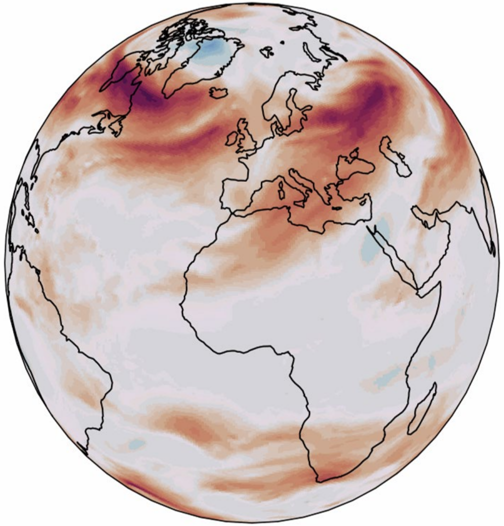
Forecasting Tomorrow(T): Foundation Model in Earth Science - Towards Atmospheric Prediction and Analysis

$T \in \mathbb{R}^+$

Zonal wind at 500 hPa



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Scales of Atmospheric Processes

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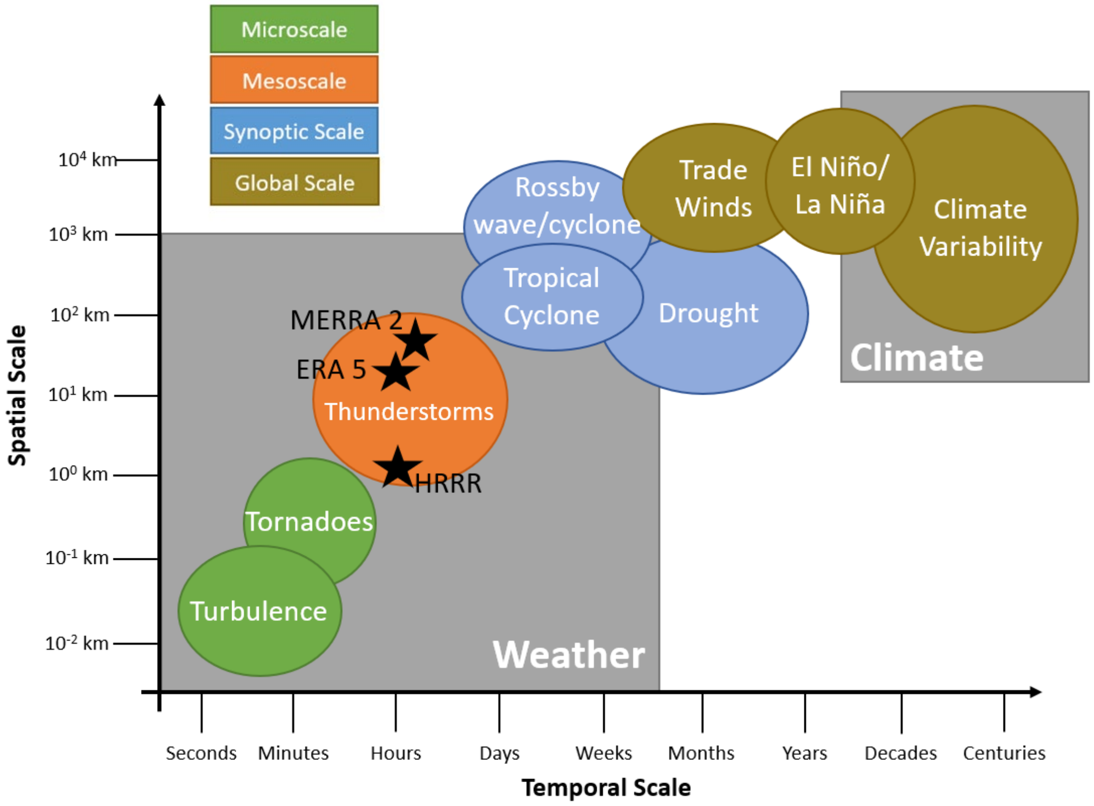


Challenges for Forecasting

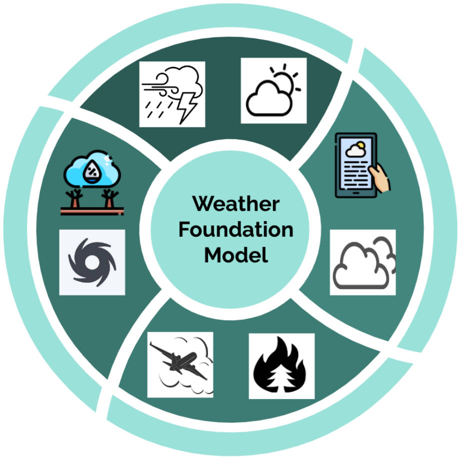
- Atmospheric phenomena occur at many scales
- Training datasets limited in scope
- Computational power limits grid resolution and thus resolvable processes

Motivation

- Weather impacts nearly every facet of daily life
  - Hence, accurate weather prediction is imperative. But it's a challenging problem.
- As a result, agencies such as NASA, NOAA, ESA, and ECMWF gather terabytes of observations everyday
- Data volume >>> insights

Objective

Design a foundation model for atmospheric prediction and analysis



Dataset

MERRA2: 11.2TB+ | ERA5: 145 TB+ | HRRR: 6 TB+

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MERRA2

Global | 1980 - 2023
Spatial Res: 0.5°x0.625°
Temporal Res.: 3 hour

ERA5

Global | 1940 - 2023
Spatial Res.: 0.25°x0.25°
Temporal Res.: 1 hour

HRRR

CONUS | 2017 - 2023
Spatial Res.: 3x3 km
Temporal Res.: 1 hour

Pressure Level Variables

ETA levels: 985 925 850 700 600 525 412 245 150 109 48 hPa

U - Wind speed/direction
V - Wind speed/direction
OMEGA - Vertical motions
T - Air temperature
QV - Specific humidity
PL - Actual mid-level pressure
H - Mid-layer height
CLOUD - Cloud fraction
QI - Cloud Ice mass fraction QL - Cloud water mass fraction

Surface Variables

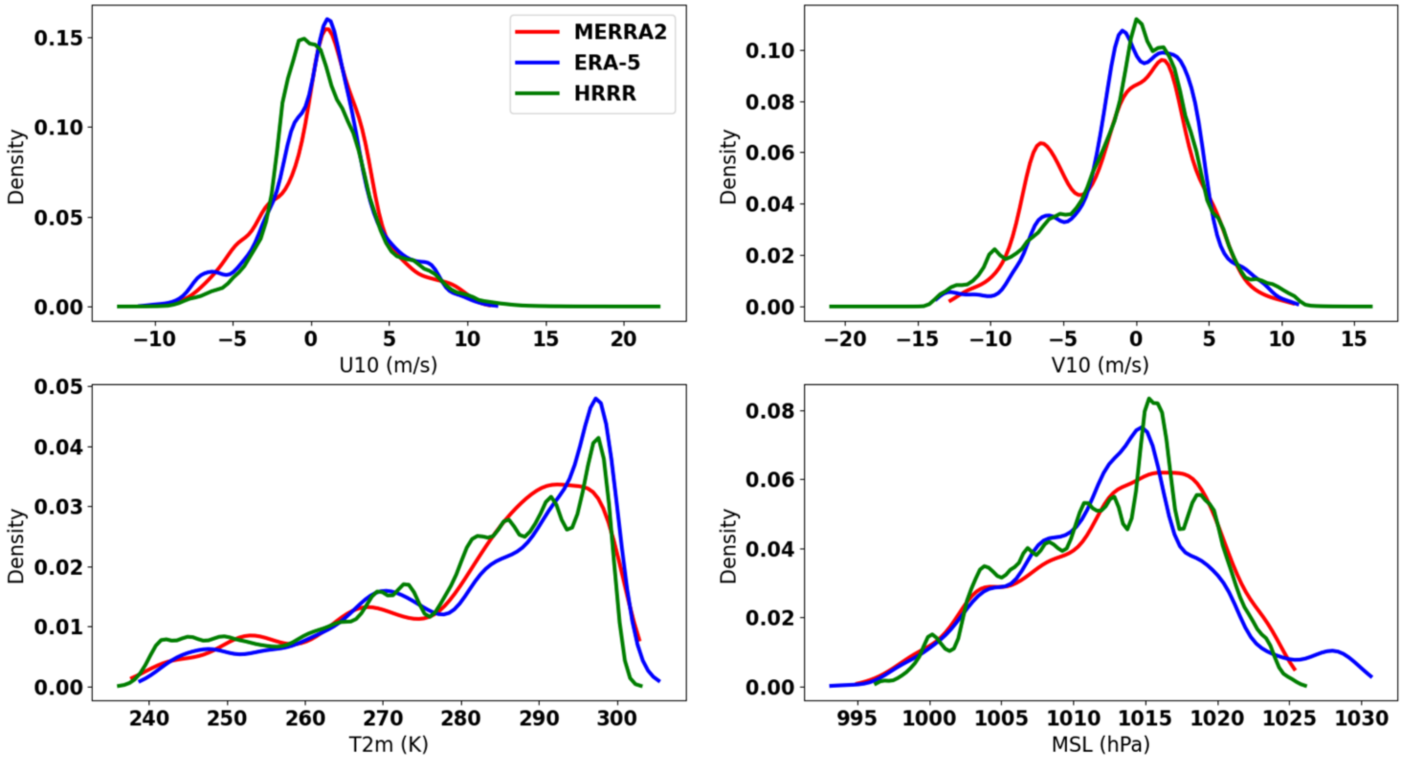
U10 - 10 m u wind
V10 - 10 m v wind
T2M - 2 m air temperature
QV2M - 2m specific humidity
PS - Surface pressure
SLP - Sea Level pressure
TS - Skin temperature
TQI - Column-total ice
TQL - Column-total liquid
TQV - Column-total water vapor
PHIS - Surface geopotential height
FRLAND - Fraction of land

Other Surface Variables

GWETROOT - Soil Moisture
LAI - Leaf area index
EFLUX - Latent heat flux
HFLUX - sensible heat flux
PRECTOTCORR - precip
Z0M - Surface roughness
LWGEM - LW radiation
LWGAB - LW radiation absorbed
LWTUP - upward LW at TOA
SWGNT - net downward SW SWTNT - net SW at TOA

Probability Distribution Function

January 01, 2022 | 00 UTC



Modeling - Brief History of Time

RMSE - Root Mean Square Error (↓)
ACC - Anomaly Correlation Coefficient (↑)
CSI - Critical Success Index (↑)

1958 -

NWP Models

2019

DLWP
RMSE (Z500) < **110 m**
(~12-day forecast)

2020

MetNet - Google Research
F1 score < **0.3**
(8-hour precipitation forecast)

2021

MetNet 2 - Google Research
CSI > 0.2
(12-hour precipitation forecast)

2022

FourcastNet - nVIDIA
ACC (Z500) > **0.7**
(7-day forecast)

Pangu - Huawei
RMSE (Z500) < **50 m**
(7-day forecast)

Graph Weather
RMSE (Z500) < **50 m**
(6-day forecast)

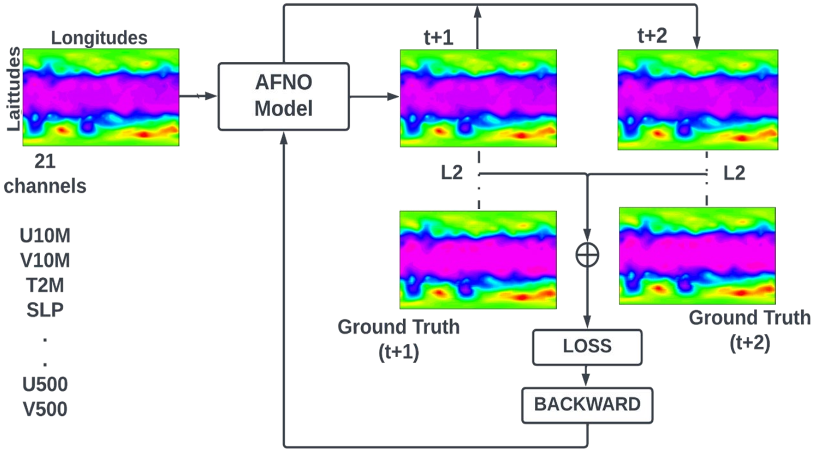
2023

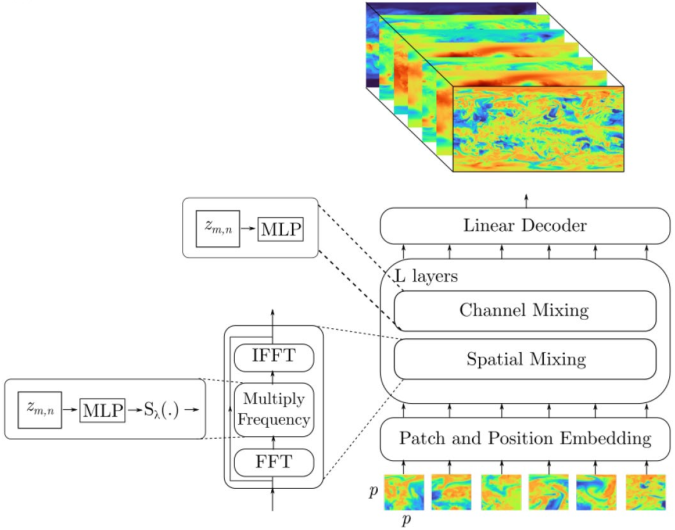
GraphCast - DeepMind
RMSE (Z500) < **60 m**
(8-day forecast)

Climax - Microsoft
RMSE (Z500) < **100 m**
(7-day forecast)

Operational data-driven, ML-based models

FourCastNet (Pathak, J. et. al., 2022)





Training Architecture

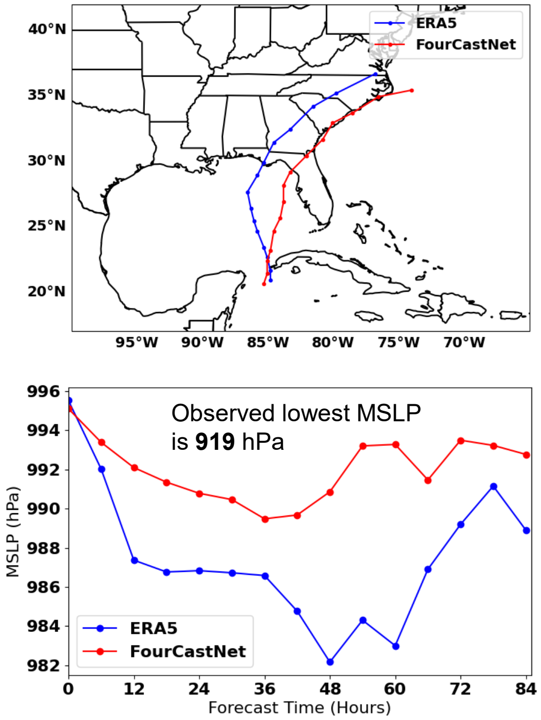
Design based on AFNO model design [1, 2]

Modified Loss

$$\sigma^2_{t:t+100,\text{lat},\text{lon},\text{lev}} = \frac{\sum_{T\in t}^{t+100} P_T(\text{lon},\text{lat},\text{lev}) - \overline{P(\text{lon},\text{lat},\text{lev},t:t+100)}}{(n_{\text{lon}} \times n_{\text{lat}} \times n_{\text{lev}} \times 100) - 1}$$

$$\text{Loss} = cos\left(\sum_{i\in 1}^{6} MSE\left(P_{Ti} - \frac{P_{Di}}{\sigma_{t:t+100,\text{lat},\text{lon},\text{lev}}}\right)\right)$$

ERA5 trained model   **MERRA2** trained model



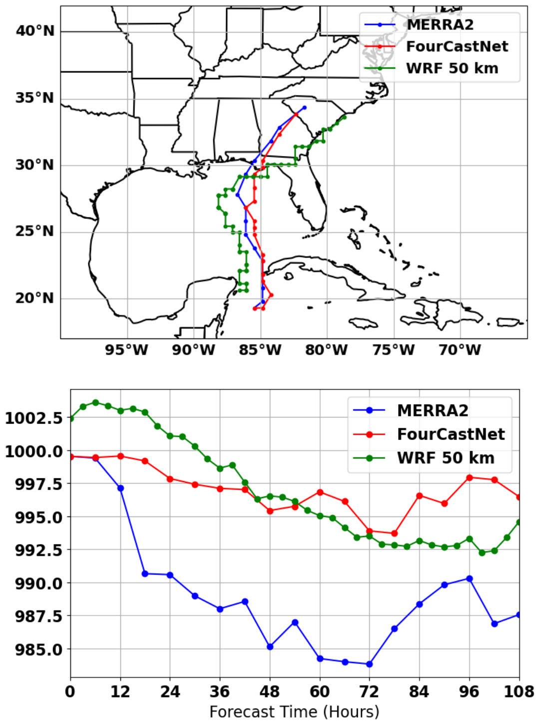
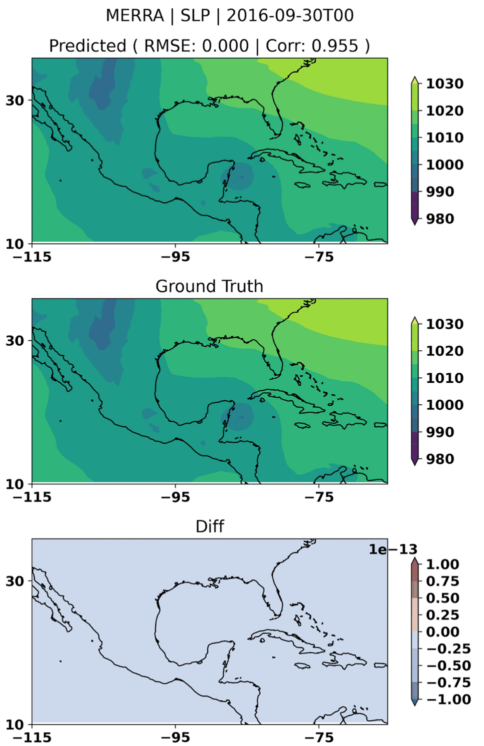


Fig. Track (location of minimum sea level pressure) and intensity (minimum sea level pressure) for Hurricane Michael (2018) from the ERA5 trained model and MERRA2 trained model. Track and intensity are overlapped from the WRF model track, simulated on 50 km spatial resolution.

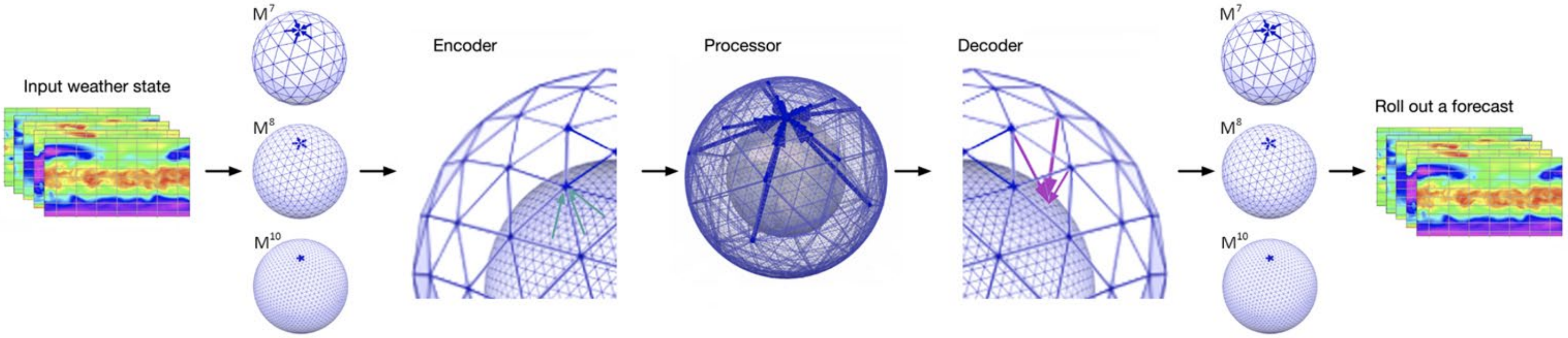


Spatial distribution of wind speed (m/s) for Hurricane Michael (2018)

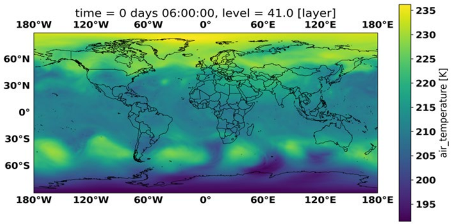
GraphCast (Lam, R. et. al., 2022)

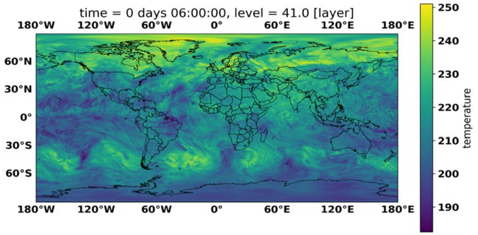
Message Passing Graph Neural Network

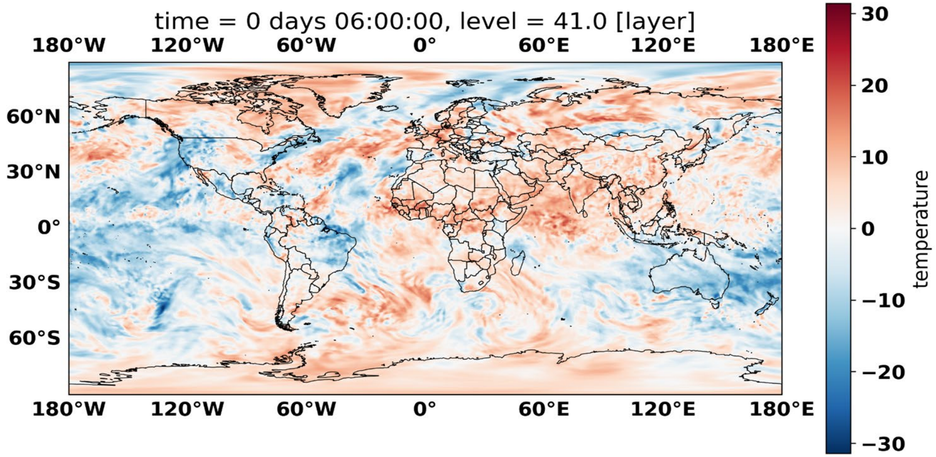
- Multiple mesh resolution



Model predictions of temperature for 20230731Z06 at 150 hPa (~8 km) using MERRA2







Model predictions of 2m_temperature using ERA5

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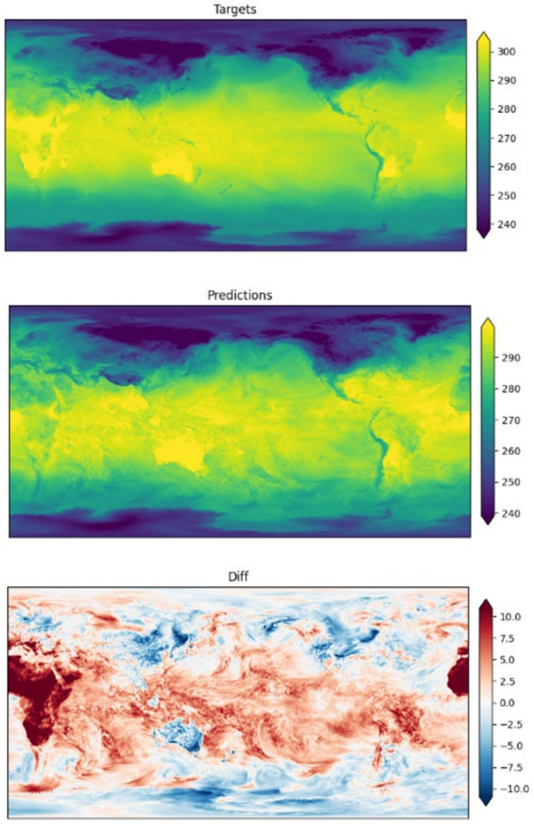
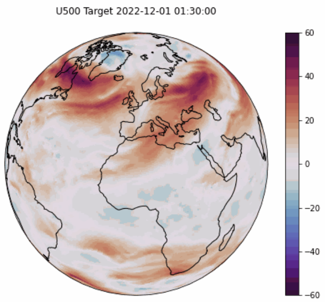
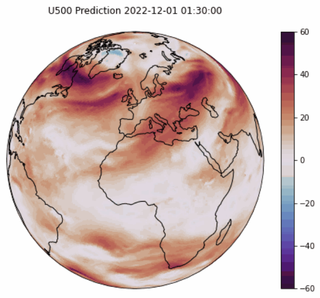
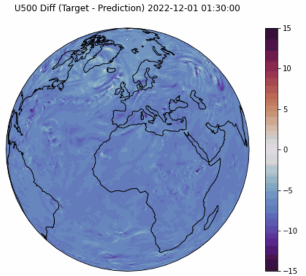


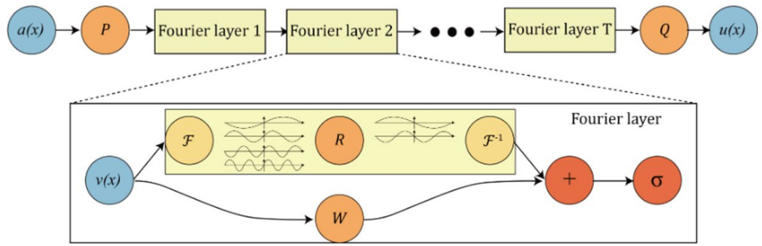
Spherical Fourier Neural Operator (Bonev, B. et. al., 2023)

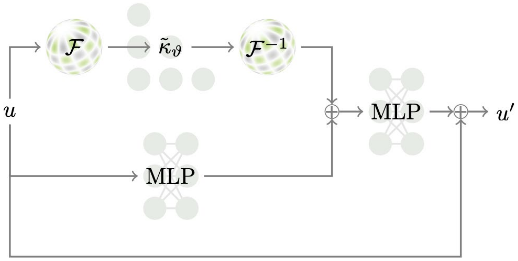




Dataset: Trained on MERRA2 dataset taking U500, V500, and Z500 to see if model is able to learn dynamics and solve PDE like shallow water equation. Trained over 7 months, predicted over 1 month.





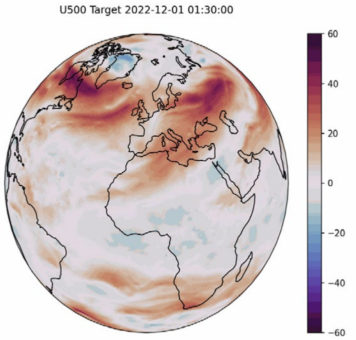


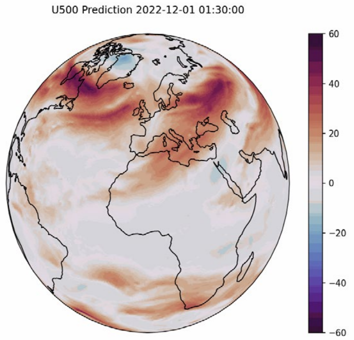
Key Takeaways:

1. Model is able to learn the dynamics related to spherical geometry.
2. Can be used to train the model to make it resolution invariant by mapping u(x) :à v(x)
3. Implementation with transformer can help in containing the manifold related information.

Clifford Fourier Neural Operator

Dataset: Trained on MERRA2 dataset taking U500, V500, and Z500 to see if the model can learn dynamics and solve PDEs like shallow water equation. Trained over 7 months, predicted over 1 month.





Implementation:

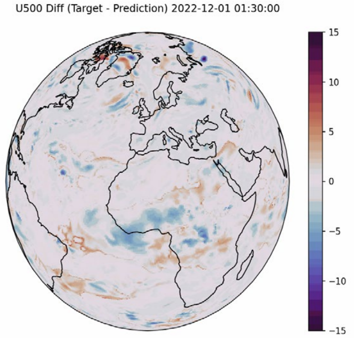
1. Defining 2 basis vector e_1, e_2 and 1 multi-vector e_1e_2

2. Take input multivector and create a dual function given by:

$$a = a_0 + a_1e_1 + a_2e_2 + a_{12}e_1e_2$$

$$(a_0 + a_{12}i_2) + e_1\,(a_1+a_2i_2)$$

Spinor **Vector**



3. Perform Clifford Fourier transform on each part and revert back and concatenate both

Key Takeaways:

1. Model is able to learn the dynamics related to geometry.
2. Can be used to train the model to make it resolution invariant by mapping u(x) : à v(x)
3. Model computation may grow as we will need to perform FFT on vector and spinor part.
4. Implementation with transformer can help in efficiently mixing tokens.

What and Why ??

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FourCastNet

- Optimised → less computation
- Can not handle multiple resolution of different models
- Super-resolution (same physics)
- Long term forecast will lead to noise over poles

Swin Transformer-Based Spatio-Temporal Mapping

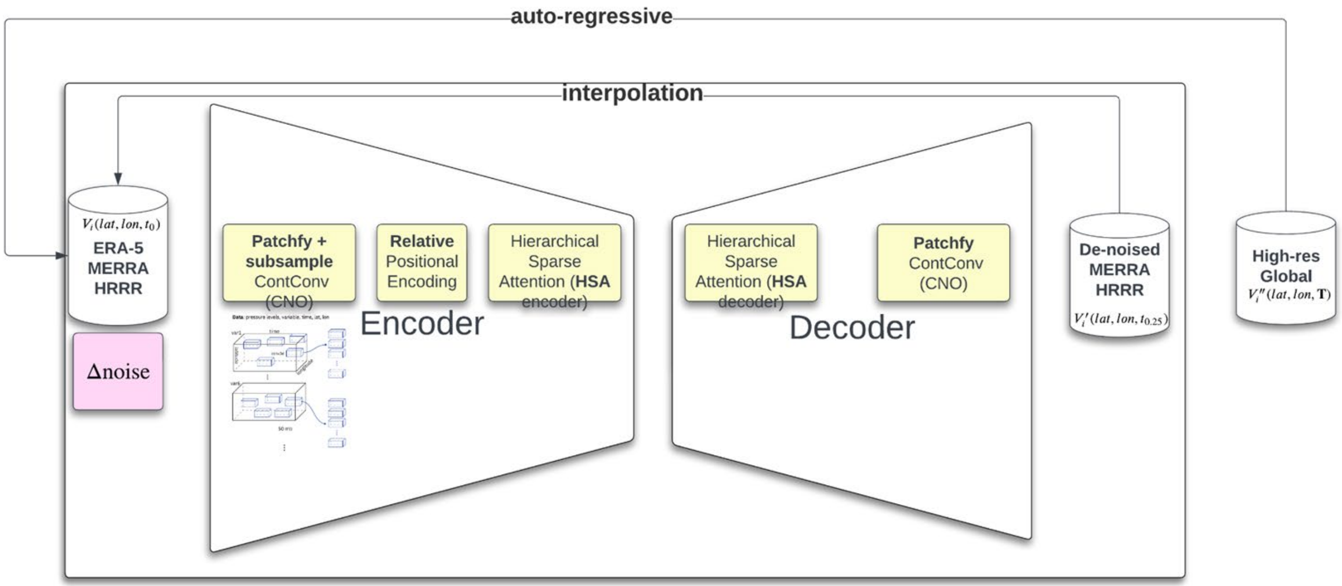
- Higher complexity
- Learning physics uncertain
- Good for observing small scale spatial changes

GraphCast

- Lower complexity
- Message passing network shows PDEs solution over meshes
- Inferences would be easy → needs GPU to fit graph
- Can handle multiple resolution
- Early stage concepts for multiple downstream applications

Operator Diffusion Enhanced Neural Network Transformer

ODE-NET



Aviation Turbulence Prediction

Objective	Spatial Scale	Temporal Scale
Predict areas where an aircraft could potentially encounter turbulence	Local	Hour-Minute

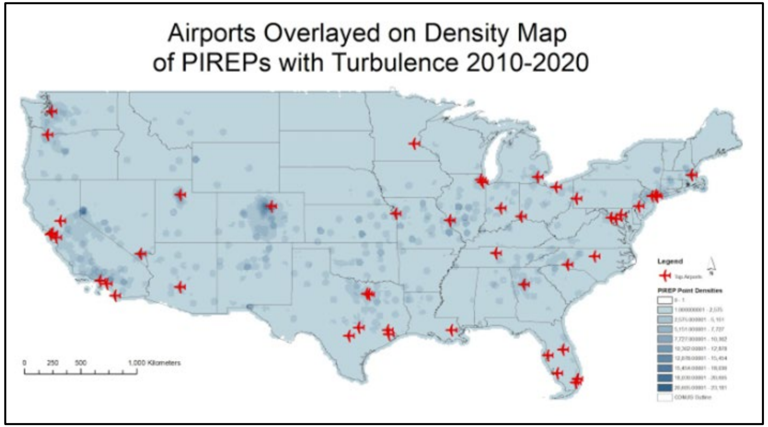


Fig: Illustration of PiREPs overlaid over the airport locations across the US

```
GSP UA /OV GSP/TM 1435/FLUNKN/TP B737/SK BKN021-TOP026/RM DURD RY22 GSP
BNA UA /OV BNA360030/TM 1417/FL360/TP BCS3/TB CONS LGT OCNL MOD 360/RM ZME
```
Fig: Sample pilot report

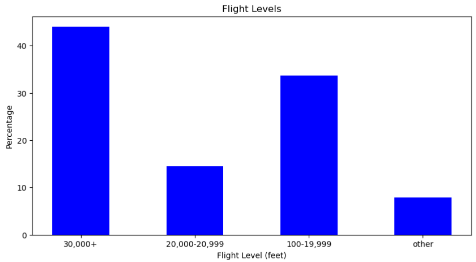


Fig: Histogram of the turbulence reports with the elevation

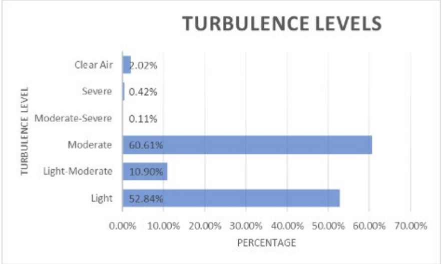


Fig: Categorization of turbulence levels based on occurence

Impact: Turbulence is hazard for commercial flights
Challenges: Data is unstandardised, reports are subjective

Temporal Extent: 2003 - Present
Spatial Extent: United States

Input: Single MERRA 2 time step
Output: Turbulence risk/likelihood
Source of the labels: PIREPS database

Hurricane Intensity and Track Estimation

Task	Objective	Spatial Scale	Temporal Scale
Curating Hurricane observed / raw data from Hurdat / JTWC	Fine-tune FM using the observed hurricane track and intensity to improve forecast	Regional	Days-Weeks

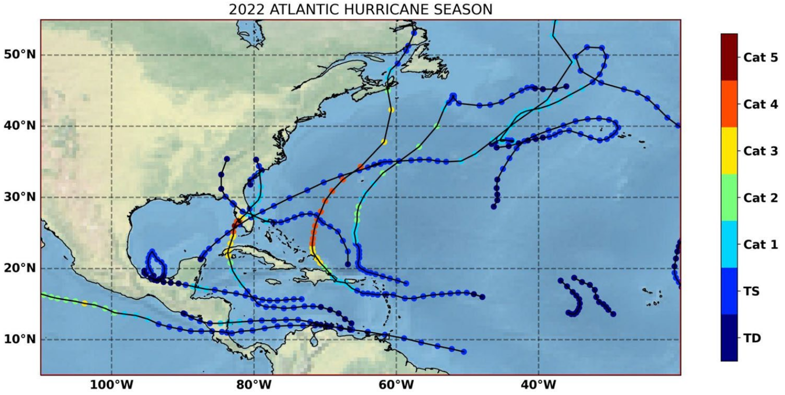


Fig: Visualization of 2022 Atlantic hurricane season

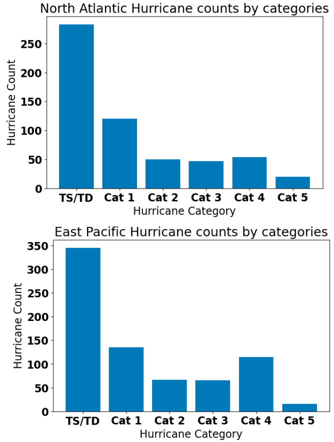


Fig: Histogram of hurricane counts with category

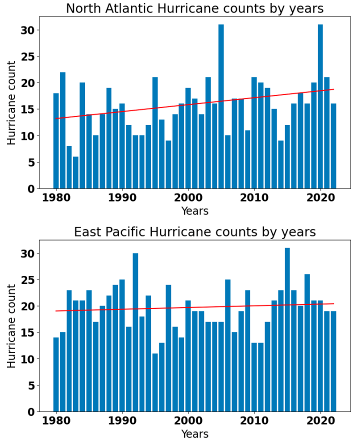


Fig: Frequency of North Atlantic and East Pacific Hurricanes since 1980

Impact: Enhanced hurricane forecasting
Reduce economic and human loss
Challenges: Dynamic problem to solve

Temporal Extent: 1850 - 2022
Spatial Extent: Global - separate for each basins

Input: Time series of 3 hourly MERRA 2 variables
Output: Hurricane center, intensity and size
Source of the labels: HURDAT

Drought Prediction

Objective	Spatial Scale	Temporal Scale
Classify droughts into the classes: 1. No drought 2. Dry 3. Moderate 4. Severe 5. Exceptional	Regional	Days-Seasonal

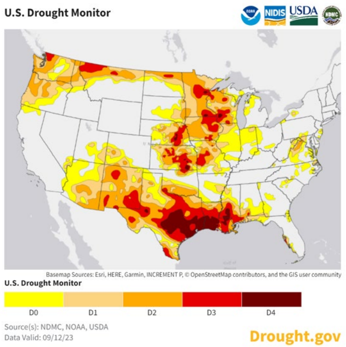


Fig: U.S. Drought Monitor drought assessment for the week of Sept. 12th, 2023

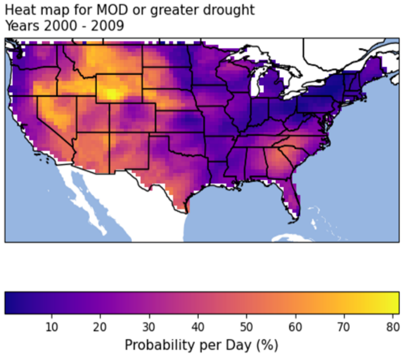


Fig: Heat map representing moderate drought over the years 2000-09

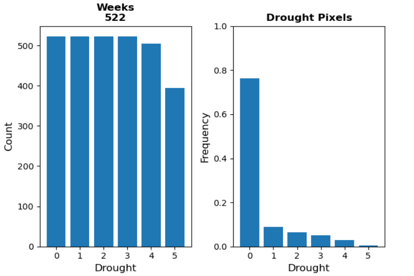


Fig: Histogram of (left) weeks with drought by category (right) Drought frequency by pixel for small for 2000-2009

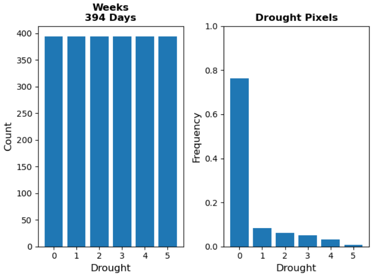


Fig: Histogram of (left) Days with at least class 5 drought (right) Drought frequency by pixel for weeks with at least class 5 drought for 2000-2009.

Temporal Extent: Weekly between 2000 – present
Spatial Extent: CONUS
Input: Time series of MERRA 2
Output: Drought monitor style drought assessment
Source of the labels: U.S. Drought Monitor

Impact: Precise resource allocation and water management
Mitigation of agricultural losses and economic impacts
Challenges: Severe class imbalance.

Generating Natural Language Weather Forecast Discussions

Objective	Spatial Scale	Temporal Scale
Creating weather forecast discussions based on weather modeling results	Local-Regional	Hours-Days

```
SPC AC 010538 Day 1 Convective Outlook NWS Storm
Prediction Center Norman OK 1138 PM CST Sat Dec
31 2022 Valid 011200Z - 021200Z ...NO SEVERE
THUNDERSTORM AREAS FORECAST... ...SUMMARY...
Severe thunderstorms are not expected on Sunday.
...Southwestern US... Southern CA upper trough
is forecast to advance into the lower CO River
Valley by early afternoon before shifting into
eastern AZ by 02/00z. This progression is
associated with an 80+kt 500mb speed max that
should translate southeast along the AZ/Sonora
border during the latter half of the period.
Cold mid-level temperatures (-20 to -24C at
500mb) will spread across much of the
southwestern US north of the jet, resulting in
steepening lapse rates and adequate buoyancy for
deep convection. Latest model guidance suggests
greatest PW values will remain south of the
international border,
...
CLICK TO GET WUUS01 PTSDY1 PRODUCT
```

Fig: Sample weather report for 01/01/2023

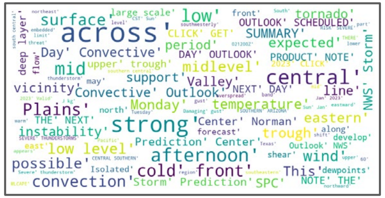


Fig: Word cloud representing the occurrence of the words in the report

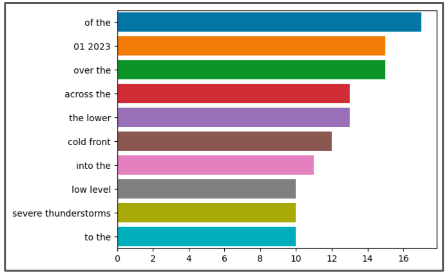


Fig: Top 10 2-grams of the words occurring in the report

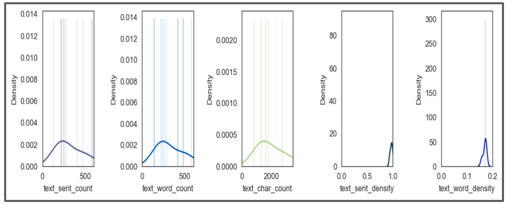


Fig: Histogram of the feature distribution of the sample weather report

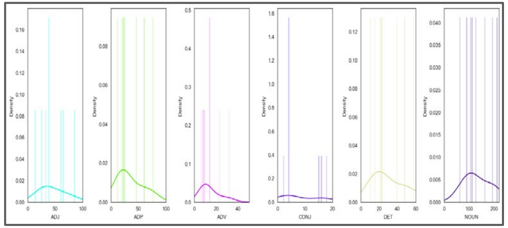


Fig: Illustration of POS tagging performed on the weather discussion

Impact: Streamlined weather reporting process
Enhanced user engagement and informed decision-making
Challenges: Designing architecture/pipeline for multi-modal model

Temporal Extent: Daily between 2003 - Present
Spatial Extent: CONUS
Input: Time series of 3 hourly MERRA 2 dataset
Output: Weather forecast discussion
Source of the labels: SPC forecast discussions

Weather Analogs (Similarity Search)

Task	Objective	Spatial Scale	Temporal Scale
Weather Analogs	Given an atmospheric state, provide a ranked list of similar states from the past for forecast or research purposes	Regional	Decadal

- Analog forecasting predicts future weather by looking for similar conditions in the past
- Requires rapid search of huge databases (potentially Petabytes)
- Useful for severe weather outbreaks, hurricanes, extreme temperature events
- Can help scientists rapidly locate significant events from the past based on current event

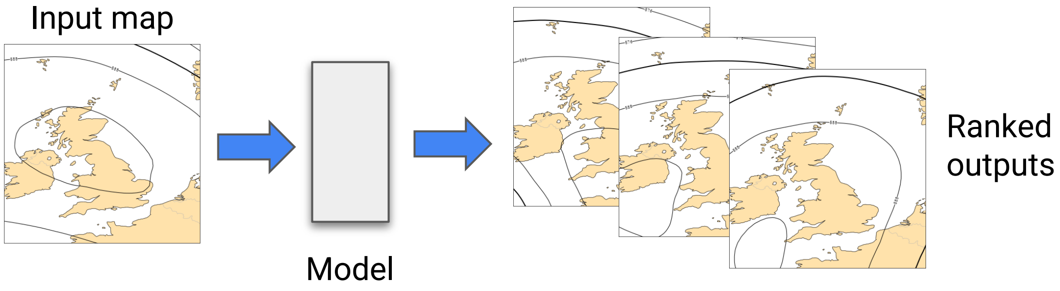


Fig: Pipeline for performing weather analog search. Example images are geopotential height over the U.K. Images located using the Copernicus weather analog search (https://cds.climate.copernicus.eu/analogues/).

Impact: Enhanced weather forecasting accuracy
Efficient historical data utilization for research and planning
Challenges: Rapidly searching large database, designing appropriate distance metric

Temporal Extent: 3 hourly between 1980 - 2020
Spatial Extent: Global
Input: Single MERRA 2 timestep
Output: Ranked list of similar scenarios in MERRA 2
Source of the labels: In-house distance metric

Outreach

arXiv > cs > arXiv:2309.10808

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Computer Science > Machine Learning

[Submitted on 19 Sep 2023 (v1), last revised 20 Sep 2023 (this version, v2)]

AI Foundation Models for Weather and Climate: Applications, Design, and Implementation

S. Karthik Mukkavilli, Daniel Salles Civitarese, Johannes Schmude, Johannes Jakubik, Anne Jones, Nam Nguyen, Christopher Phillips, Sujit Roy, Shraddha Singh, Campbell Watson, Raghu Ganti, Hendrik Hamann, Udaysankar Nair, Rahul Ramachandran, Kommy Weldemariam

Machine learning and deep learning methods have been widely explored in understanding the chaotic behavior of the atmosphere and furthering weather forecasting. There has been increasing interest from technology companies, government institutions, and meteorological agencies in building digital twins of the Earth. Recent approaches using transformers, physics-informed machine learning, and graph neural networks have demonstrated state-of-the-art performance on relatively narrow spatiotemporal scales and specific tasks. With the recent success of generative artificial intelligence (AI) using pre-trained transformers for language modeling and vision with prompt engineering and fine-tuning, we are now moving towards generalizable AI. In particular, we are witnessing the rise of AI foundation models that can perform competitively on multiple domain-specific downstream tasks. Despite this progress, we are still in the nascent stages of a generalizable AI model for global Earth system models, regional climate models, and mesoscale weather models. Here, we review current state-of-the-art AI approaches, primarily from transformer and operator learning literature in the context of meteorology. We provide our perspective on criteria for success towards a family of foundation models for nowcasting and forecasting weather and climate predictions. We also discuss how such models can perform competitively on downstream tasks such as downscaling (super-resolution), identifying conditions conducive to the occurrence of wildfires, and predicting consequential meteorological phenomena across various spatiotemporal scales such as hurricanes and atmospheric rivers. In particular, we examine current AI methodologies and contend they have matured enough to design and implement a weather foundation model.

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Earthdata / News / Building an AI Foundation Model for Weather and Climate

Building an AI Foundation Model for Weather and Climate

A recent workshop brought together experts from NASA, Oak Ridge National Laboratory (ORNL), IBM Research, NVIDIA, and several universities to develop a plan to create an artificial intelligence foundation model (AI FM) for weather and climate.

Dr. Rahul Ramachandran, NASA IMPACT
Dr. Tsengdar Lee, NASA Headquarters
Sep 26, 2023

The saying, "If you want to go fast, go alone; if you want to go far, go together," perfectly encapsulates the essence of open science and the necessity of collaboration in addressing complex issues. In this spirit of open science, a workshop was convened at NASA's Marshall Space Flight Center in Huntsville, Alabama, on September 20 and 21, 2023. The workshop brought together members of NASA's Interagency Implementation and Advanced Concepts Team (IMPACT), representatives from NASA Headquarters, scientists and engineers specializing in artificial intelligence (AI) model

https://arxiv.org/pdf/2309.10808.pdf

https://www.earthdata.nasa.gov/news/weather-ai-fm-workshop

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