Improving 1-month Forecasts in South Korea through the Dynamical Downscaling of Machine Learning-based Global Predictions

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Scan for Abstract

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I. Introduction

- **Need for Extended-Range Forecasts**

  Extended-range forecasts beyond typical short-term forecast periods of 7-10 days can benefit many weather-dependent sectors, such as agriculture, but remain challenging to achieve with sufficient accuracy and reliability.

- **Development of Machine Learning (ML) Models**

  While traditional physical models have long been the foundation of weather forecasting, recent advancements in ML models for weather prediction have demonstrated promising forecasting skills that are comparable to, or even surpass, those of physical models.

- **Study Objectives**

  This study evaluates the 1-month forecasting performance of a physical model (CFSv2) and an ML-based model (FuXi-ENS), with dynamical downscaling employed, aiming to provide valuable insights for enhancing extended-range (*or* subseasonal) forecasts in South Korea.

II. Methodology

- Study Period: July 2018 and 2023
- Observational Data (OBS): 87 ASOS stations in South Korea
- Forecast Data: (1) Seasonal Forecasting System 5 (**SEAS5**)
  (2) Climate Forecast System version 2 (**CFSv2**)
  (3) **FuXi-ENS**

Model		SEAS5	CFSv2	FuXi-ENS
Institution		ECMWF (C3S)	NCEP	Fudan Univ.
Initial Conditions		1st UTC00 of each month	Every 6 hours	30th UTC12 of each month
Ensemble Members		51 members	1 member every 6 hours	51 members
Spatial Resolution		1° x 1°	T126 (~1°)	0.25° x 0.25°
Temporal Resolution	Surface	6 hourly		
	Pressure	12 hourly	6 hourly	

Table 1. Forecast data used in this study

Step 1. Selection of CFSv2 and FuXi-ENS Members for Dynamical Downscaling

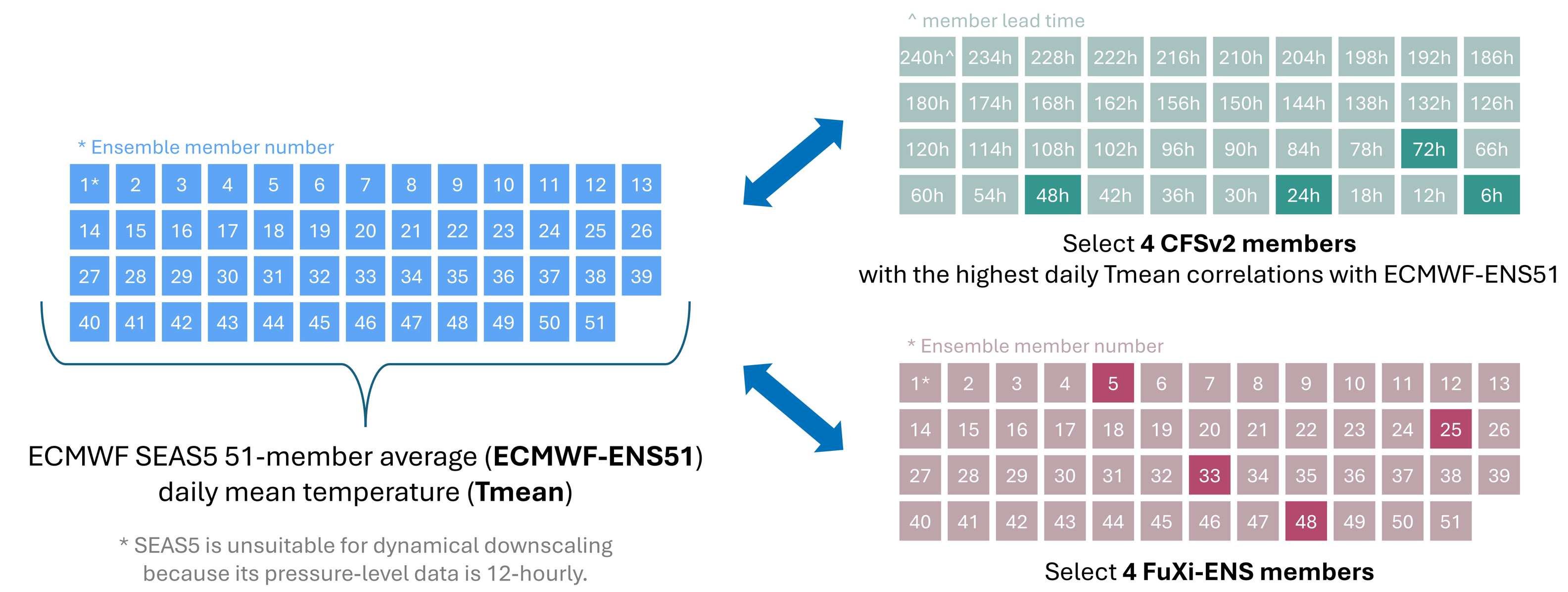
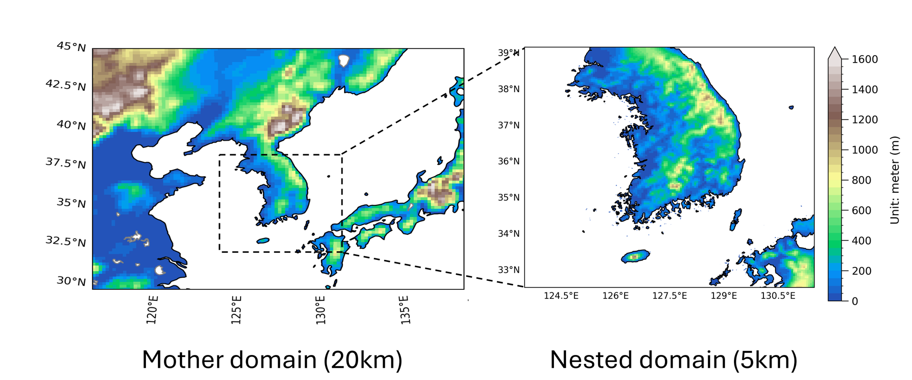


Figure 1. Diagram illustrating the selection process of CFSv2 and FuXi-ENS members for dynamical downscaling

Step 2. Dynamical Downscaling using WRF

- Weather Research Forecasting (**WRF**) model with Advanced Research WRF (ARW) dynamic core (Version 4.5)

Domains (Double-Nested System)



Physical Parameterizations	
Microphysics	WSM3
Radiation Physics	RRTMG longwave and shortwave
Surface Layer	Revised MM5 Monin-Obukhov scheme
Land Surface	Noah Land Surface Model
Planetary Boundary Layer	Yonsei University scheme
Cumulus Parameterization	Kain-Fritsch scheme

Table 2. WRF model configuration used in this study

Step 3. Construct Forecast Ensembles by Averaging the 4 Selected Dynamically Downscaled Forecasts from Each Model

III. Results

- **Relationship between Daily Temperature Fluctuations and Forecast Predictability**

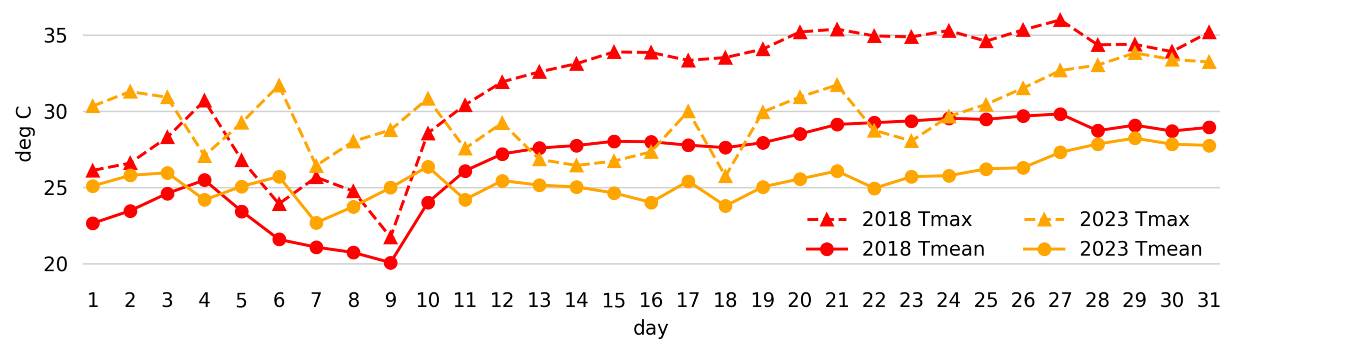


*Figure 2. Observed (OBS) daily maximum and mean temperature (**Tmax and Tmean**) for July 2018 and 2023*

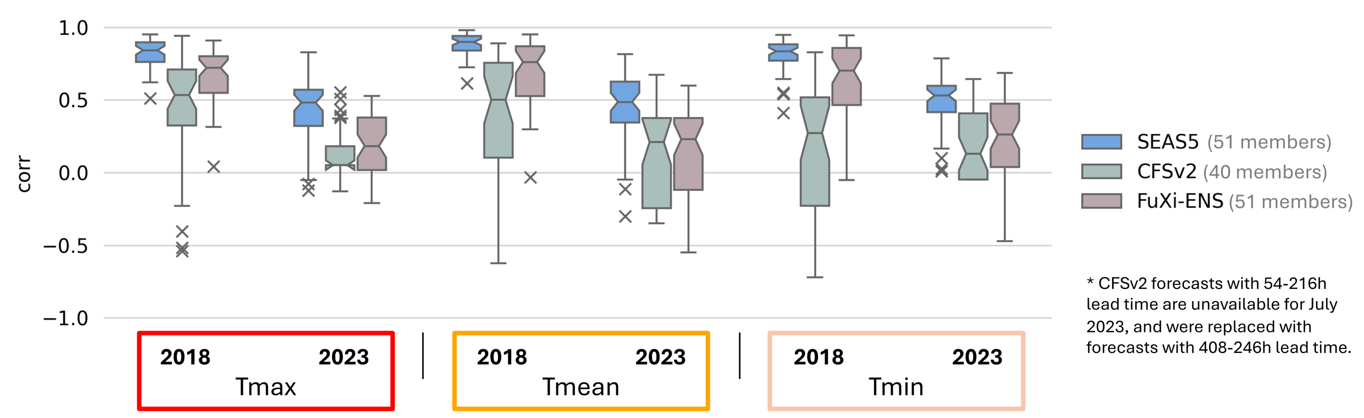


*Figure 3. Boxplots of **daily Tmax/Tmean/Tmin correlations** of SEAS5, CFSv2, and FuXi-ENS with OBS*

Compared to July 2018, temperature fluctuated much more during July 2023, both in frequency and magnitude (See *Figure 2*), and this **large interdiurnal variability likely reduces forecast predictability.** All SEAS5, CFSv2, FuXi-ENS forecasts show better temperature predictability for July 2018 than for July 2023. Among the models, **SEAS5 demonstrates the highest skill** with the smallest variability across different members, **followed by FuXi-ENS, while CFSv2 shows the lowest skill** (See *Figure 3*).

- **Dynamically Downscaling Member Selection Results**

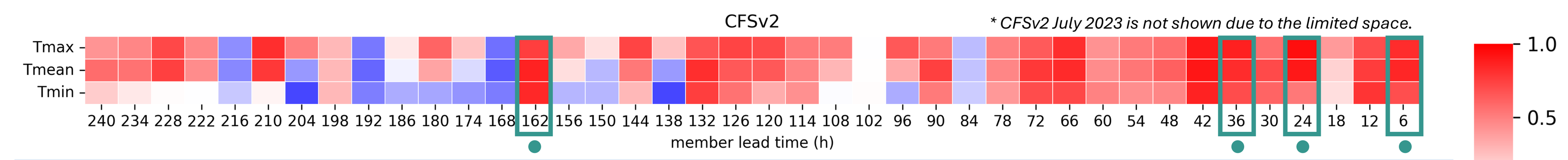


*Figure 4a. Heatmaps of **daily Tmax/Tmean/Tmin correlations of CFSv2 with OBS for July 2018 and the selected members** for dynamical downscaling based on the comparison with ECMWF-ENS51 (in green boxes)*

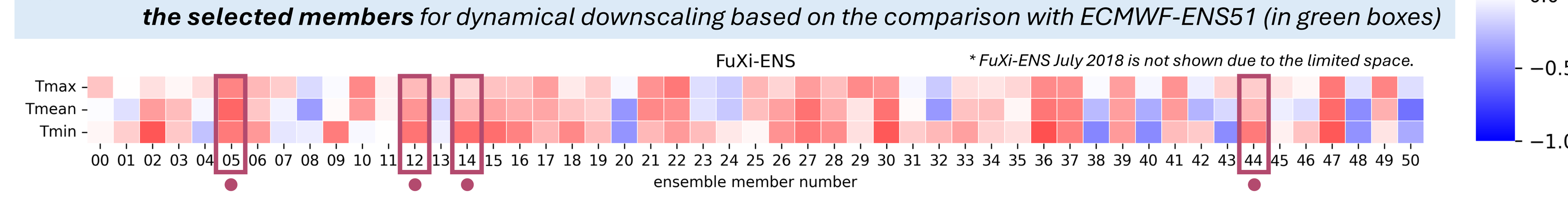


*Figure 4b. Heatmaps of **daily Tmax/Tmean/Tmin correlations of FuXi-ENS with OBS for July 2023 and the selected members** for dynamical downscaling based on the comparison with ECMWF-ENS51 (in purple boxes)*

(a)

Year	Selected CFSv2	Daily Tmean Correlations with ECMWF-ENS51	Daily Tmean Correlations with OBS
2018	24h	0.932	**0.891**
	36h	0.912	**0.883**
	162h	0.877	**0.855**
	6h	0.875	**0.833**
2023	234h	0.845	**0.540**
	228h	0.725	**0.461**
	24h	0.685	**0.380**
	30h	0.590	**0.451**

(b)

Year	Selected FuXi-ENS	Daily Tmean Correlations with ECMWF-ENS51	Daily Tmean Correlations with OBS
2018	40	0.942	**0.952**
	39	0.937	**0.936**
	37	0.935	**0.924**
	13	0.913	**0.880**
2023	44	0.741	**0.295**
	5	0.725	**0.598**
	14	0.714	**0.293**
	12	0.704	**0.421**

*Table 2. **Daily Tmean correlations of the selected (a) CFSv2 and (b) FuXi-ENS members** with ECMWF-ENS51 (selection criteria) and **with OBS (true values)** for July 2018 and 2023*

ECMWF SEAS5 demonstrates its usefulness as a benchmark for selecting CFSv2 and FuXi-ENS members to be dynamically downscaled. Although not always the best, the **CFSv2 and FuXi-ENS members selected based on their comparison with ECMWF-ENS51 consistently achieve positive correlations with OBS** (true values).

- **Enhanced Predictability from Dynamically Downscaled Forecasts**

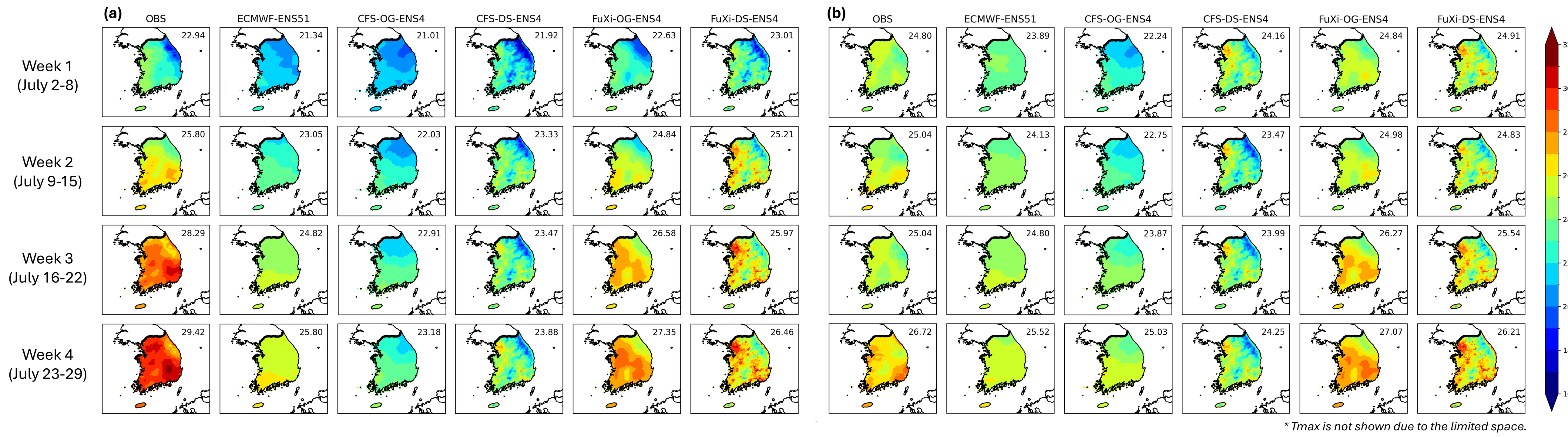


*Figure 5. **Spatial distribution of weekly Tmean from OBS** (interpolated from 87 stations)**, ECMWF-ENS51,** 4-selected-member ensembles of CFSv2 original (OG) forecasts and downscaled (DS) forecasts (**CFS-OG-ENS4 and CFS-DS-ENS4**), and 4-selected-member ensembles of FuXi-ENS original forecasts and downscaled forecasts (**FuXi-OG-ENS4 and FuXi-DS-ENS4**) for July (a) 2018 and (b) 2023 (Upper right: spatial mean values)*

Note: the OBS spatial distribution is interpolated from only 87 ASOS stations, which may not be fully comparable to the 5-km downscaled forecasts.

- While **ECMWF SEAS5** shows the highest daily temperature correlations with OBS (as presented in *Figure 3*), its **low spatial resolution leads to a general underestimation of temperature and an inability to capture regional details**. CFSv2 original forecasts (CFS-OG) with a resolution similar to SEAS5, show even greater underestimation.
- Meanwhile, FuXi-ENS original forecasts (FuXi-OG) with relatively higher resolution show little to no underestimation in terms of spatial mean – particularly no underestimation in 2023, and only slight underestimation in 2018 (noting that S. Korea experienced a record-breaking summer in 2018). However, **even FuXi-OG remains too coarse to accurately capture fine-scale regional variability.**
- **After dynamic downscaling, both CFSv2 and FuXi-ENS forecasts show significant improvements**, particularly in simulating region-specific temperature features, benefitting from high-resolution simulations. In terms of spatial mean values, the temperature underestimation apparent in CFS-OG-ENS4 is slightly reduced in CFS-DS-ENS4.
- When comparing CFSv2 and FuXi-ENS, FuXi-OG-ENS4 already outperforms CFS-OG-ENS4; after downscaling, **FuXi-DS-ENS4 shows even more pronounced improvements over CFS-DS-ENS4**, with spatial mean values closer to OBS, demonstrating the **great potential of ML-based models** like FuXi-ENS for extended-range forecasting.

IV. Summary and Future Work

ECMWF SEAS5, which provides the best temperature predictability for South Korea but cannot be directly used for dynamic downscaling, was utilized **as a reference to select CFSv2 (physical model) and FuXi-ENS (ML-based model) members for dynamically downscaled forecast ensembles**. The selected CFSv2 and FuXi-ENS members show improved predictive skill after dynamic downscaling, benefitting from the high-resolution simulations, with **FuXi-ENS consistently outperforming CFSv2**. Future work will expand the temperature analysis to additional years, incorporate more evaluation metrics (e.g., RMSE), and include precipitation — another critical variable alongside temperature.

V. Acknowledgements

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