Validating GFS and GEFS Forecast of Arctic Surface Fluxes against Saildrone Observations

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Introduction

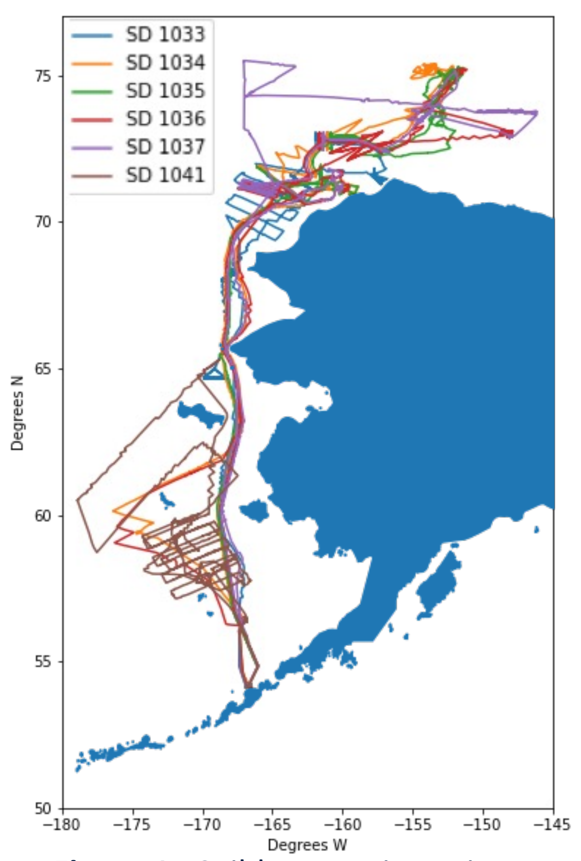

Figure 1. Saildrone trajectories from Arctic deployments in 2019

- Arctic amplification poses risks to global climate
- Surface flux measurements help assess air-sea interaction and associated climate change impacts
- Saildrones collect in-situ data in Arctic waters which provides insight into the Arctic environment
- Model validation helps improve surface flux forecasts

Figure 2. Images of Saildrones in Pacific Ocean (left) and deployed in the Arctic (right) (Saildrone 2022, 2023)

Objective: Identify biases in Global Forecast System and Global Ensemble Forecast System predictions by comparing predictions to in-situ measurements

Materials and Methods

Global Forecast System
V14, V15.1

0.25° x 0.25° global grid

0-240 hours (10 days)

6-hour frequency
(00, 06, 12, 18 UTC)

Analysis and 6-hr forecast
- Relative humidity (R2)
- Sea surface temperature (T)
- Air temperature (T2M)
- Wind speed (GUST)

6-hr averages
- Sensible heat flux (QS)
- Latent heat flux (QL)

Global Ensemble Forecast System
V11.0

1° x 1° global grid

0-384 hours (16 days)

6-hour frequency
(00, 06, 12, 18 UTC)

20 ensemble members

6-hr averages
- Sensible heat flux (QS)
- Latent heat flux (QL)

- Saildrone measurements taken between 05/14/2019 – 10/13/2019
- Linear interpolation of model forecasts onto Saildrone observation coordinates
- Temporal alignment of flux variables by averaging 6-hour Saildrone observations
- Unit and vertical level conversion of variables

- Statistical examination and modeling of GFS to evaluate influence of state variables
- Initial examination of GEFS fluxes using ensemble statistical methods

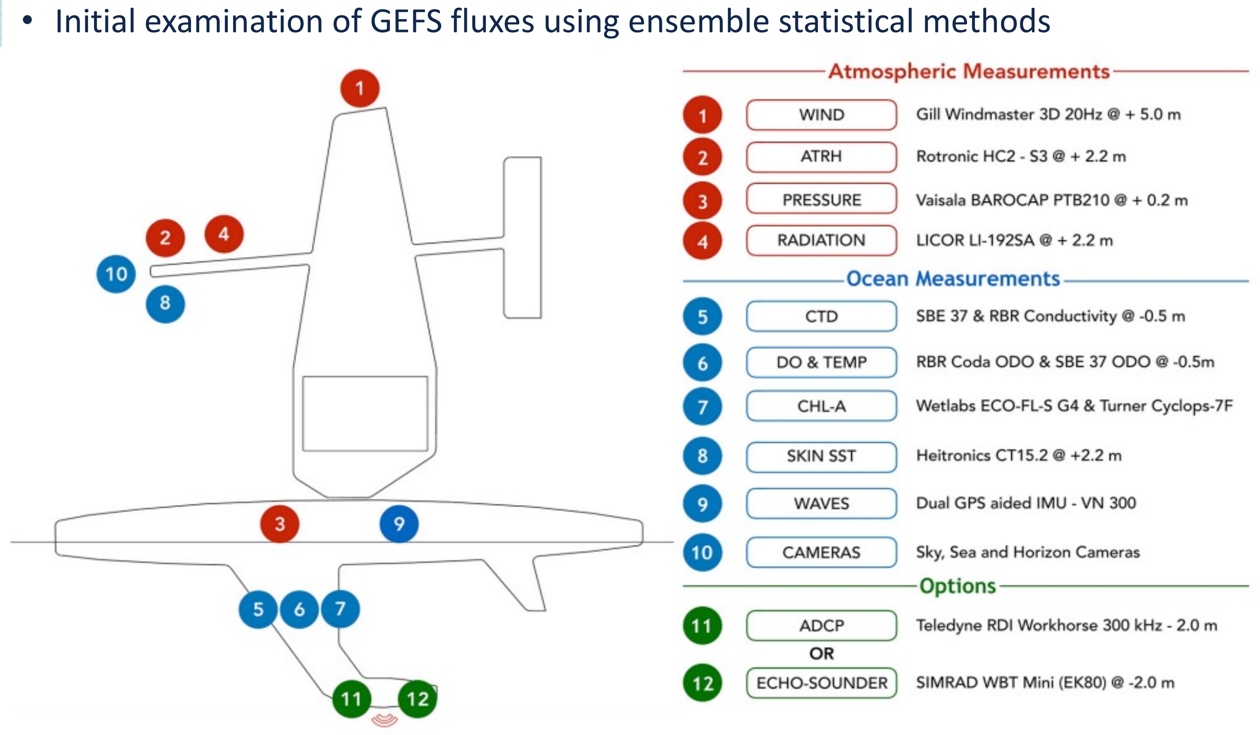

Figure 3. Diagram of Saildrone sensors (Meinig, 2019)

Analysis of Global Forecast System Fluxes

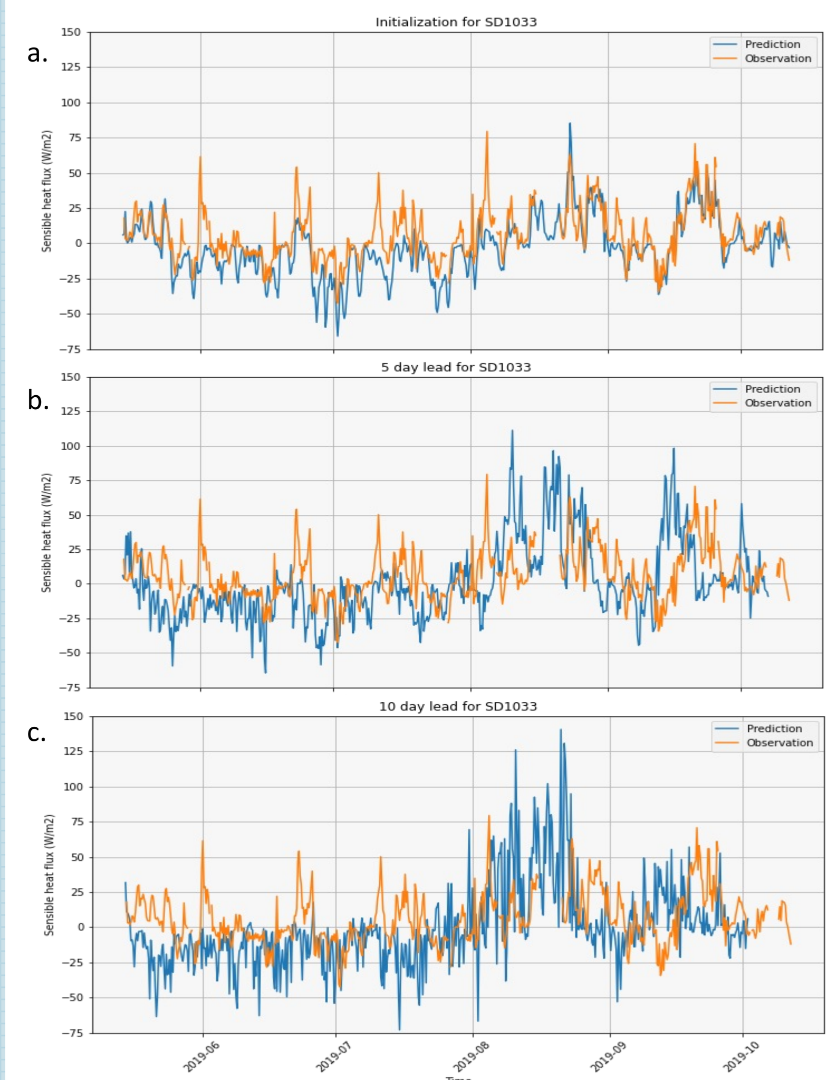

Figure 4. Time series of saildrone observations and GFS predictions of QS at a) initialization, b) t= 5 days and c) t=10 days

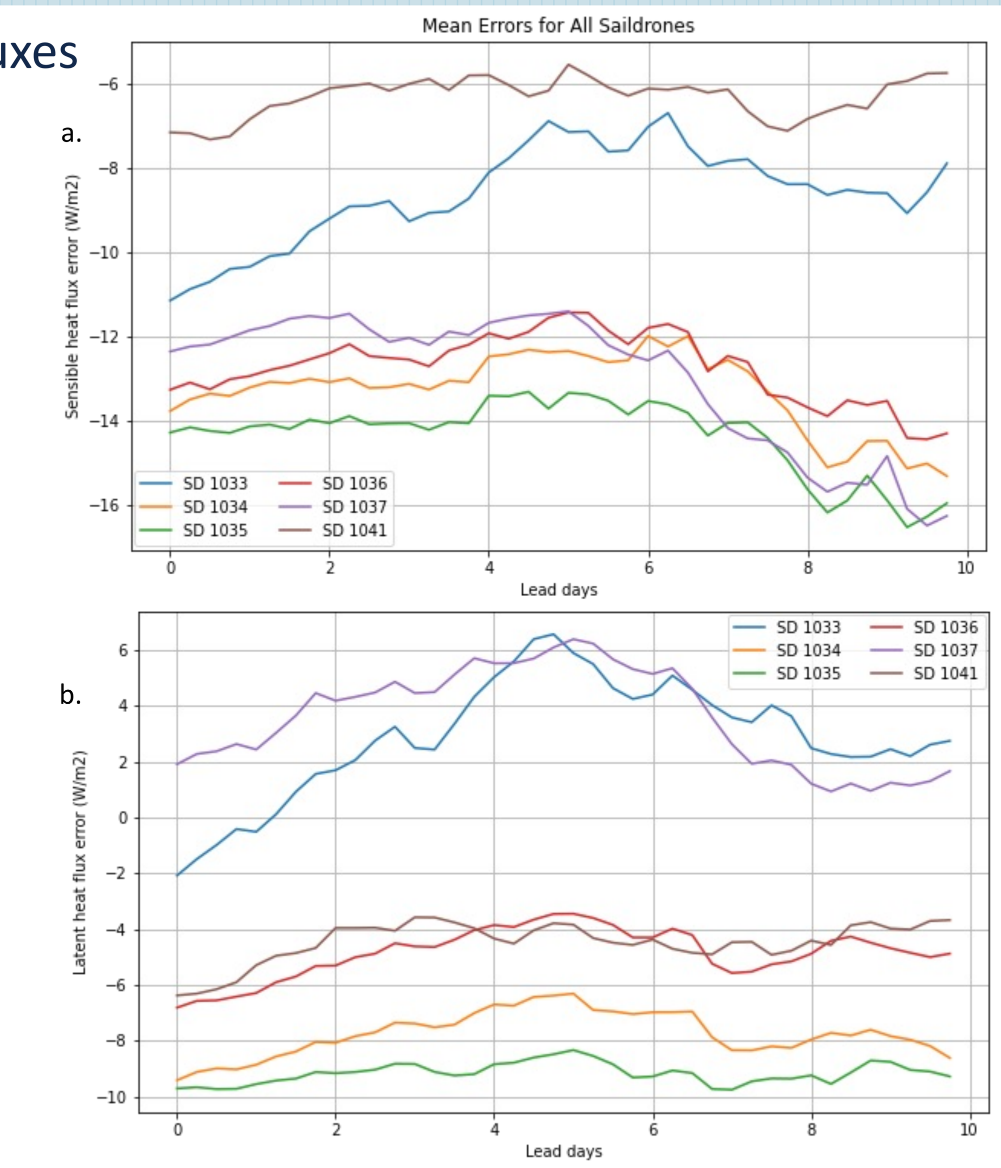

Figure 5. Averaged error as a function of forecast time for each saildrone trajectory for a) QS and b) QL

- Variance in error of predictions for both fluxes and all state variables increases as lead time of forecast increases.
- Error magnitude differs between Saildrone tracks.
  - The temporal component of the data is not responsible for this difference. Spatial difference in trajectories is a likely contributor.

Spatial Error Model of Flux Error

- Generalized Method of Moments (GMM) framework
- Queen contiguity weights matrix used

$$QS_{err} = -0.96 - 0.08\,R2_{err} + 7.17\,T_{err} - 7.54\,T2M_{err} + 0.62\,GUST_{err} + 0.52\,W\varepsilon + u \qquad \text{Pseudo } R^2 = 0.6045$$

$$QL_{err} = -2.45 - 1.25\,R2_{err} + 7.59\,T_{err} - 7.24\,T2M_{err} + 1.85\,GUST_{err} + 0.51\,W\varepsilon + u \qquad \text{Pseudo } R^2 = 0.6608$$

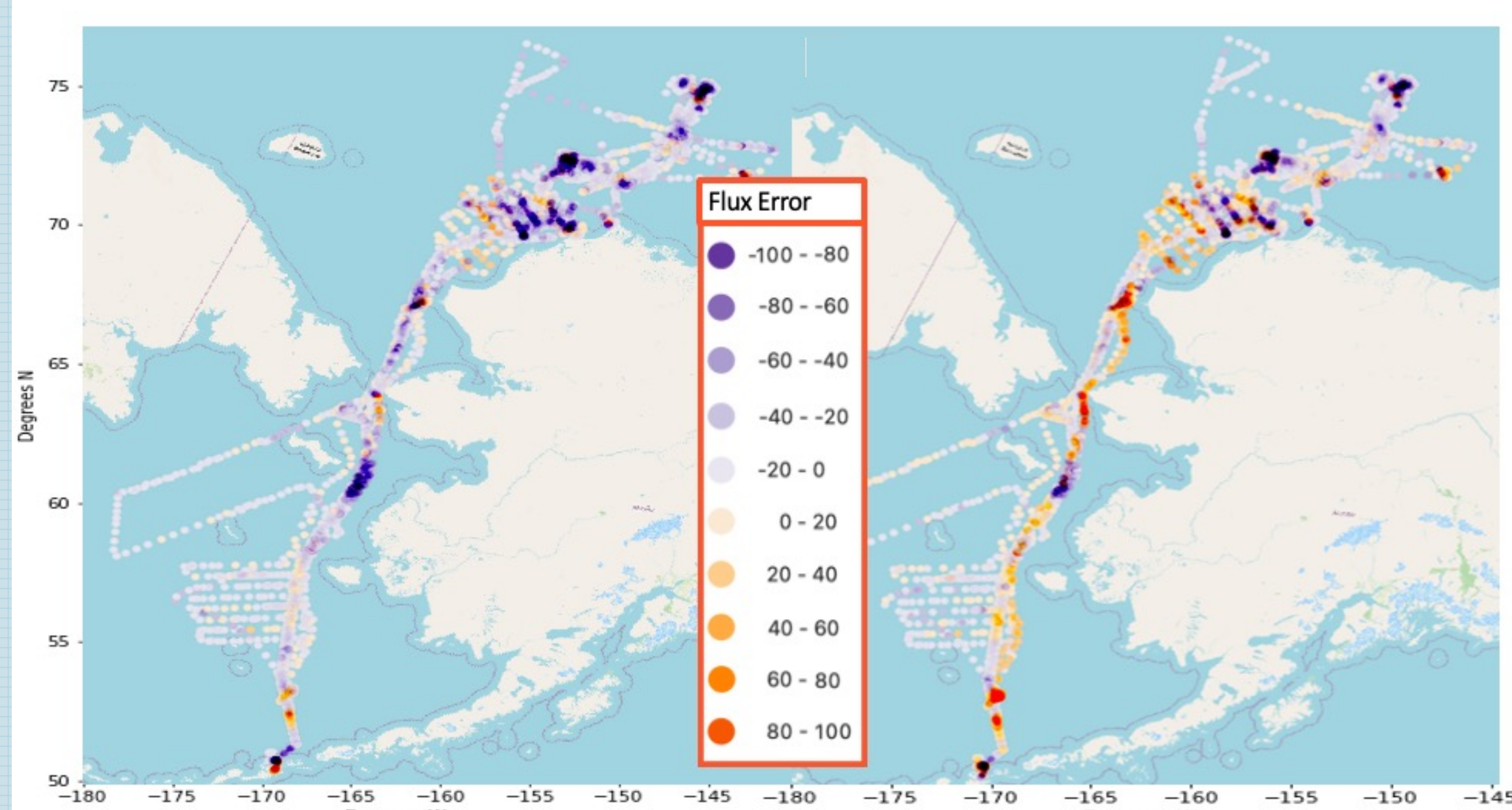

Figure 6. Plot of errors of flux (W/m²) predictions for sensible heat flux (left) and latent heat flux (right)

- Air and sea surface temperature are the most influential parameters in both models.
- Relative humidity and wind speed have small but significant contributions to prediction of sensible heat flux error. Contributions of these variables are larger in magnitude in latent heat flux model.
- Spatial influence of unexplained error is nearly identical between models.

Global Ensemble Forecast System Fluxes Statistics

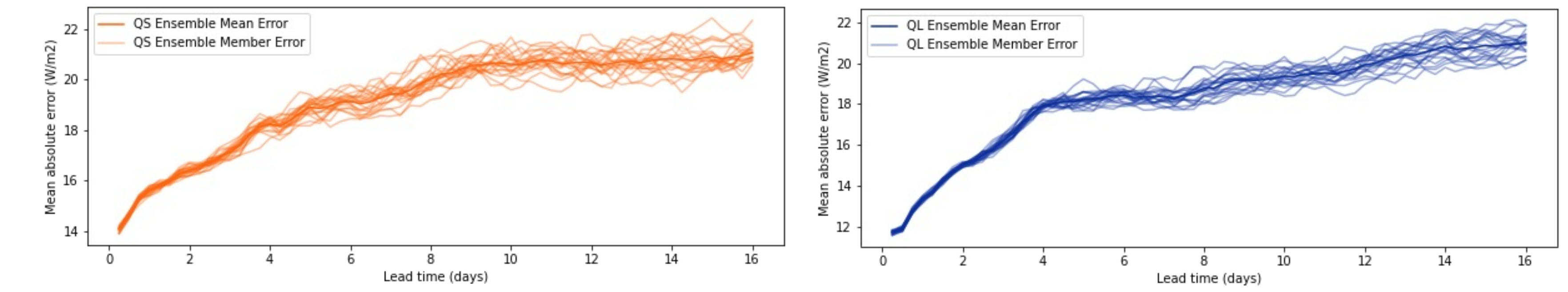

Figure 7. Ensemble mean and member absolute errors over forecast time for sensible (left) and latent heat flux (right)

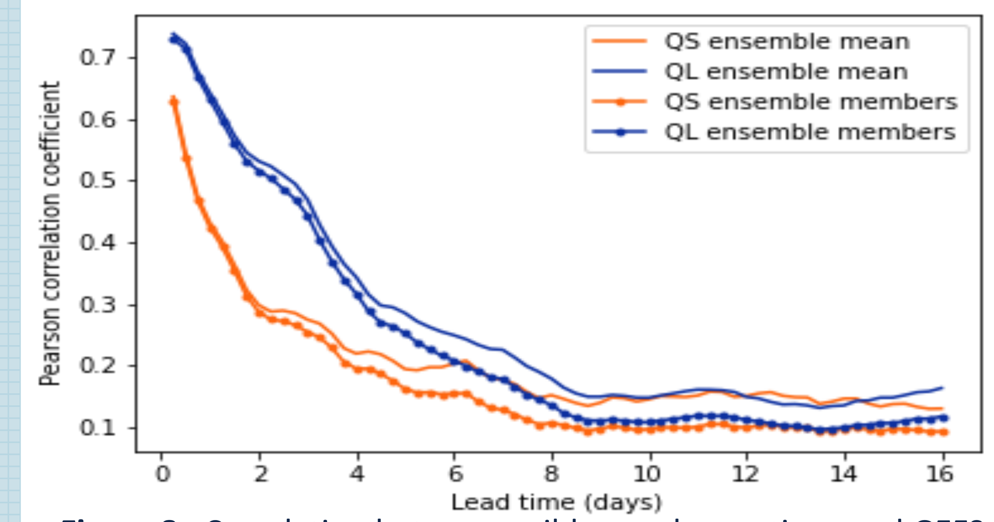

Figure 8. Correlation between saildrone observations and GEFS means and members as a function of lead time for QS and QL

GEFS skill for predicting fluxes exhibits exponential decay as lead time increases. Forecasts are minimally useful beyond approximately four days lead time.

The spread/skill plot indicates that the ensemble member predictions are consistently underdispersive for both latent and sensible heat flux or that the GEFS flux predictions have a large bias.

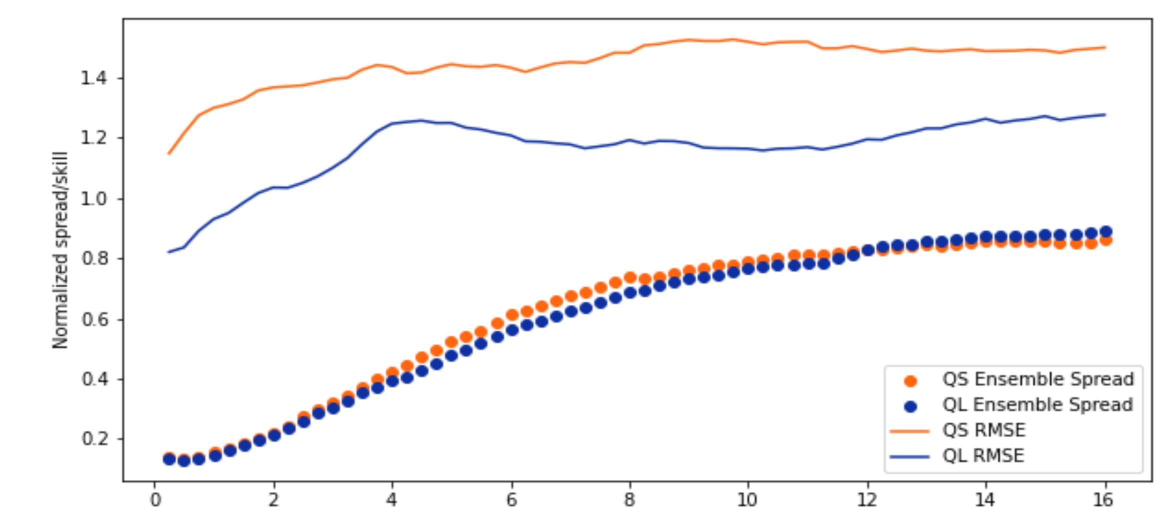

Figure 9. Ensemble spread and RMSE as a function of lead time for QS and QL

Discussion

- GFS and GEFS exhibit overall negative bias when predicting surface flux.
  - GFS has minimal trend in bias over forecast time.
  - GEFS bias increases over forecast time.
  - Error variance increases over time for both models.
- GFS state variable prediction error and spatial patterns in flux error account for over half of the variability in the predictive error of fluxes.
- Future work will examine GEFS fluxes in more depth, including evaluation of state variables and examination of spatiotemporal relationships.

References

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(Saildrone, 2019)