DUNE: A MACHINE LEARNING DEEP UNET++ BASED ENSEMBLE APPROACH TO MONTHLY, SEASONAL, AND ANNUAL CLIMATE FORECASTING

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ABSTRACT

Capitalizing on the recent availability of long-term data records of mean atmospheric and climate fields based on high-resolution reanalysis, deep learning architectures offer an alternative to physics-based numerical weather predictions of subseasonal to seasonal (S2S) and annual means. We introduce a novel Deep UNet++-based Ensemble (DUNE) architecture employing multi-encoder-decoder structures with residual blocks, which produced the first AI-based annual and seasonal mean forecasts of 2-meter temperatures (T2m) over the US from a prior year. These forecasts outperformed persistence and climatology and were comparable to NOAA operational forecasts from a prior two-week seasonal forecast. RMSE and ACC error statistics for mean monthly and seasonal forecasts are better than recent AI-based daily forecasts. Moreover, DUNE forecasts demonstrate superior accuracy compared to operational probabilistic outlook forecasts. We use ERA5 monthly mean data for T2m over land, monthly sea surface temperatures (SST) over oceans, and monthly solar radiation at the top of the atmosphere for each month of 40 years as input to the ML training model. Validation forecasts are performed for an additional two years, followed by five years of evaluation to account for natural annual variability. Error statistics and map evaluations show a remarkable performance advantage over persistence and climatology. We present the monthly, seasonal, and annual mean forecasts globally, specifically over land, the oceans, the USA, Australia, and the Boreal region. A unique capability of trained inference forecast weights is the ability to generate forecasts in seconds, enabling the production of ensemble forecasts.

INTRODUCTION

Traditional weather prediction models struggle with accuracy beyond two weeks, even with advanced physics-based ensembles. Machine learning (ML) techniques show similar limitations for 2-4 week forecasts. To improve this, we propose a Deep UNet++ Ensemble (DUNE) model using long-term ERA5 reanalysis data for Subseasonal-to-Seasonal and Annual (S2SA) 2-meter temperature (T2m) forecasts. Reliable S2SA T2m forecasts are vital for predicting drought indices and managing wildfires, as higher temperatures and drought conditions increase wildfire risk. Our AI model enhances summer and annual T2m predictions, aiding in proactive wildfire management and addressing climate change trends, and is also applicable for operational subseasonal to seasonal weather prediction.

Contributions

- A novel deep learning architecture called the Deep UNet++ Ensemble (DUNE), specifically designed to incorporate intermediate ensemble inferences (i.e., forecasts) to account for the natural variability in S2S predictions for a range of global climate parameters, including T2m, SST, U10, V10, and more.
- Present AI-based forecasts for monthly, seasonal, and annual means, validated against monthly ground truth (Reanalysis) data for the past five years (2019-2023).
- We show the DUNE AI model, trained specifically on anomalies to forecast anomalies rather than actual parameters.
- Demonstrate the use of intrinsic ensembles within the DUNE AI model, improving forecast accuracy during fall and winter when temperature variability is the highest.
- Trained the DUNE AI model on T2m over land and SST over oceans, enabling simultaneous forecasting of both SST and T2m in a single forecast.
- Illustrate the global temperature increase over the past 85 years, presenting data month-by-month at 20-year intervals.

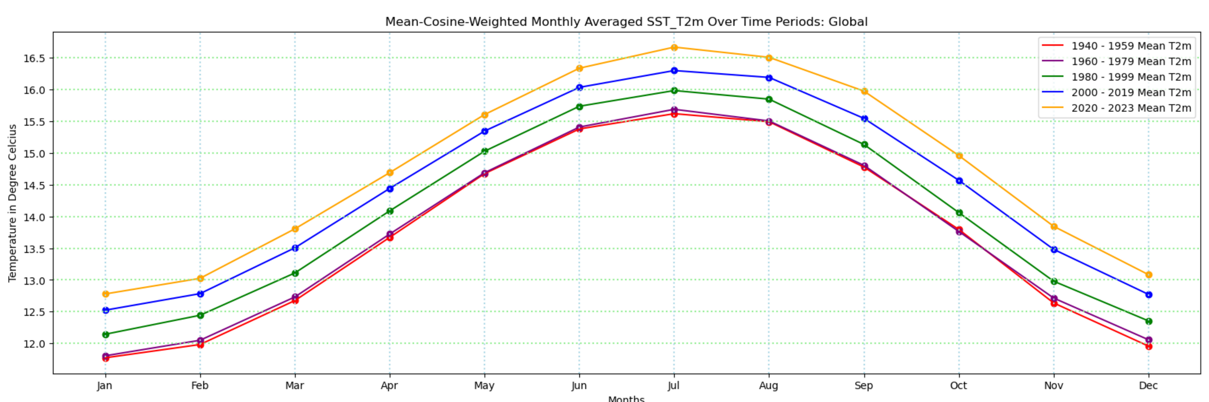

Fig. 1: Mean-Cosine-Weighted monthly averaged SST_T2m over time periods. It shows the temperature trends over months at 20-year intervals.

METHODOLOGY

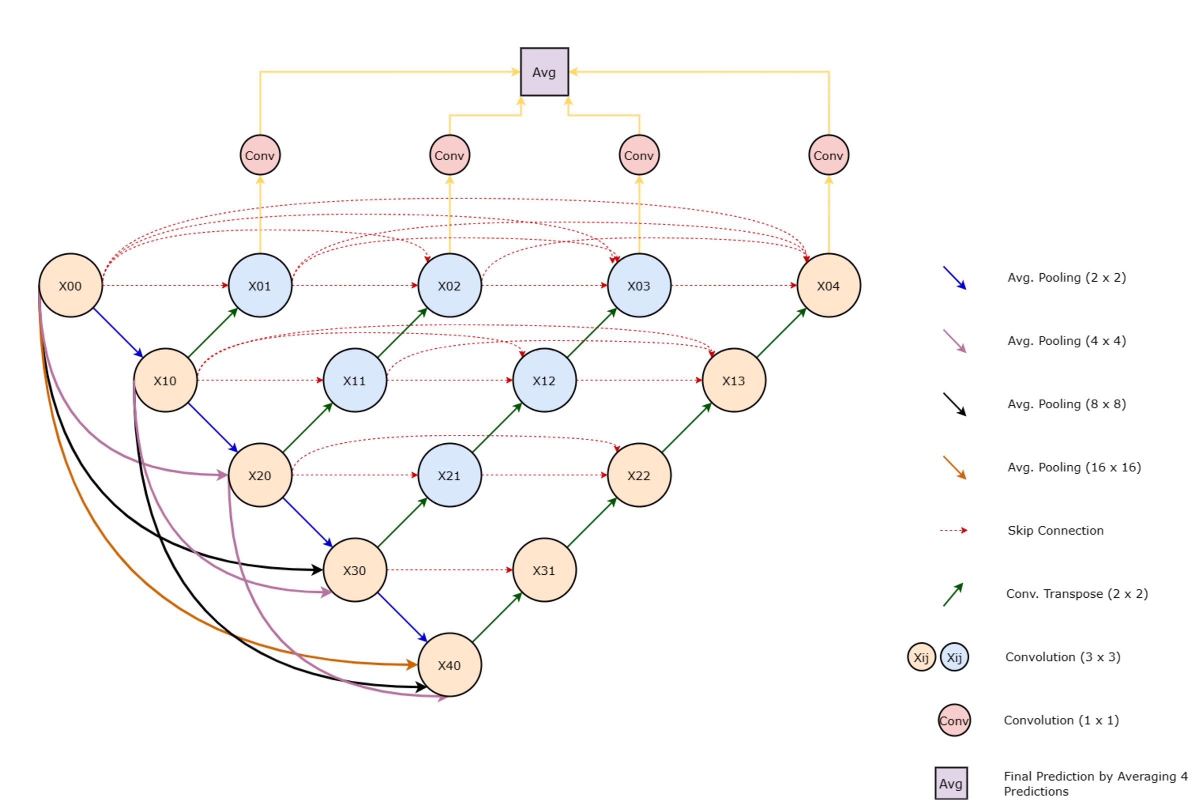

Fig. 2: The DUNE (Deep Unet++ Ensemble) AI architecture. For monthly mean forecasts, the prior month is used to forecast the next month. The DUNE AI model is trained using 6 constant channels and one temperature channel as an input. It has the ability to forecast monthly, seasonal, and annual mean climate parameters such as T2m, SST, U10, and V10.

Read the full paper here: https://arxiv.org/abs/2408.06262

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RESULTS

We tested the DUNE AI forecast model for monthly, seasonal, and annual mean forecasts for five years from 2019 to 2023. The table below shows the average RMSE and ACC over these periods. For the monthly mean forecast, it is an average of 60 months; for the seasonal mean, it is an average of 20 seasons; and for the annual mean, it is an average of 5 years. We evaluated our model forecast using the following matrices.

RMSE (Root Mean Squared Error): The lower, the better

ACC (Anomaly Correlation Coefficient): The higher, the better. [-1, 1]

Method	RMSE	ACC	Field
Persistence (PM)	2.76	0.33	Monthly Mean T2m
Persistence (PYSM)	1.52	0.53	
Climatology (1950 – 1979)	1.60	0	
DUNE AI Method	1.07	0.74	
Persistence (PS)	6.24	0.12	Seasonal Mean T2m
Persistence (PYSS)	1.09	0.67	
Climatology (1950 – 1979)	1.37	0	
DUNE AI Method	0.87	0.77	
Persistence	0.67	0.83	Yearly Mean T2m
Climatology (1950 – 1979)	1.20	0	
DUNE AI Method	0.63	0.85	

Moving Window Approach	Method	RMSE	ACC
-	Persistence (PM)	2.76	0.33
-	Persistence (PYSM)	1.52	0.53
-	Climatology (1950-1979)	1.60	0
One Month	DUNE AI Method	1.07	0.74
Two Months	DUNE AI Method	1.13	0.70
Three Months	DUNE AI Method	1.16	0.69
Four Months	DUNE AI Method	1.17	0.68
Six Months	DUNE AI Method	1.20	0.66
Twelve Months	DUNE AI Method	1.27	0.61

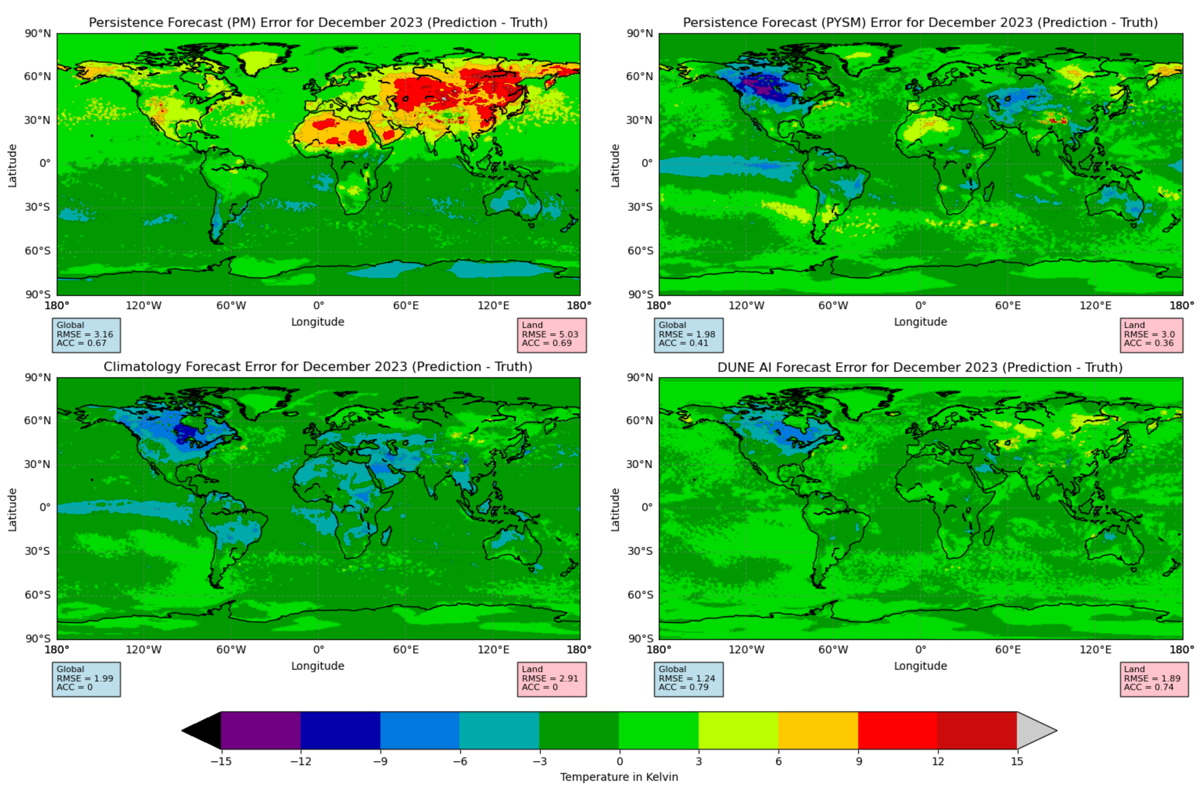

Fig. 3: We compare the monthly mean forecast errors for December 2023 with three baselines. It shows the forecast error (prediction-truth) for (a) Persistence (PM), (b) Persistence (PYSM), (c) Climatology (d) DUNE AI. The closer it is to 0, the better the forecast.

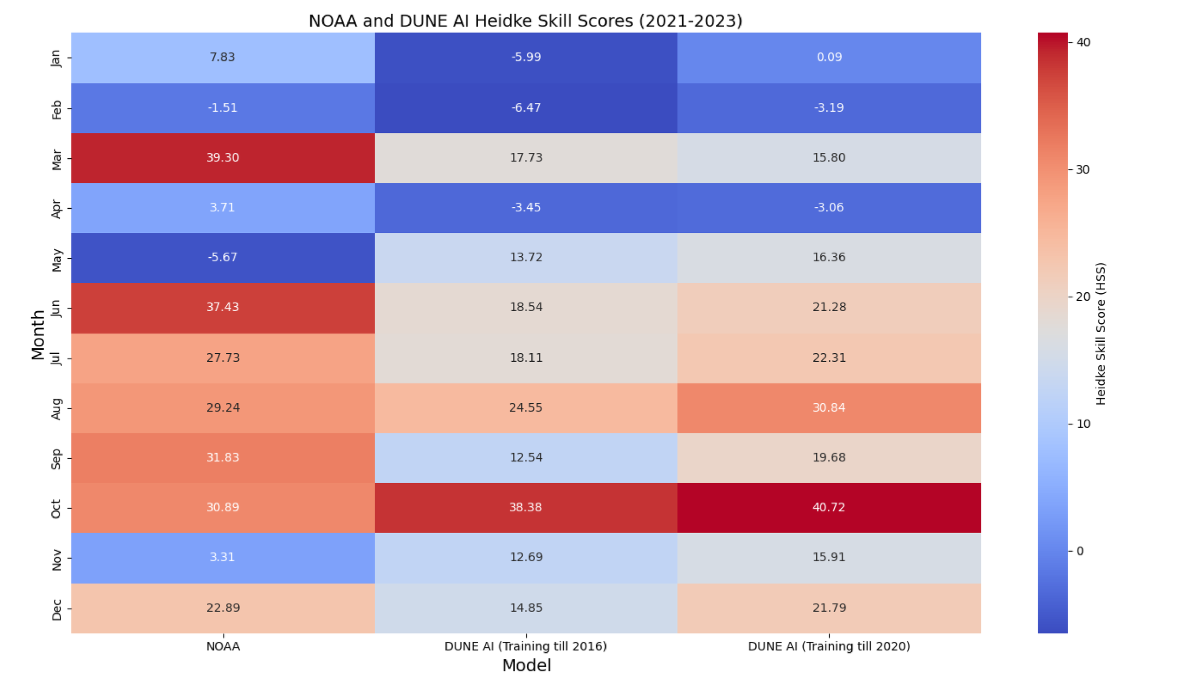

Figure 4: Heidke Skill Score (HSS) Comparison for Monthly Averaged Forecasts (2021-2023). Heatmap of the HSS for NOAA operational forecasts and DUNE AI inferences.

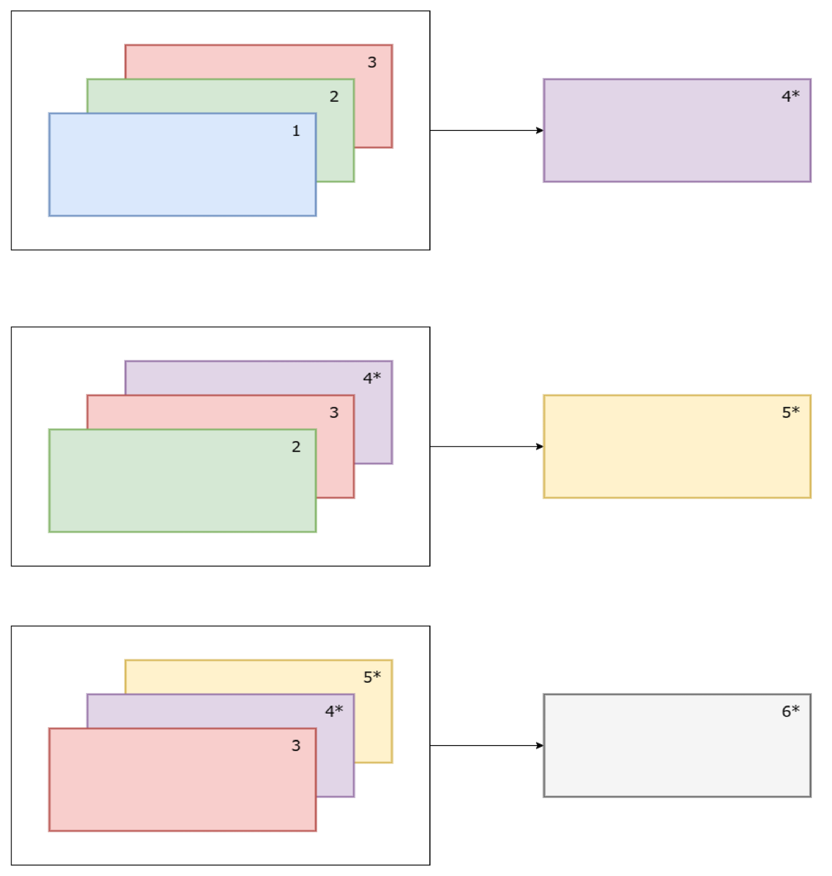

Fig. 5: The DUNE AI method can forecast climate parameters more than one monthly, seasonal, or annual mean in advance using the moving window approach. Here, we replace the ground truth with the forecast to make the next forecast. Figure 3 shows how we can use the moving window approach for forecasting 3 months in advance. It uses the temperature of the prior three months along with the constants to make these forecasts.

CONCLUSION

We have implemented DUNE, a deep learning UNet++-based self-forming ensemble AI model, that has the property of removing the atmospheric variability of monthly or seasonal generated T2m forecasts over global or land-based regional domains, namely the US, Boreal Forests, and Australia. We demonstrate the effectiveness of DUNE by comparing the monthly and seasonal RMSE and ACC error statistics with persistence, climatology, and other published physics-based model forecasts and AI product outputs for multiple years. In all cases, the DUNE error statistics outperformed other methods of forecasts. Moreover, we present, for the first time, the RMSE and ACC error statistics of successive monthly mean forecasts for the most recent 5 years in terms of RMSE and ACC of annual forecasts compared with the reanalysis of ERA5 yearly monthly means. In addition, we include a forecast for 2024 that awaits verification. The only comparable results are from climate models, which have not been directly compared with observations.

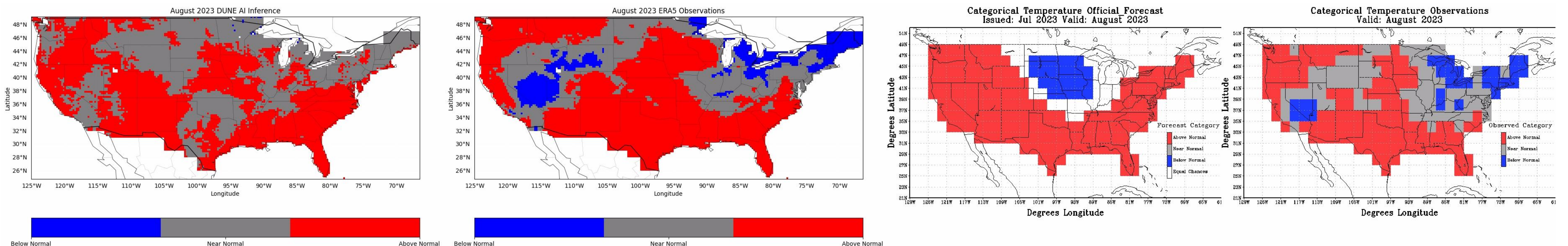

Fig. 6: Comparison of forecasts and observations for August 2023. DUNE AI HSS: 34.18, NOAA HSS: 23.49. The DUNE AI model successfully inferred above-normal temperatures on the west coast, midwest, and southeast coast. The DUNE AI model in the northeast predicted near-normal temperatures, while NOAA forecasted higher temperatures. However, the actual temperatures in the northeast were below normal.

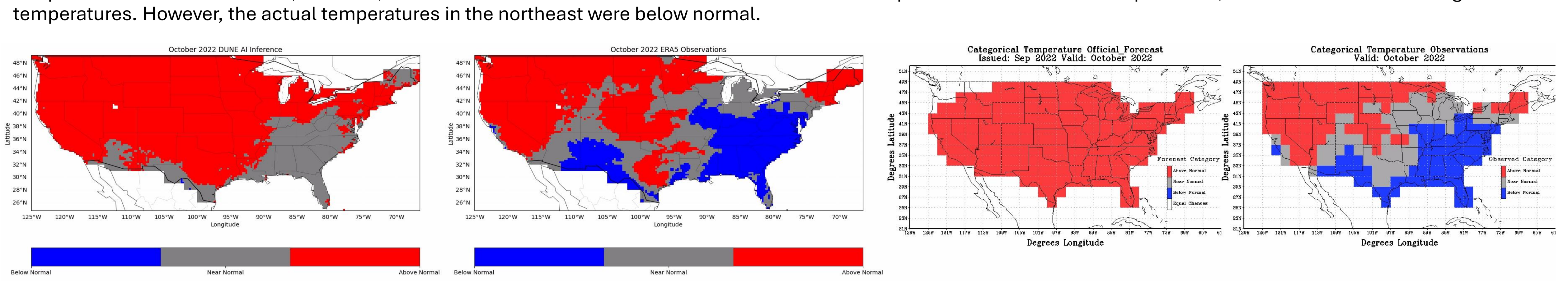

Fig. 7: Comparison of forecasts and observations for October 2022. DUNE AI HSS: 29.97, NOAA HSS: 7.33. The DUNE AI model successfully captured the higher temperature anomalies in the western region of the United States. However, it failed to capture the below-normal anomalies in the southeastern region. The DUNE AI model performed comparatively better when comparing the DUNE AI and NOAA forecasts in the southeast region. It predicted near-normal temperatures, whereas the NOAA forecast predicted above-normal temperatures, even though the observed values were below normal.

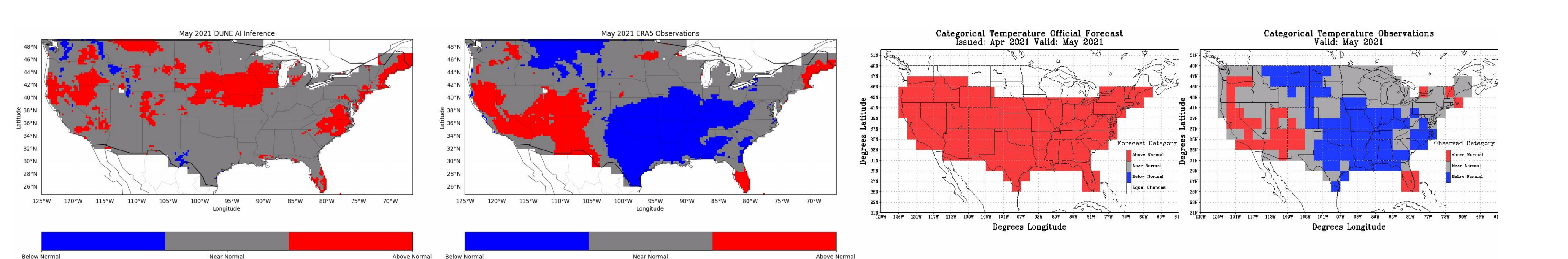

Figure 8: Comparison of forecasts and observations for May 2021. DUNE AI HSS: 15.71, NOAA HSS: -16.59. In May 2021, DUNE AI and NOAA performed poorly in temperature forecasting. However, the DUNE AI model captured above-normal temperatures in Florida, the northeastern coast, and parts of the western coast. Notably, in the central region, where below-normal temperatures were observed, the DUNE AI model inferred near-normal temperatures, while NOAA predicted above-normal temperatures.