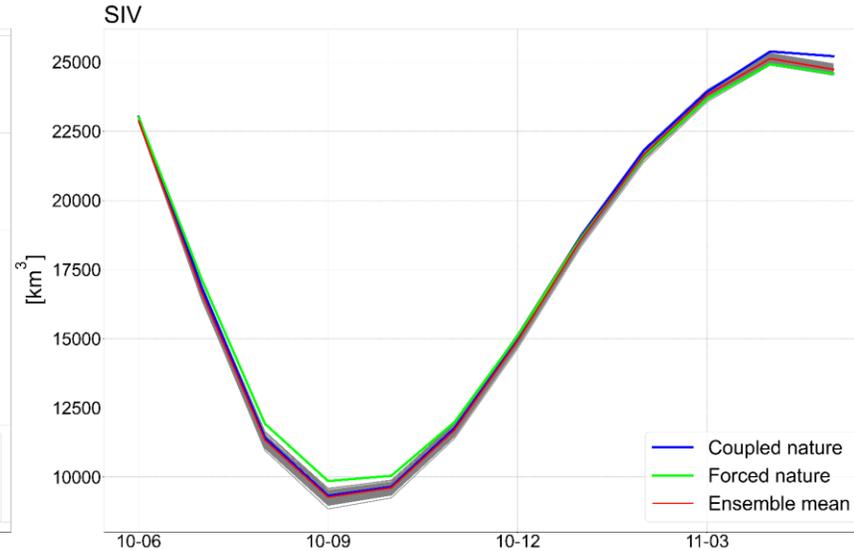
Day et al. (2022)

Free-forecast

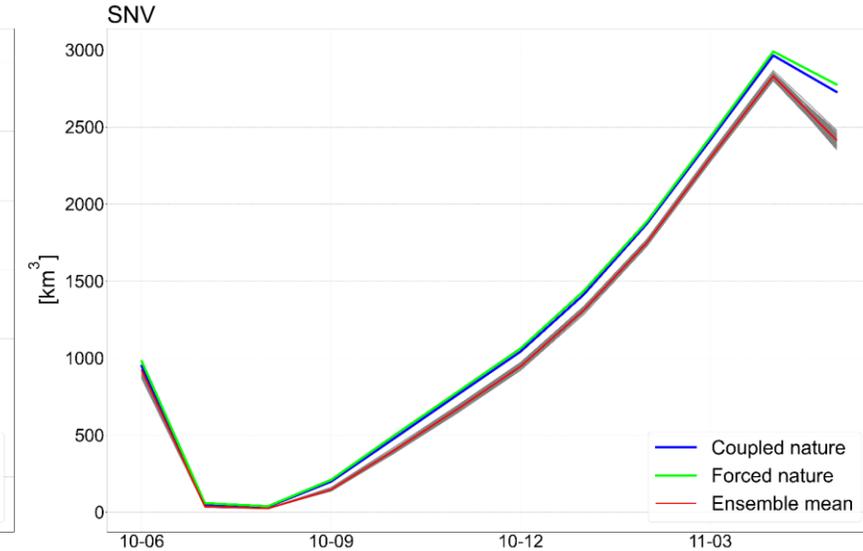
Sea ice area



Sea ice volume



Snow volume



Adjustment: 2010.06.01 ~ 2011.06.01

- 1-year free-forecast of **coupled nature**, **forced nature**, and **standalone ensemble**
- Even with constrained ATM errors, ice volume & snow volume show large errors
- Snow volume shows non-linear response with a negatively biased ensemble throughout the year

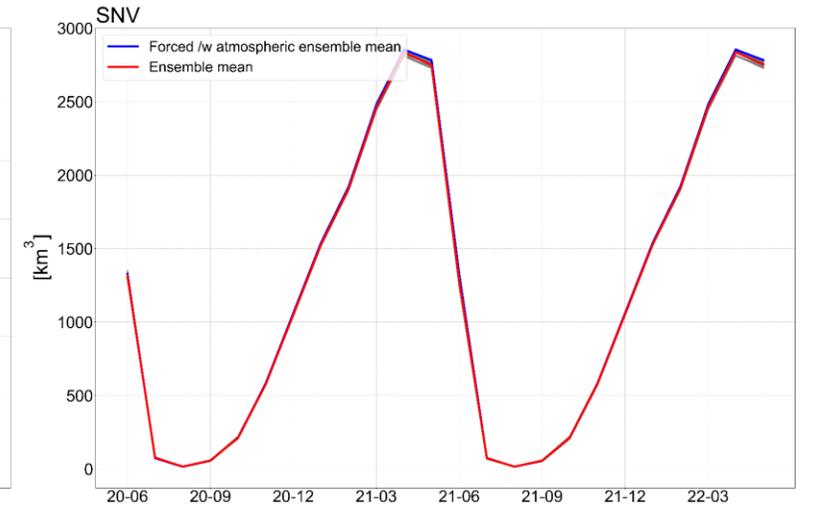
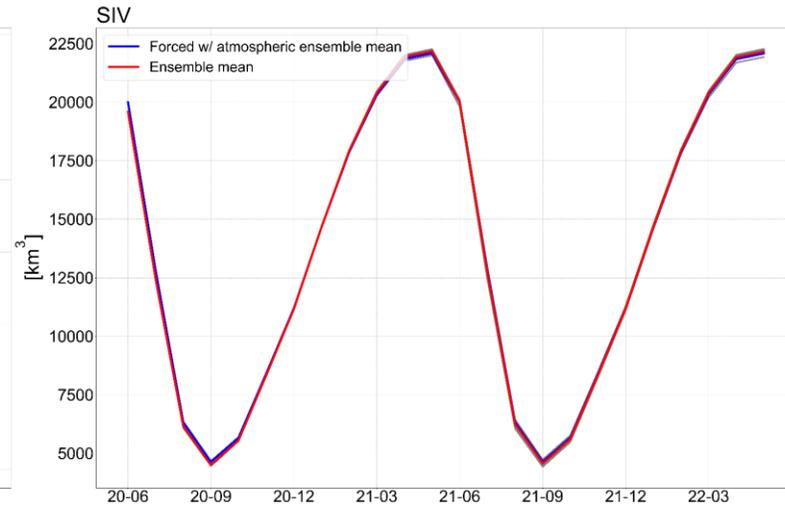
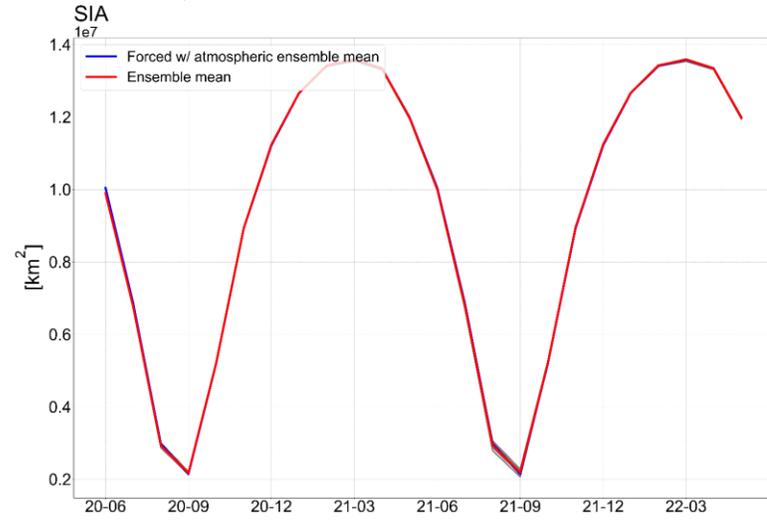
Non-linear snow volume forecast

Name	Forcing	Initial condition
EXP1	Mean value from 10-member of Raedar forcing	2020-06-01 (After 10-year spinup)
EXP2	10-member Raedar reanalysis	2020-06-01 (After 10-year spinup)
EXP3	10-member generated via perturbation (centered about mean of Raedar forcing)	2020-06-01 (After 10-year spinup)
EXP4	Nature run forcing	2020-06-01 (After 10-year spinup)
EXP5	10-member generated via perturbation (centered about nature run)	2020-06-01 (After 10-year spinup)

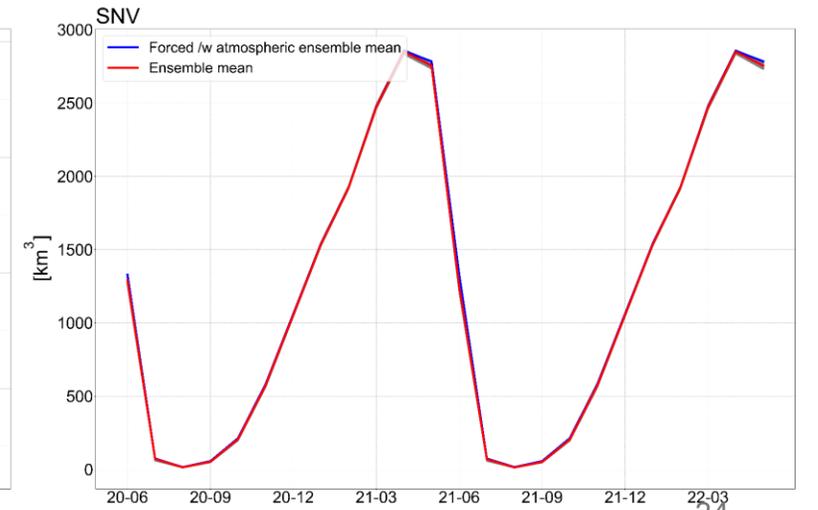
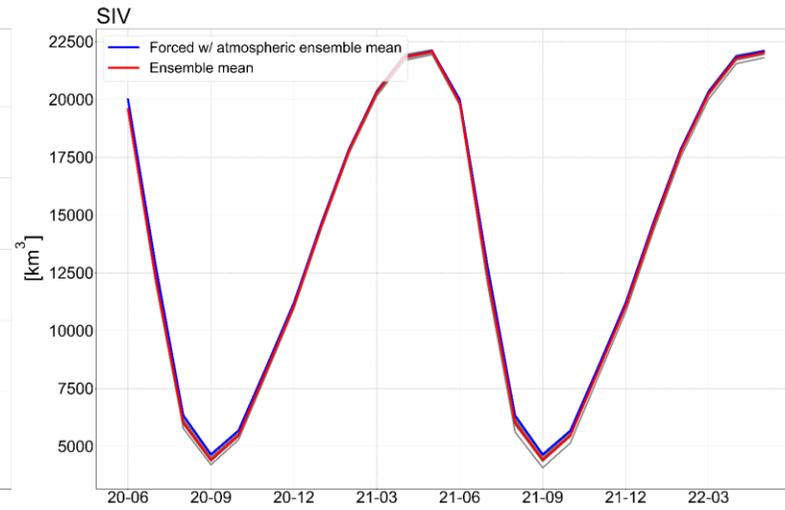
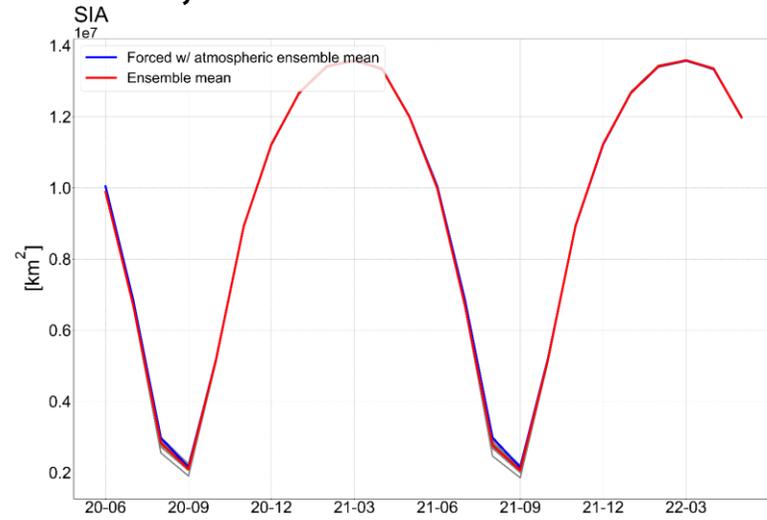
1. Does this also happen from an actual atmospheric reanalysis? → (EXP1, EXP2) vs (EXP1, EXP3)
2. Does atmospheric mean-state affect the results? → (EXP1, EXP3) vs (EXP4, EXP5)

Non-linear snow volume forecast

EXP1, EXP2

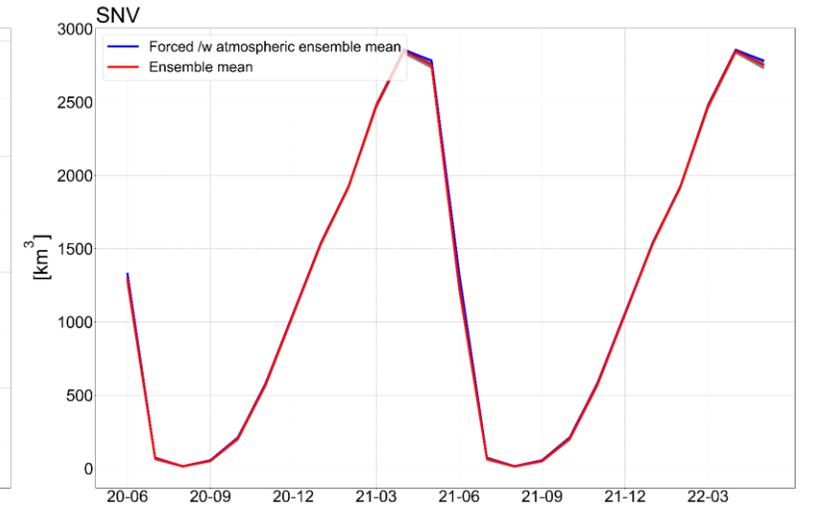
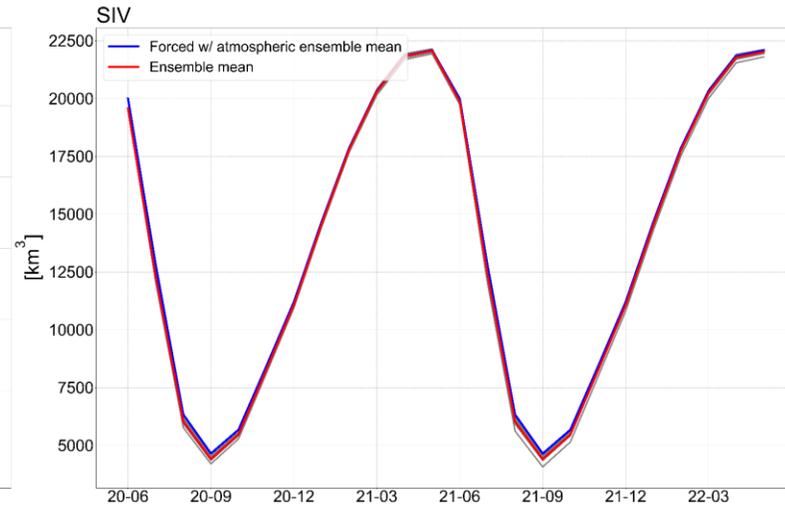
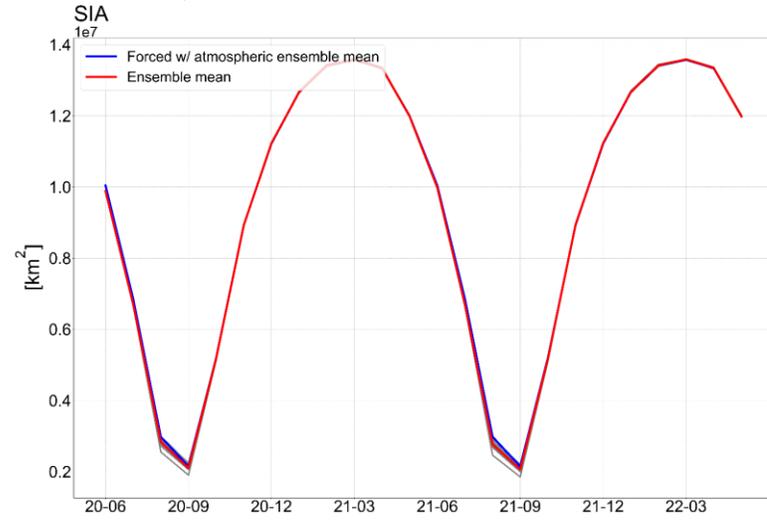


EXP1, EXP3

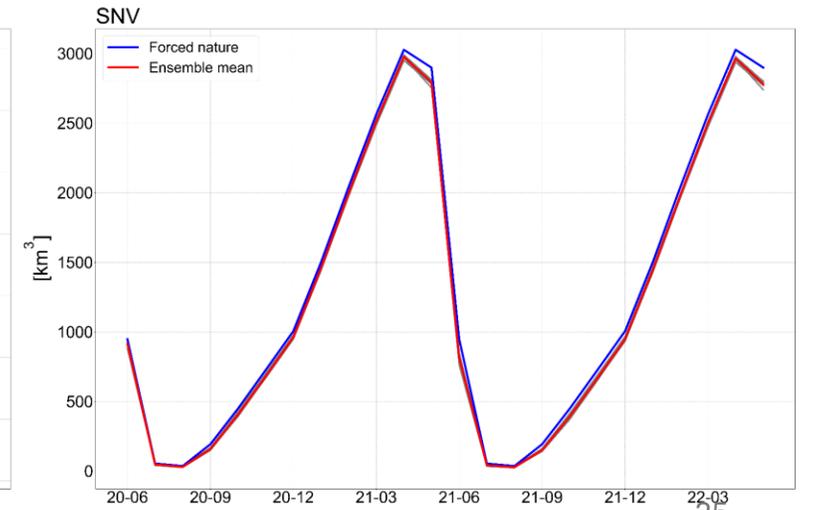
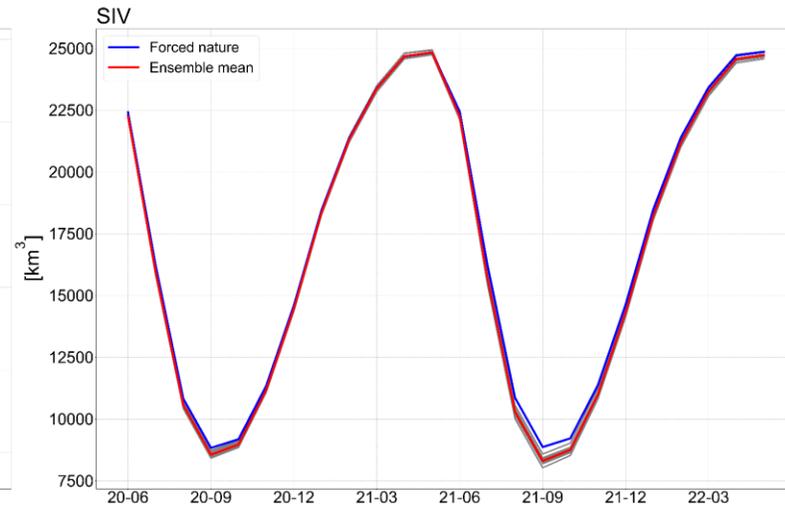
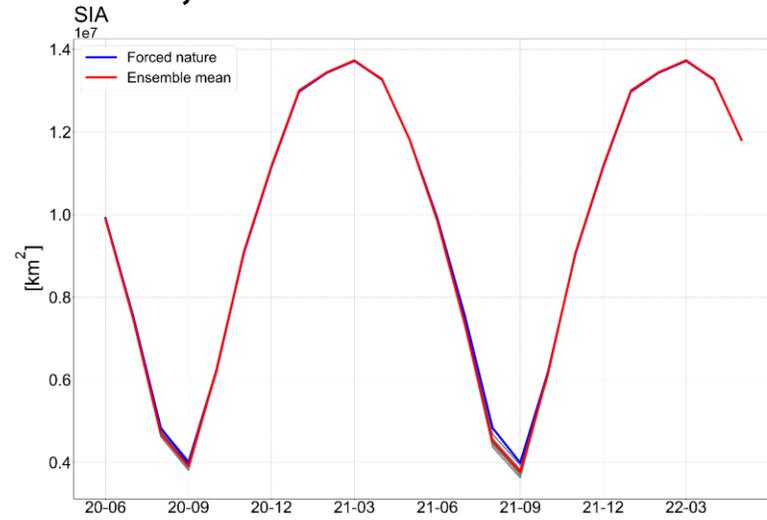


Non-linear snow volume forecast

EXP1, EXP3

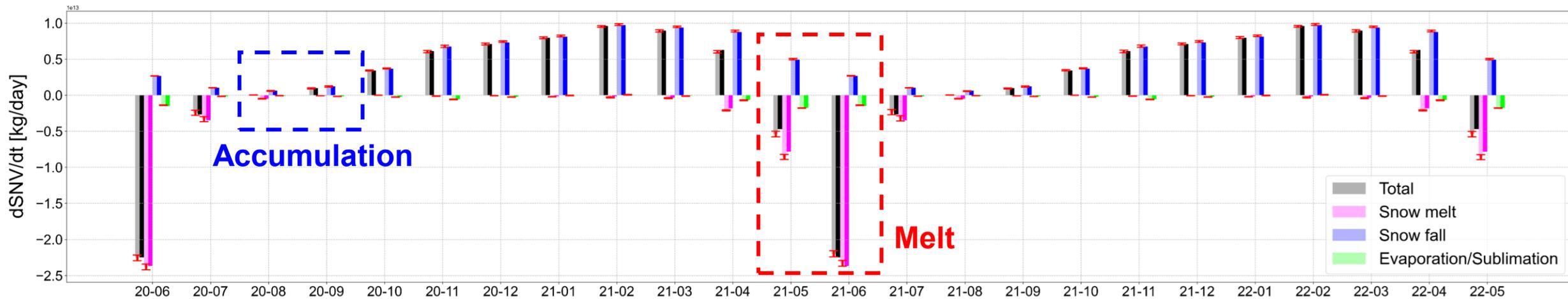


EXP4, EXP5

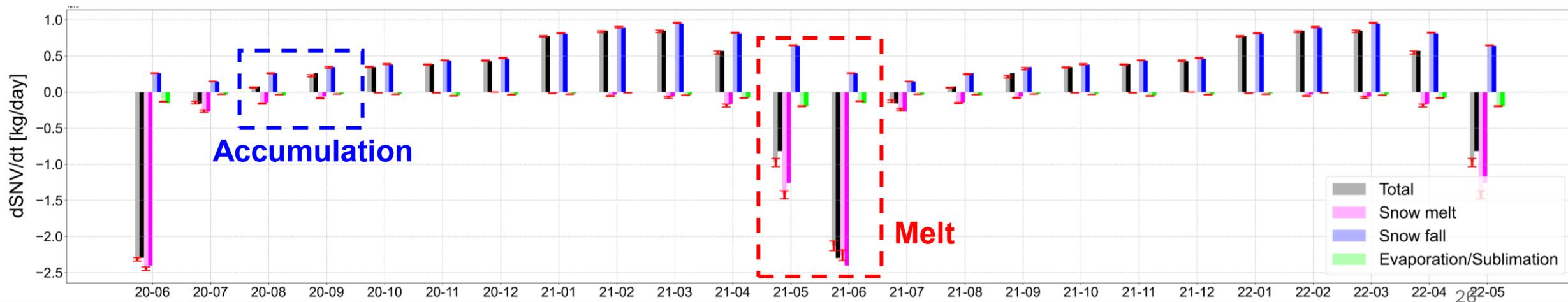


Non-linear snow volume forecast

EXP1: Darker bars, EXP3: Lighter bars

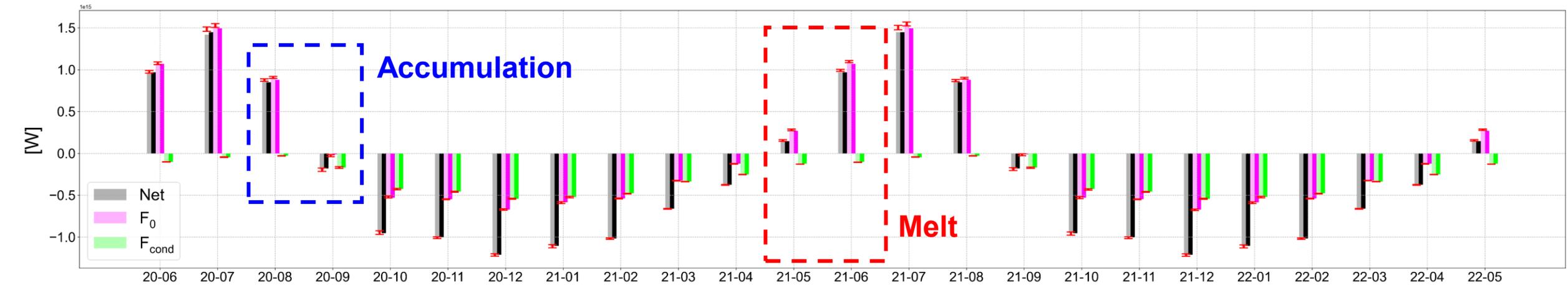


EXP4: Darker bars, EXP5: Lighter bars

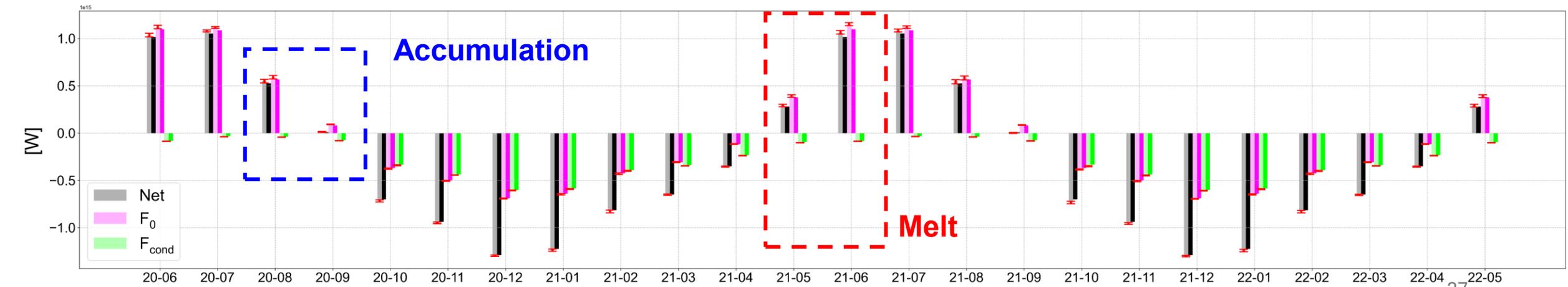


Non-linear snow volume forecast

EXP1: Darker bars, EXP3: Lighter bars



EXP4: Darker bars, EXP5: Lighter bars



Non-linear snow volume forecast

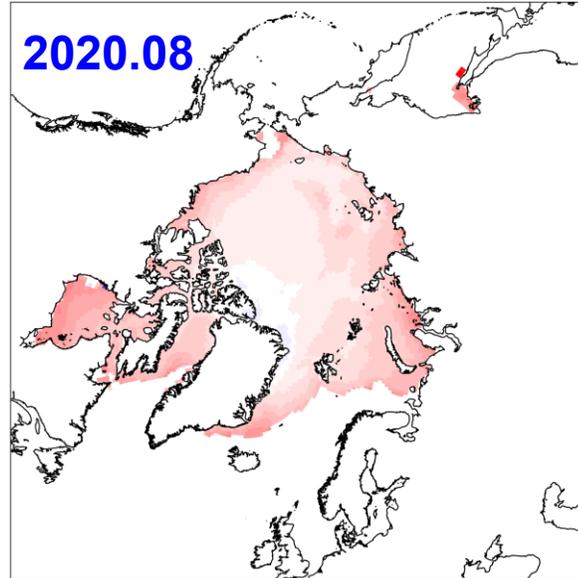
$$F_{\text{net}} = F_0 + F_{\text{cond}}$$

$F_{\text{net}} < 0 \rightarrow$ Snow/Ice doesn't melt

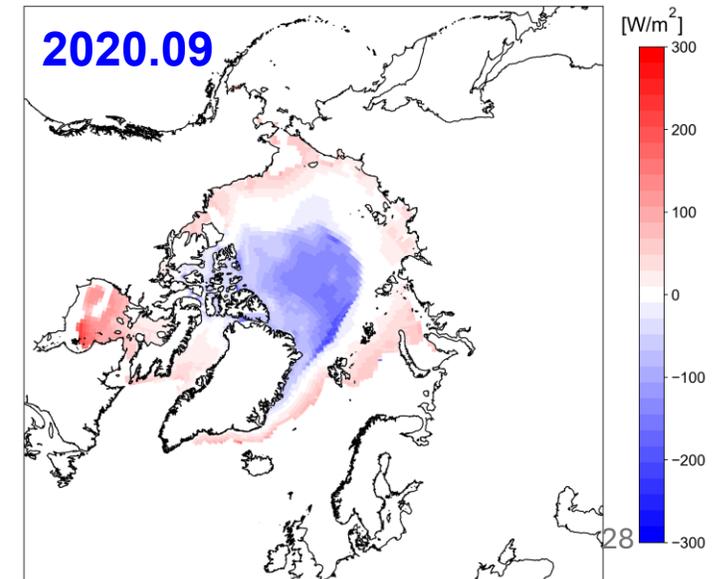
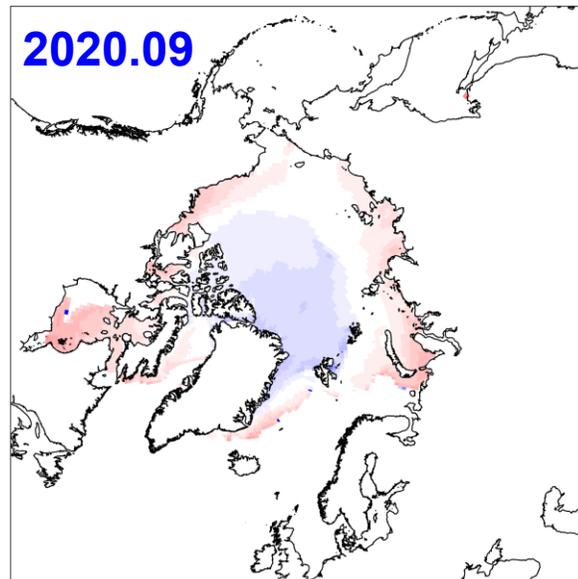
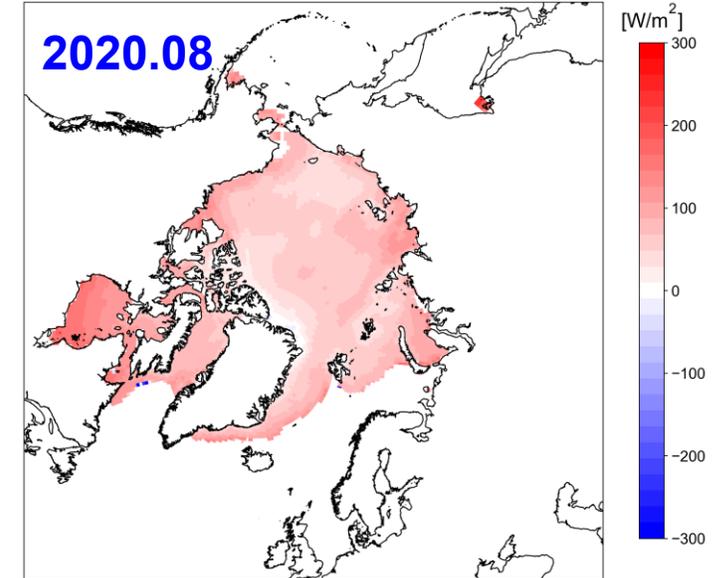
$F_{\text{net}} > 0 \rightarrow$ Snow/Ice melts

Atmospheric state is more susceptible to **additional** melt from random perturbation in EXP4

EXP4



EXP1



Non-linear snow volume forecast

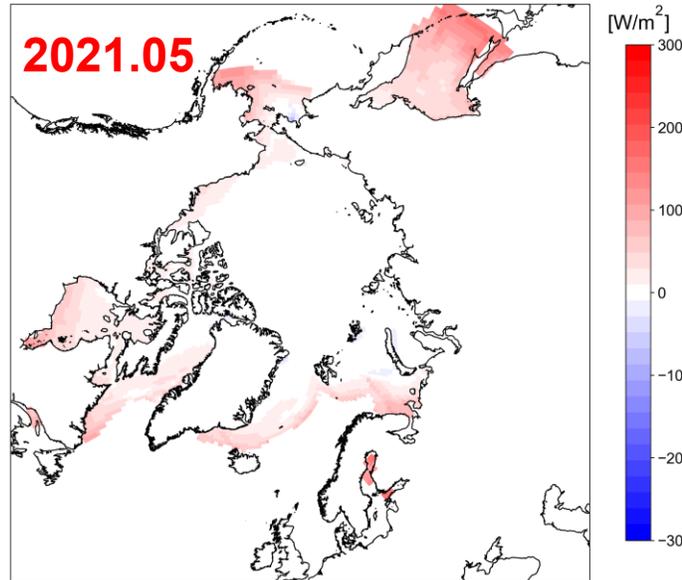
$$F_{\text{net}} = F_0 + F_{\text{cond}}$$

$F_{\text{net}} < 0 \rightarrow$ Snow/Ice doesn't melt

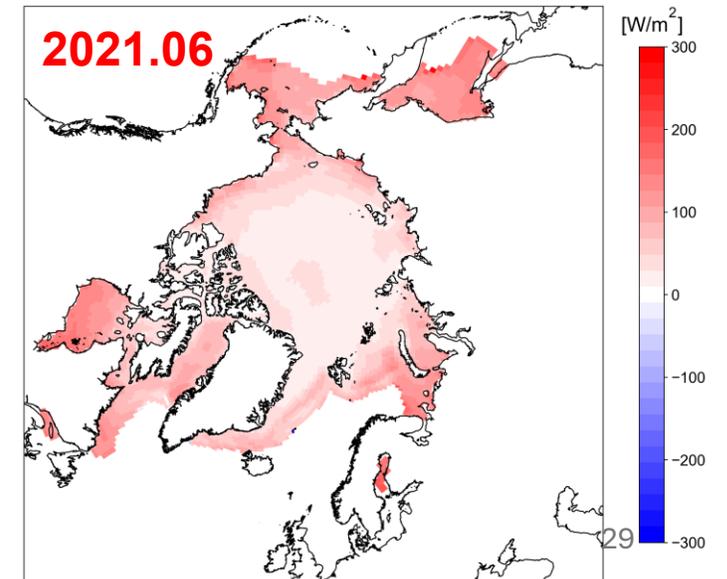
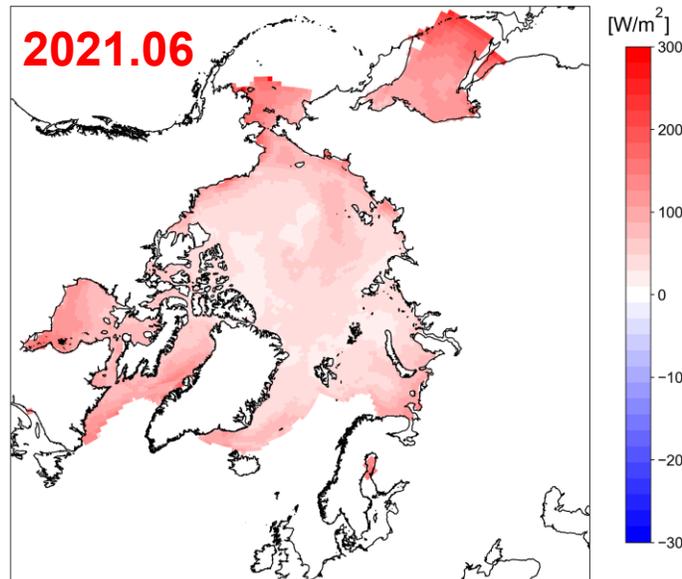
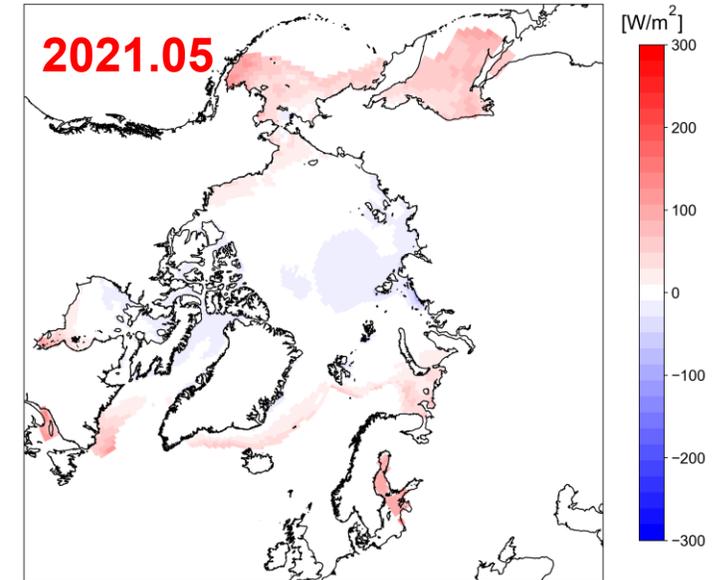
$F_{\text{net}} > 0 \rightarrow$ Snow/Ice melts

Atmospheric state is more susceptible to **additional** melt from random perturbation in EXP4

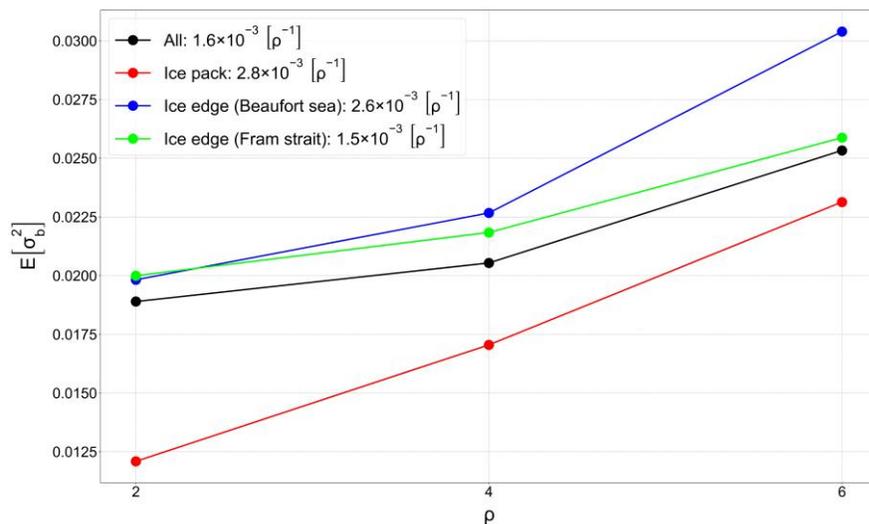
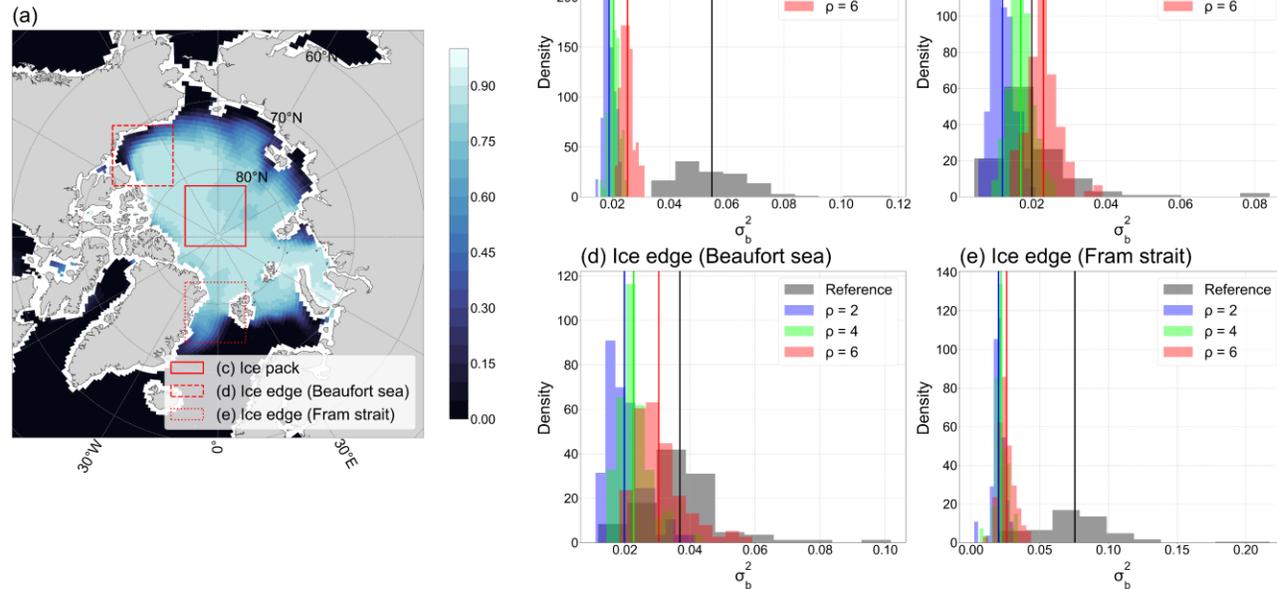
EXP4



EXP1

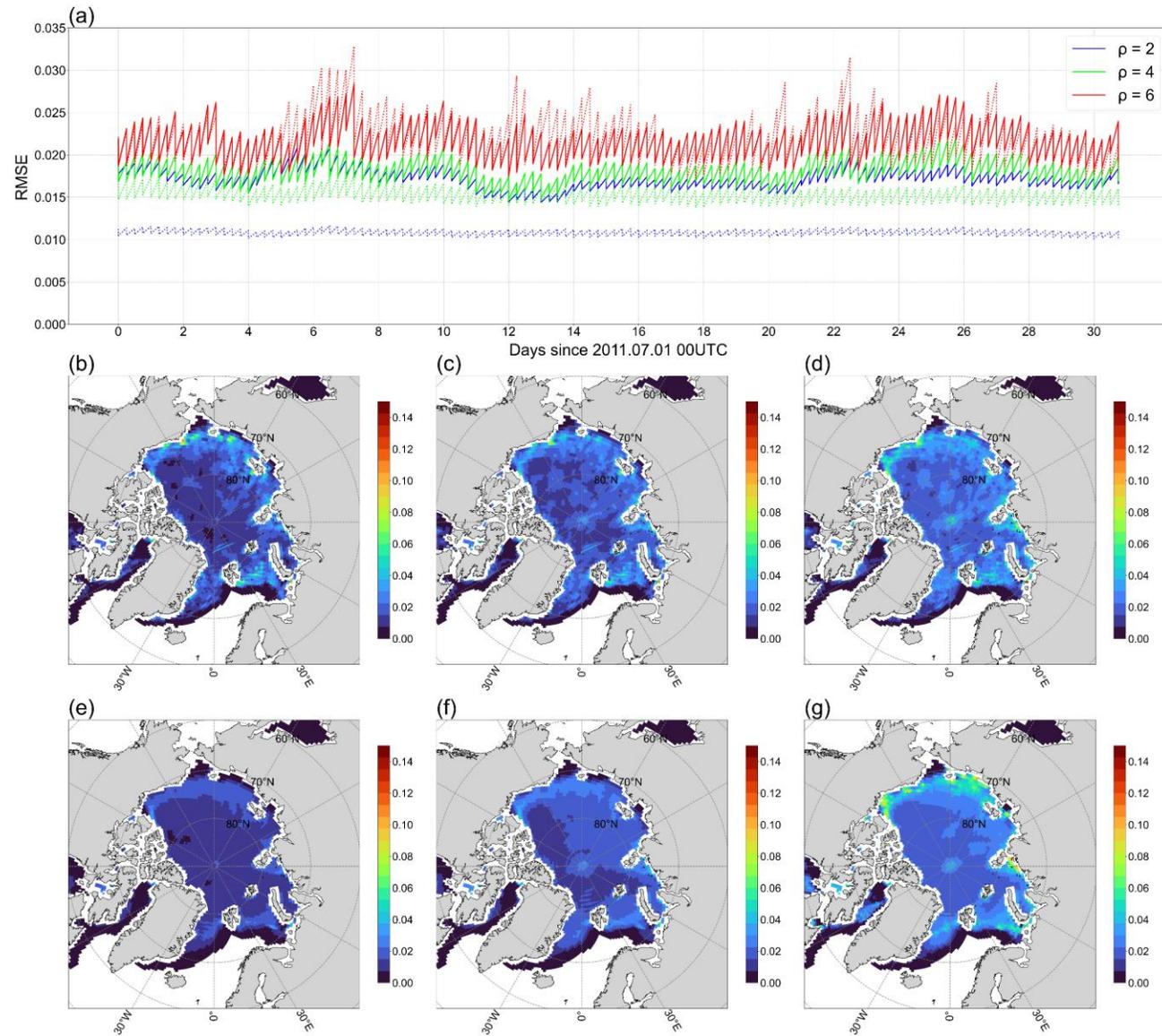


Realistic background errors

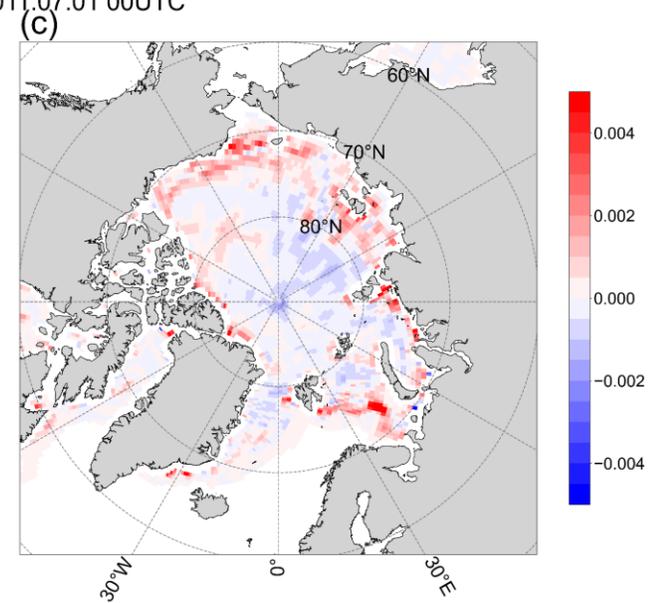
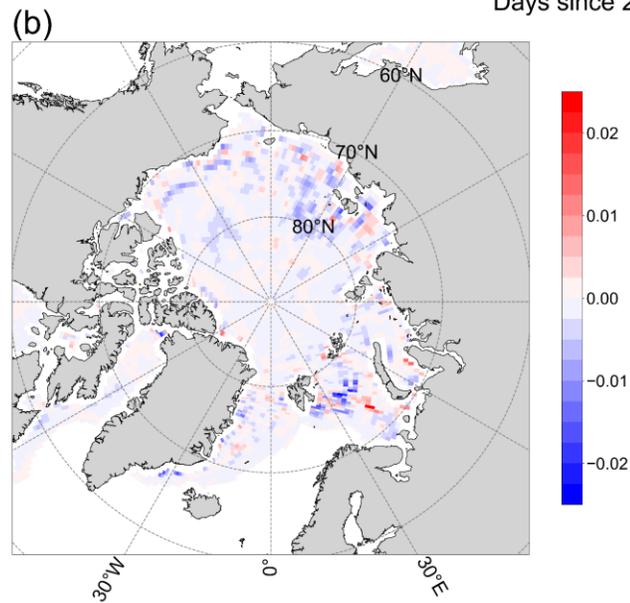
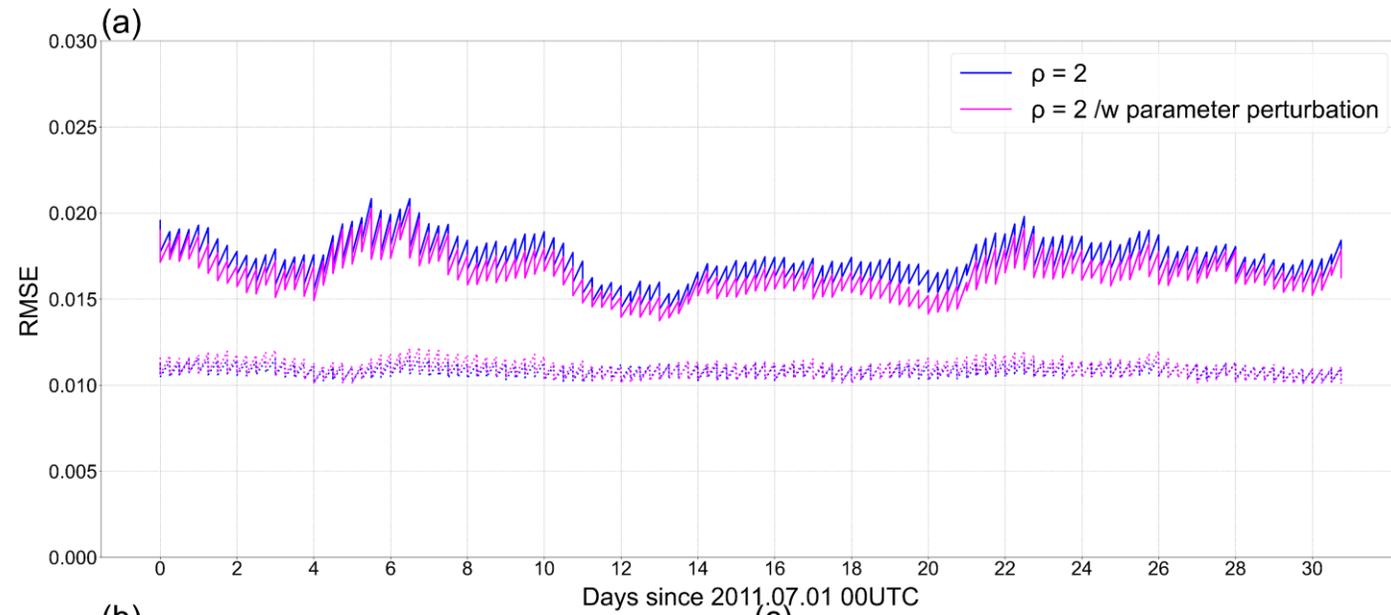


- Histograms of background error magnitudes
- Over the ice pack, enhanced atmospheric forcing errors can be used to match the actual background errors of a coupled ICE-ATM-OCN DA system
- Less sensitive over regions such as Fram strait

Different ρ

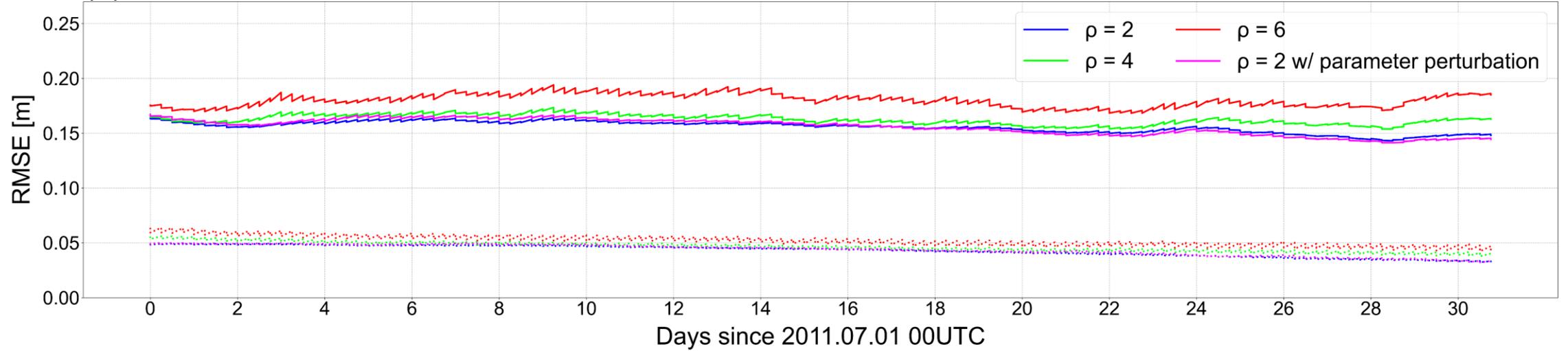


Parameter perturbation



Multivariate updates

(a) Ice thickness



(b) Snow depth

