Subseasonal-to-Seasonal strategies for the Earth System Foundation Model (ESFM)

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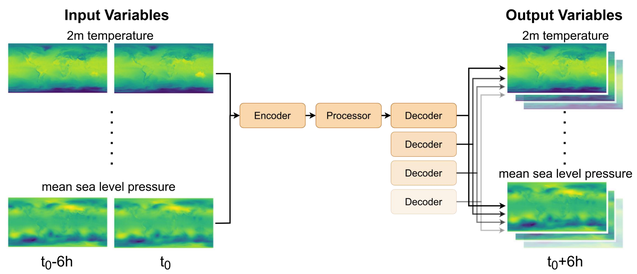
Introduction

Earth System Foundation Model (ESFM) [1]:

A recently released foundation model for the Earth System. It is a large transformer-based model, pretrained on ERA5 and eight CMIP6 climate datasets to simulate the Earth System by predicting its state at the $t_0 + \Delta t$ timestep using data from the $t_0 - \Delta t$ and t_0.

Subseasonal-to-seasonal (S2S) forecasts:

Prediction window covering the temporal gap between medium-range weather (up to two weeks) and seasonal climate forecasting (several months). In this project, we aim to utilize the capabilities of ESFM and adjust it for S2S timescales.



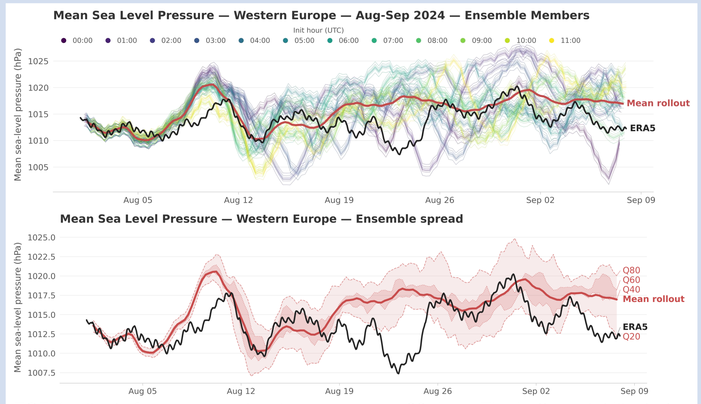
ESFM architecture. The input data of numerous variables from timesteps $t_0 - \Delta t$ and t_0 are mapped into a latent space. A 3D Swin Transformer [2] then processes these representations. The decoder maps these rich latent representations back into the physical domain, utilizing multiple specialized heads that simultaneously predict distinct future trajectories

S2S prediction techniques

Relying on a single deterministic forecast is insufficient in the S2S timescales and necessitates using ensembles to characterize the probability distribution. We generate the **ensemble members** with:

1. **Decoder tails:** Multiple decoder heads produce a range of future trajectories in a single forward pass.

2. **Multiple initial times:** Multiple initial times allow the model to capture a wider range of potential trajectories derived from different starting points.

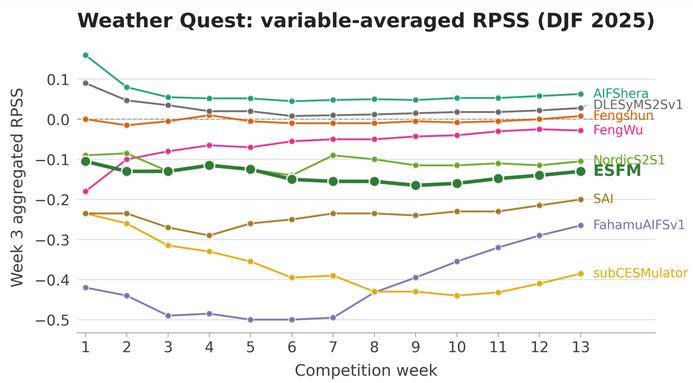


ESFM rollouts for mean sea level pressure over 38 days. The bottom plot illustrates the uncertainty obtained by aggregating the 96 ensemble members. The top plot shows the breakdown of the trajectories produced by each individual member.

ESFM generates reliable S2S forecasts. The model exhibits low initial spread, which naturally widens with the rollout length, capturing increasing uncertainty

AI Weather Quest

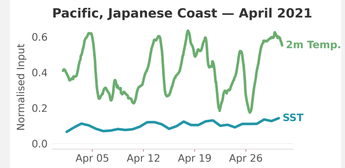
ESFM participates in the **AI Weather Quest** [3] competition organized by ECMWF to harness ML in advancing sub-seasonal forecasting.



Ranked Probability Skill Score (RPSS ↑) for selected ML-based models for the AI Weather Quest in the period spanning from December 2025 to February 2026.

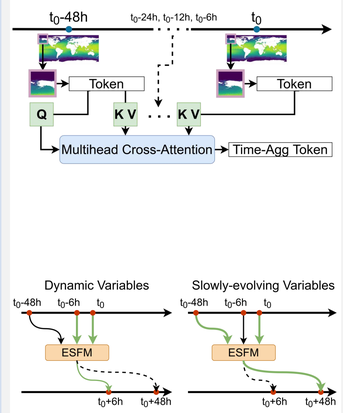
Slowly-evolving variables

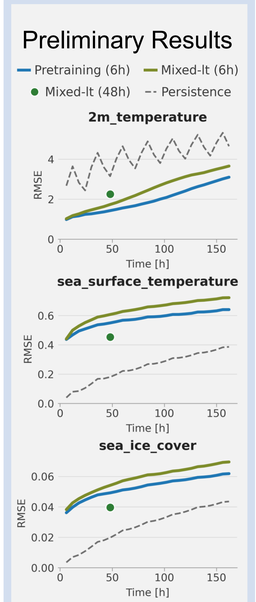
S2S forecasts are greatly influenced by slowly-evolving components of the Earth system, such as sea surface temperature, soil moisture, and sea ice cover.



Incorporating more timesteps in ESFM input via Temporal Attention Aggregator (TAA) aims to help the model learn slowly-evolving variables' dynamics. **TAA** is a mechanism allowing ESFM to select which timesteps are crucial for encoding each variable.

We train the model using **different lead times** to encourage ESFM to use distant timesteps for slower variables.





RMSE of TAA mixed lead time training compared to 6h lead time

Conclusions

- ESFM produces **reliable S2S forecasts** utilizing the ensemble members produced by different initial conditions and decoder tails.
- ESFM demonstrates stable and reasonable performance against other ML-based contenders in the AI Weather Quest.
- We believe the performance can be pushed further by **efficiently encoding slowly-evolving variables.**

References

[1] Özdemir et al, "Earth System Foundation Model (ESFM): A unified framework for heterogeneous data integration and forecasting", ArXiv, 2026

[2] Yang, Yu-Qi, et al. "Swin3d: A pretrained transformer backbone for 3d indoor scene understanding." Computational Visual Media 11.1, 2025

[3] https://aiweatherquest.ecmwf.int/

ESFM GitHub

EGU Abstract

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