UN GEONOW 2024
首届联合国地信周

风乌：数据驱动的地球监测预测系统

Fengwu: Data-driven Earth Monitoring and Forecasting System

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Significance

Monitoring, Predicting, and Understanding the Earth System is the foundation of our world’s daily operation, and the key for improving our ability to respond to extreme weather events, and building a more sustainable and resilient future.

Energy

Agriculture

Diaster Preventing

Aircraft

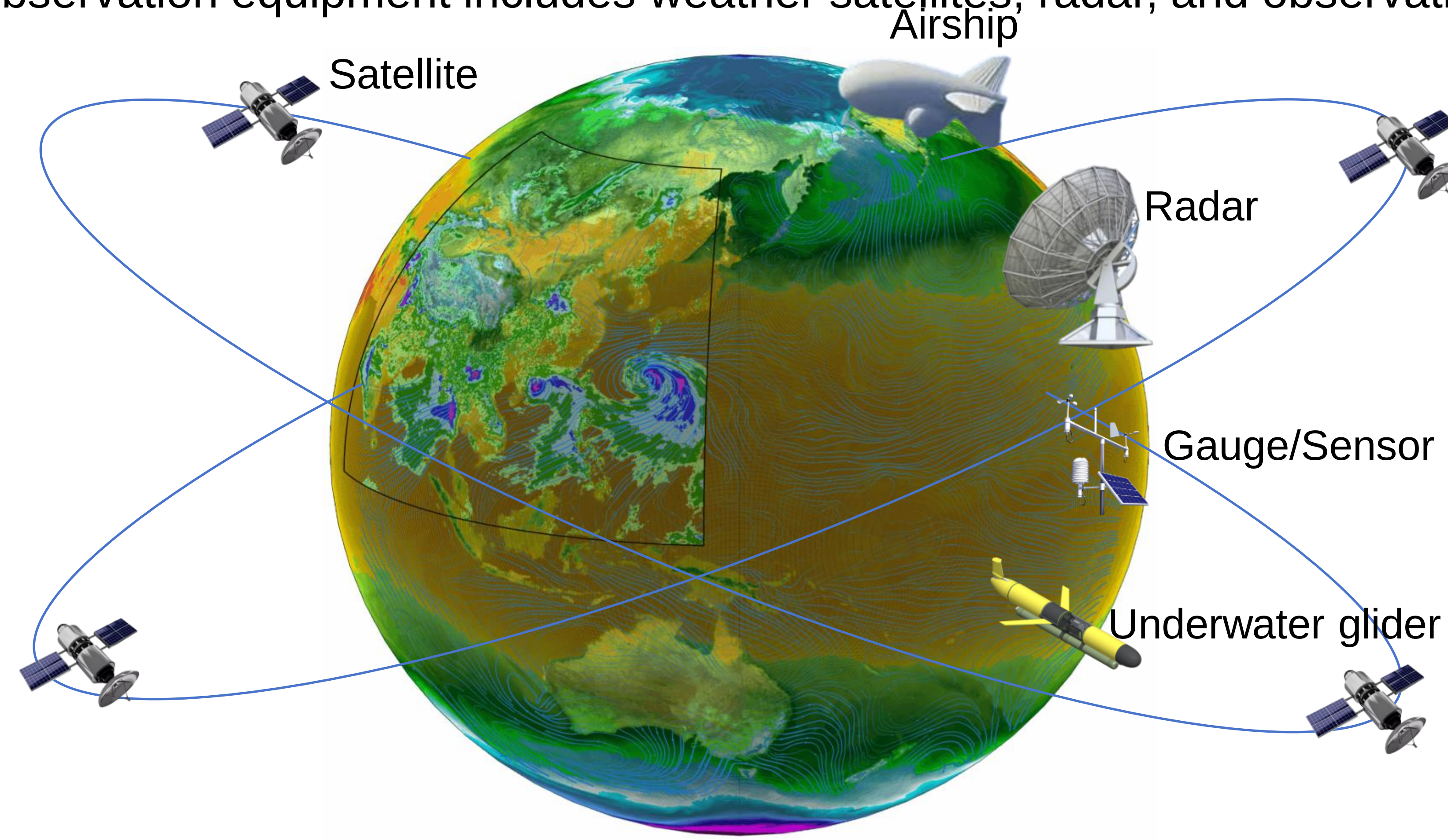
Urban

Seafaring

Earth Observations

- Earth observation systems provide diverse data for weather monitoring, prediction, and understanding.

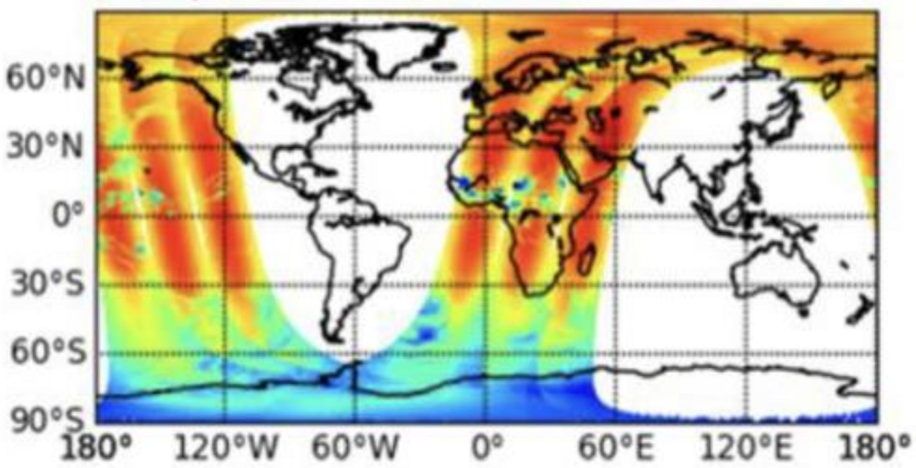
- Common observation equipment includes weather satellites, radar, and observation stations, among others.

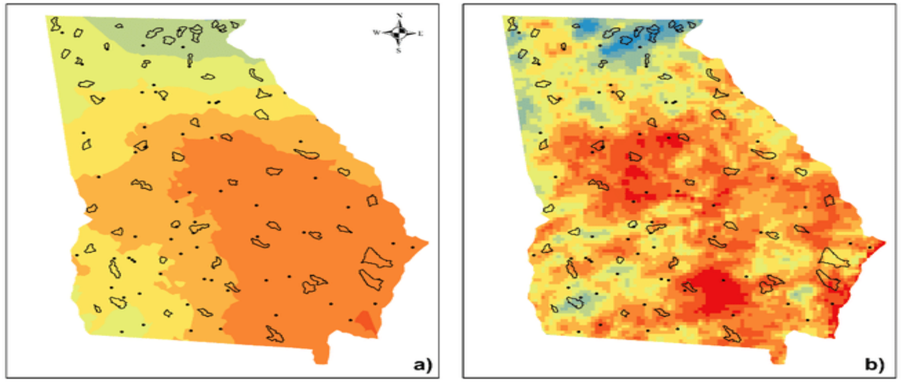


The Chanllenges of Data Characters

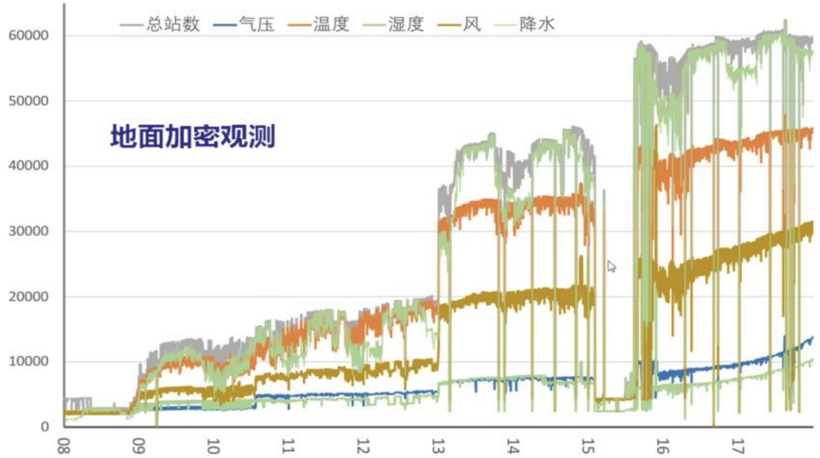
Chanllenge: Different Earth observation equipment generates data with varying spatiotemporal resolutions and coverage areas.

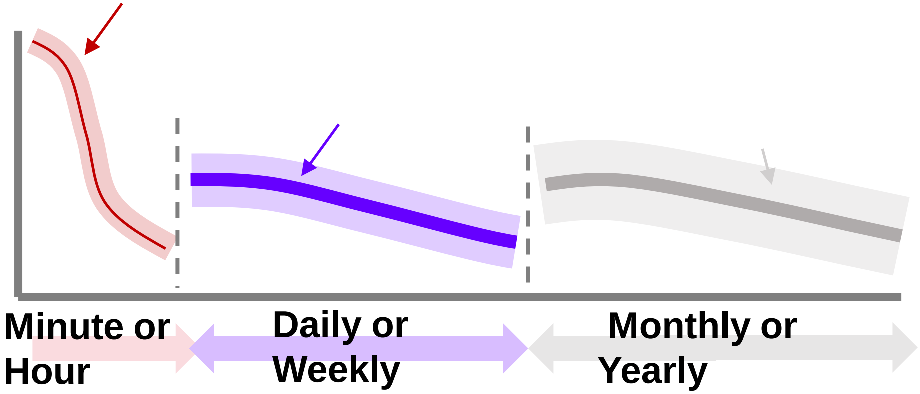
Spatial coverage and resolution





Temporal coverage and resolution





Data Characters and Chanllenges

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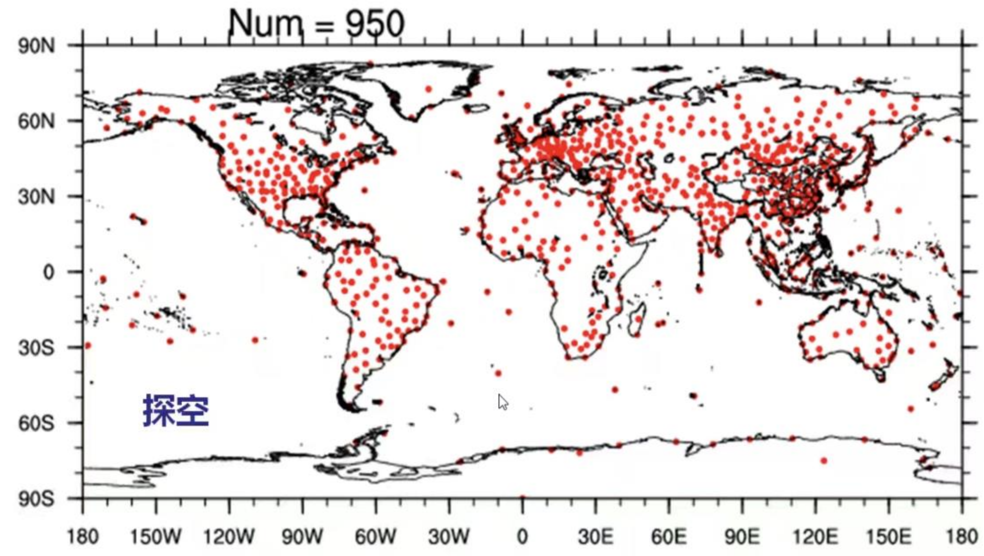
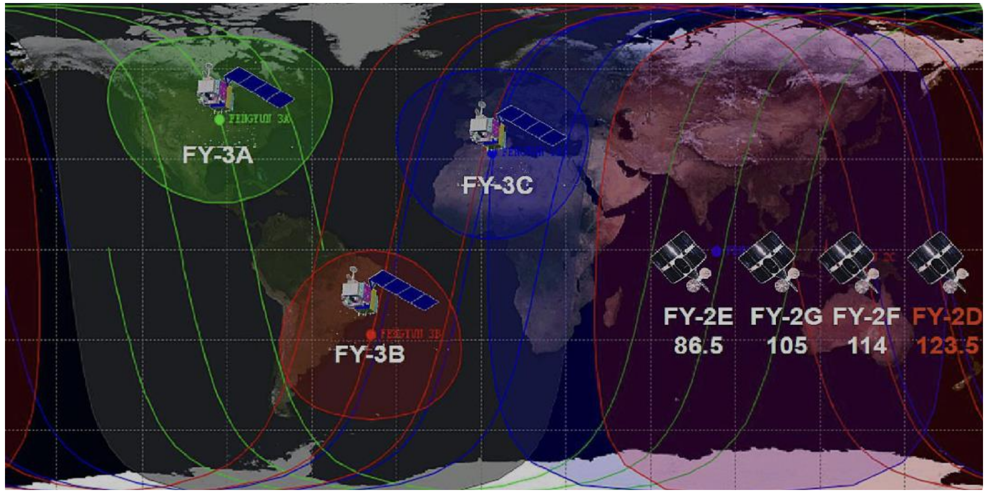
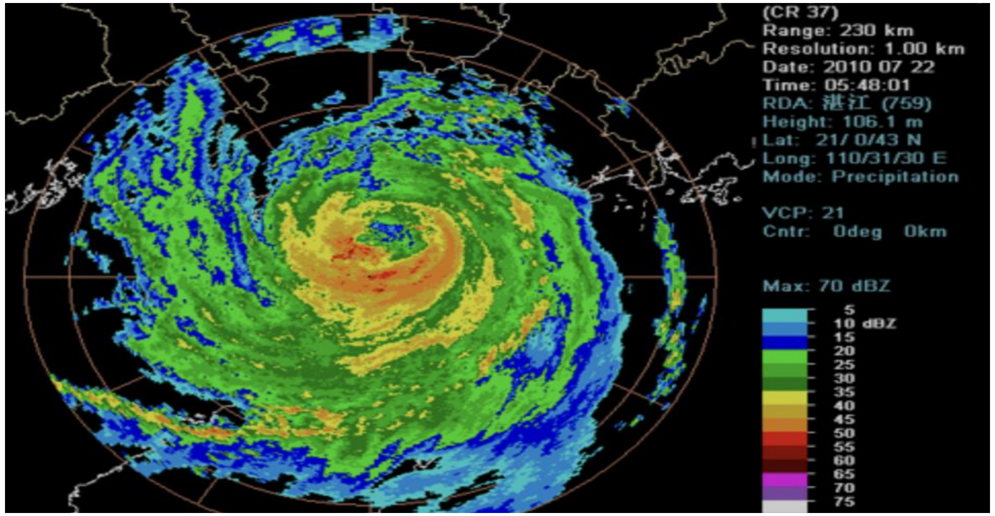
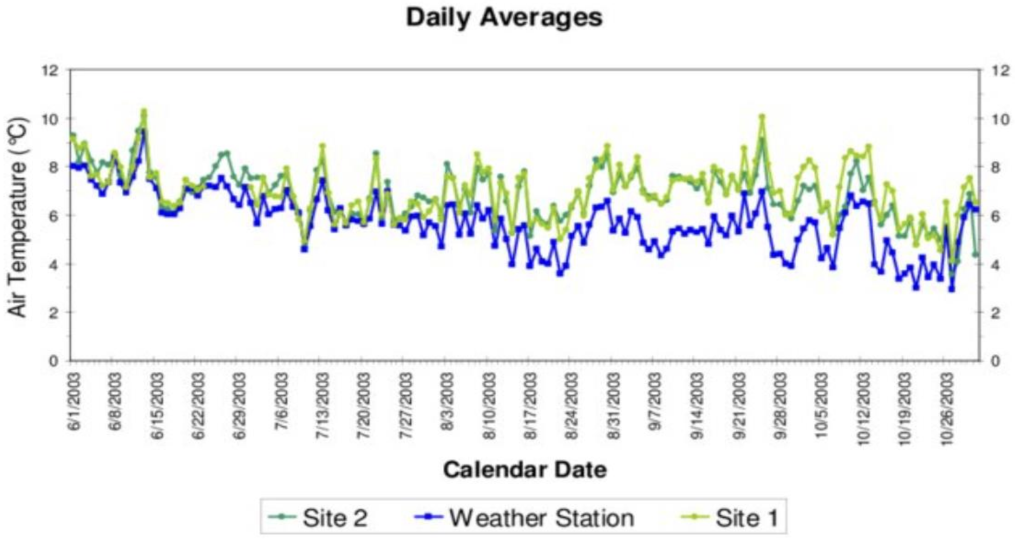
Sparsity





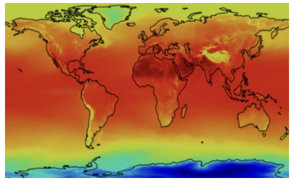
Multi-modal

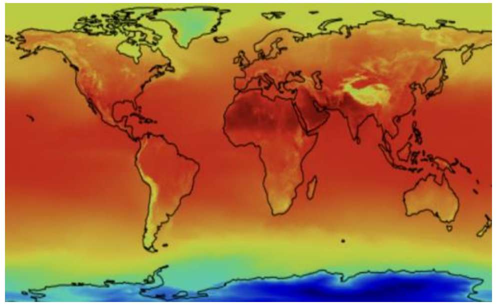




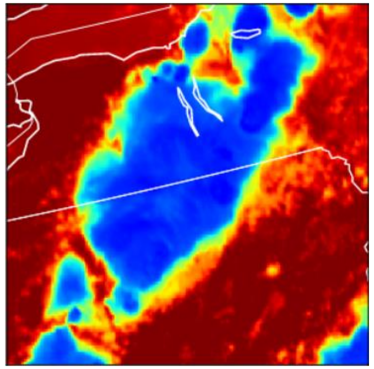
Earth Monitoring and Forecasting

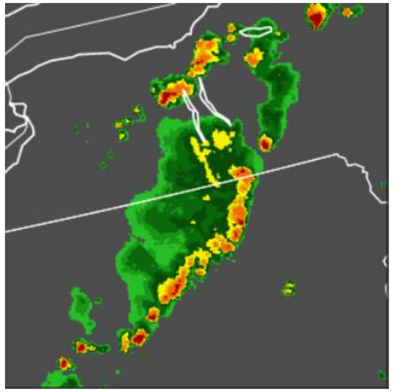
Super-resolution (Downscaling)



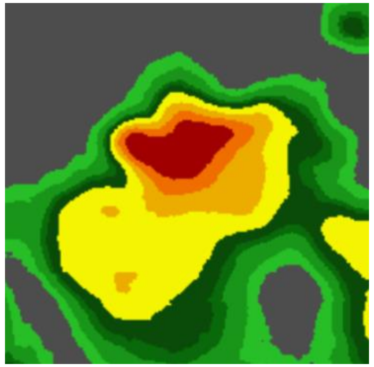


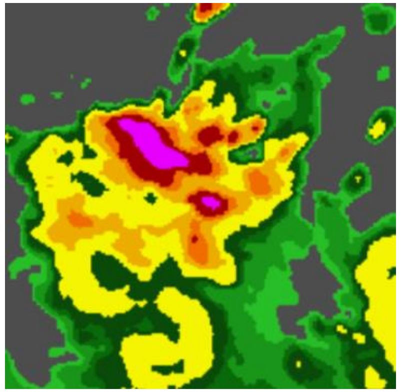
Variable synthesis



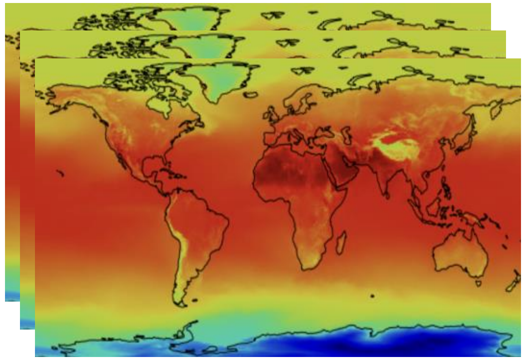


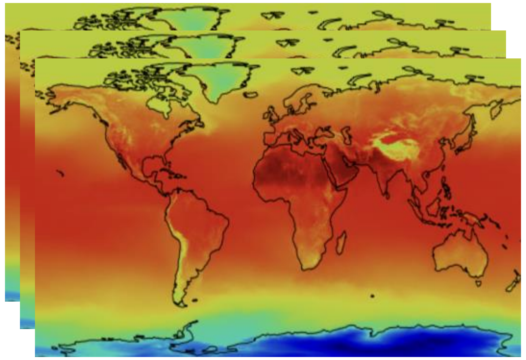
Post-processing



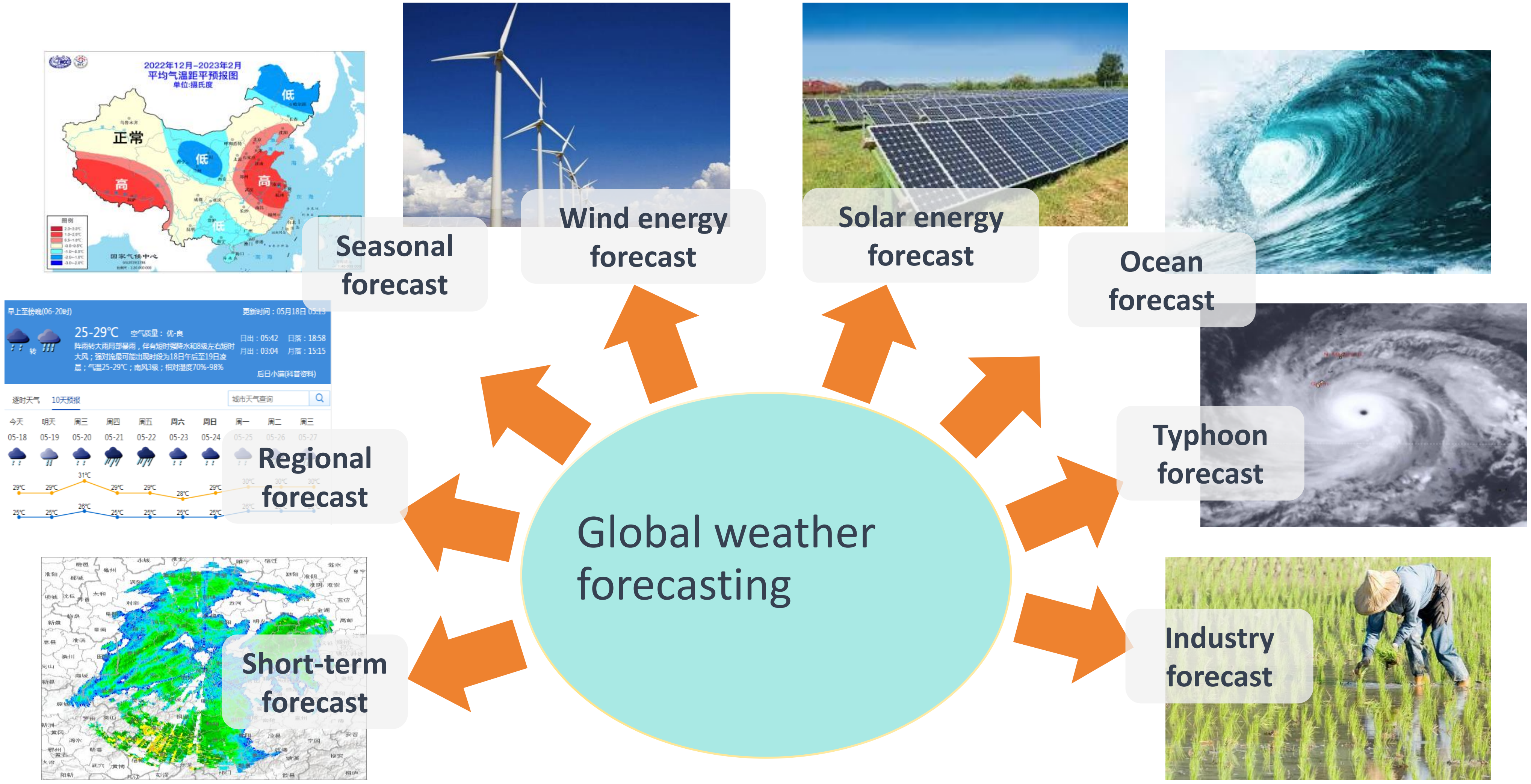


Prediction





❑ Build AI-powered foundation model for global weather and climate forecasting



From ECMWF

ECMWF's ML Strategy: with **a very busy and FAST evolving landscape**

2018 – ECMWF's ML scientific publication

Jan 2021 – Machine Learning Roadmap

Feb 2022 – Full medium-range NWP

Oct 2022 – 1km^2 global

Nov 2022 – Tropical cyclones

Dec 2022 – Extensive predictions

Jan 2023 – Global & Limited Area

Apr 2023 – 7-day+ scores improve

ECMWF's Peter Dueben and Peter Bauer publish a paper on using ERA5 at ~500km resolution to predict future z500.

ECMWF
Strategy to embed Machine Learning deeply into the ECMWF operational chain

Keisler - GraphNN 1°, competitive with GFS
NVIDIA – FourCastNet Fourier+ , 0.25°
O(10^4) faster & more energy efficient than IFS

Jua.ai
1x1km global 48 hours lead time
5 minute timesteps

Huawei – PanguWeather 0.25° hourly product
"More accurate tracks" than the IFS.

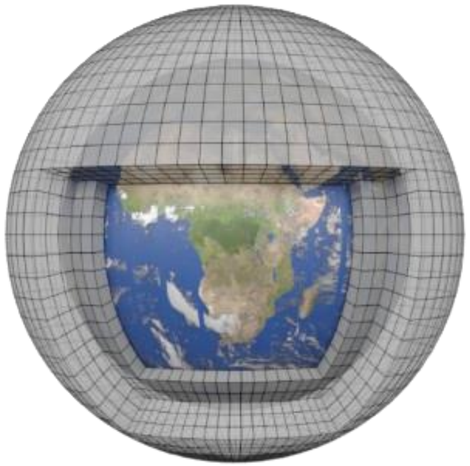
Deepmind – GraphCast 0.25° 6-hour product
Predicts many variables and pressure levels with comparable skill to IFS.

Microsoft – ClimaX
Forecasting various lead-times at various resolutions, both globally and regionally

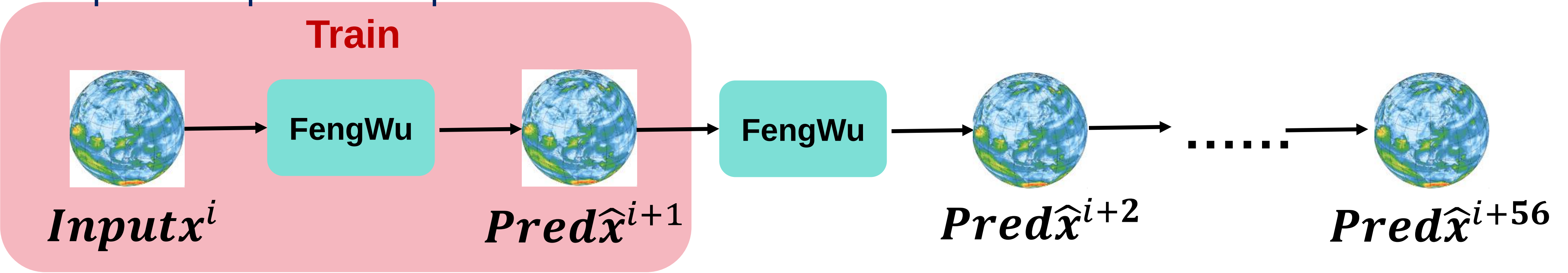
FengWu – China academia + Shanghai Meteorological Bureau 0.25° 6-hour product
Improves on GraphCast for longer leadtimes (still deterministic)

FengWu-v1: Task Definition

- **Problem：Predicting future global atmospheric conditions up to fourteen days**
  - Resolution：**0.25 (720*1440) / 0.09**
  - Region：**Global**
  - Height level：**37 / 13 levels**
  - Atmosphere variables：geopotential、temperature、humidity、u component of wind、v component of wind

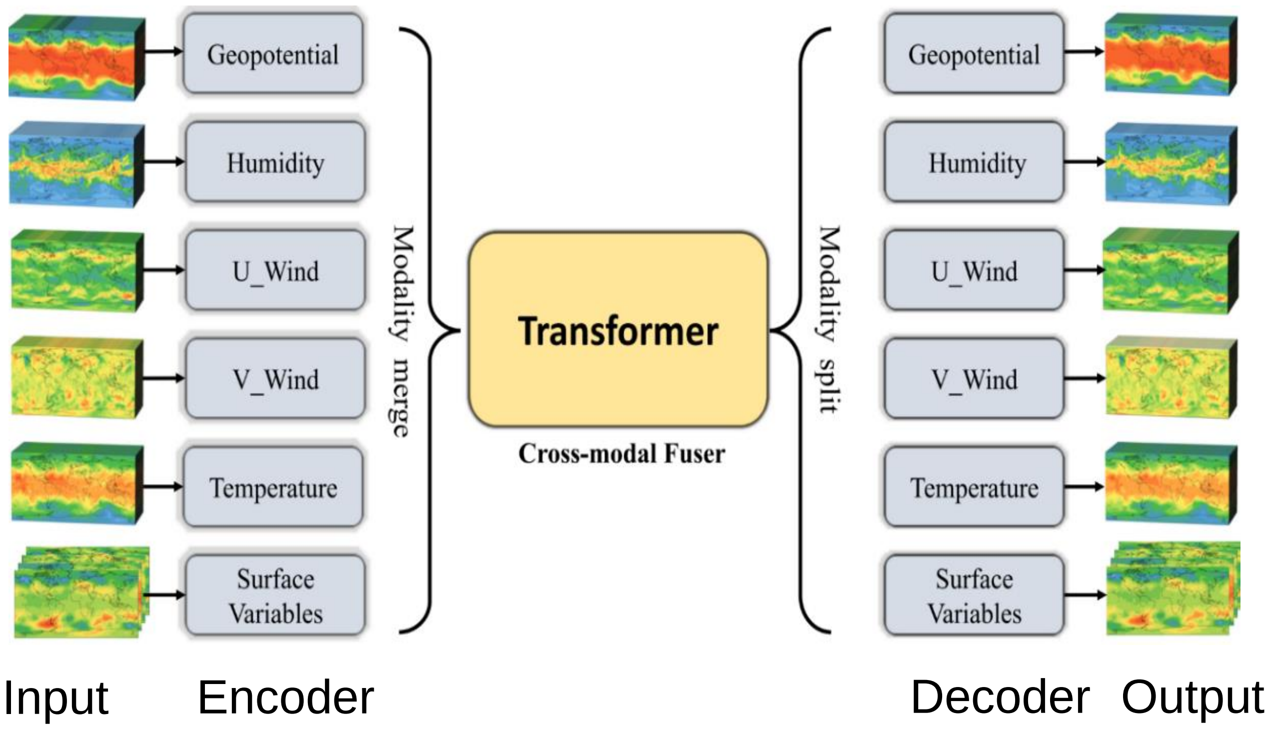


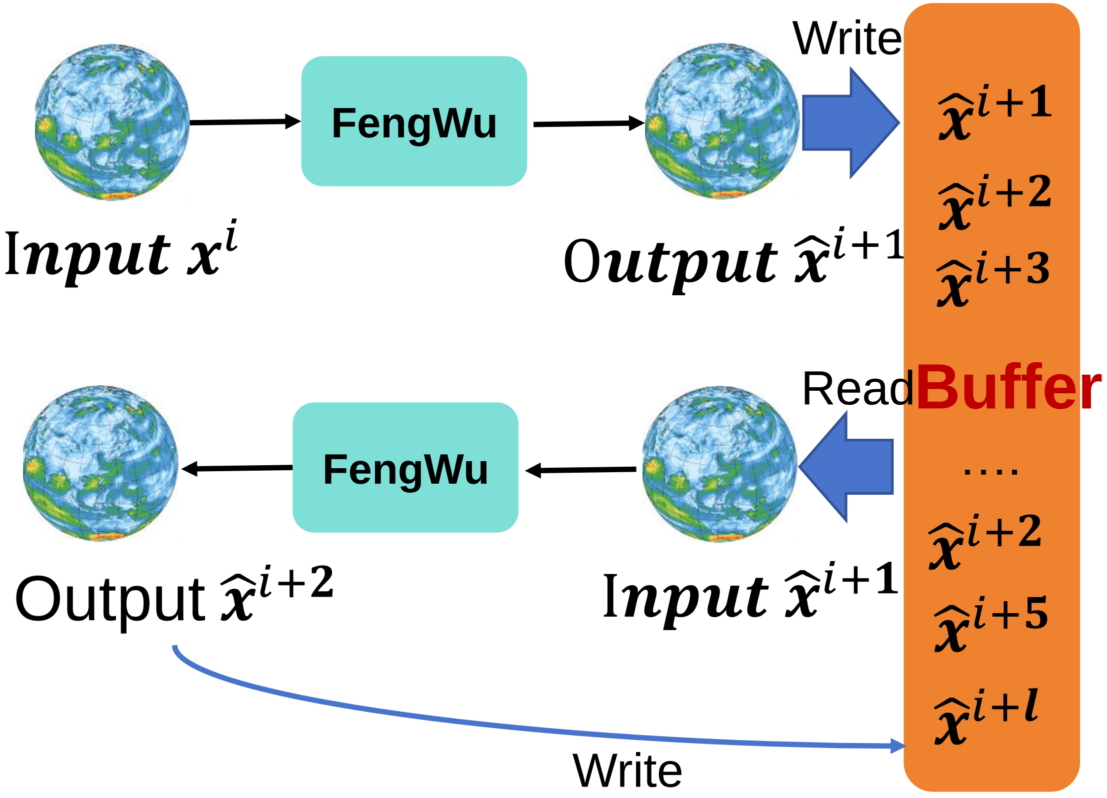
- **Modeling：**
  - Like physical model，the goal of FengWu is to predict the atmospheric variables at the next moment，and then all predictions are obtained by autoregressive method
  - Spatiotemporal extrapolation



FengWu-v1: Models

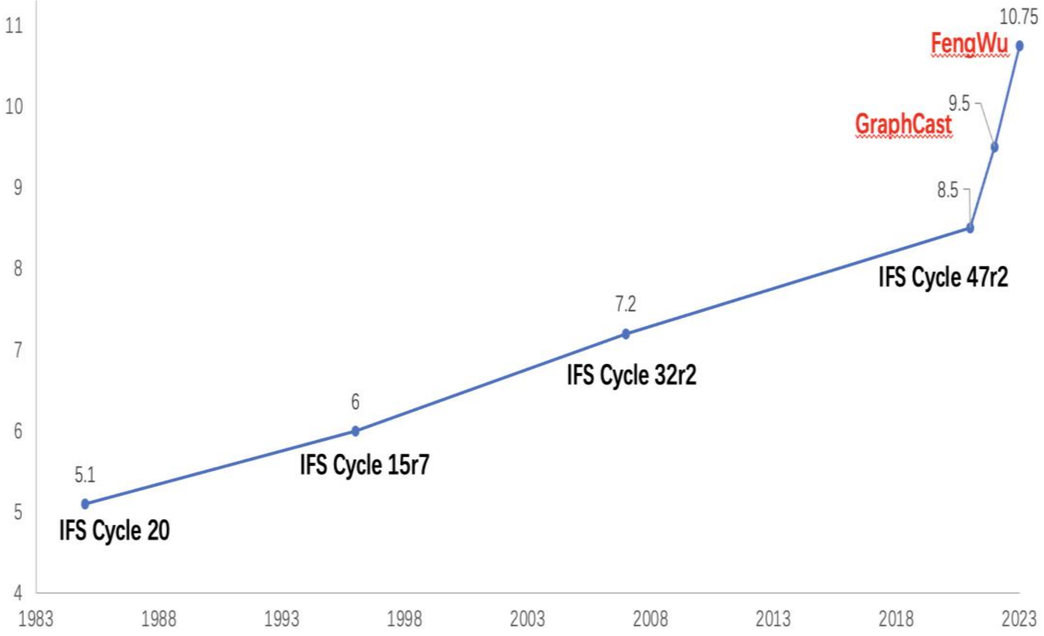
- **Designs**
  - Multi-modal network for efficient high-dimensional data representation
  - Multi-task loss for efficient model training
  - Replay buffer mechanism for long-lead forecasting





FengWu-v1

- **Long lead skillful forecasting**
  - **from 8.5 days to 10.75 days from Z500, and 14 days for t2m**
  - **Fast development**
- **Efficiency: Generating the predictions for the next 10 days of all regions in the world with 1 GPU cards with 30 seconds**



Physical models require over 10K nodes runing one hour for generating 10 days' forecasts

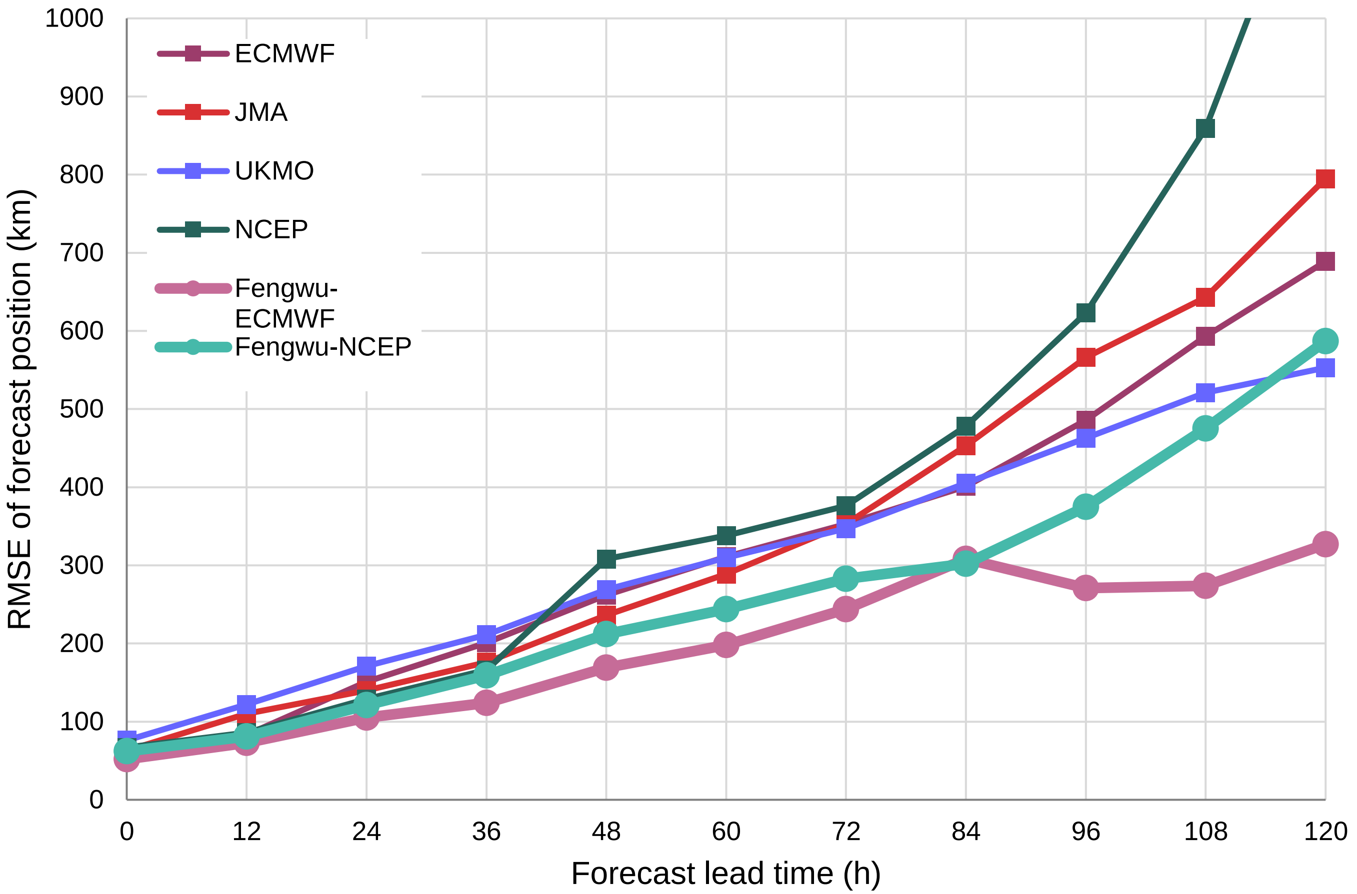
FengWu only requires one GPU card running 30 seconds for generating 10 days' forecasts

Redue the computation costs over 2000 times

The model has been deployed in National Meteorological Center of CMA and Hongkong Observation

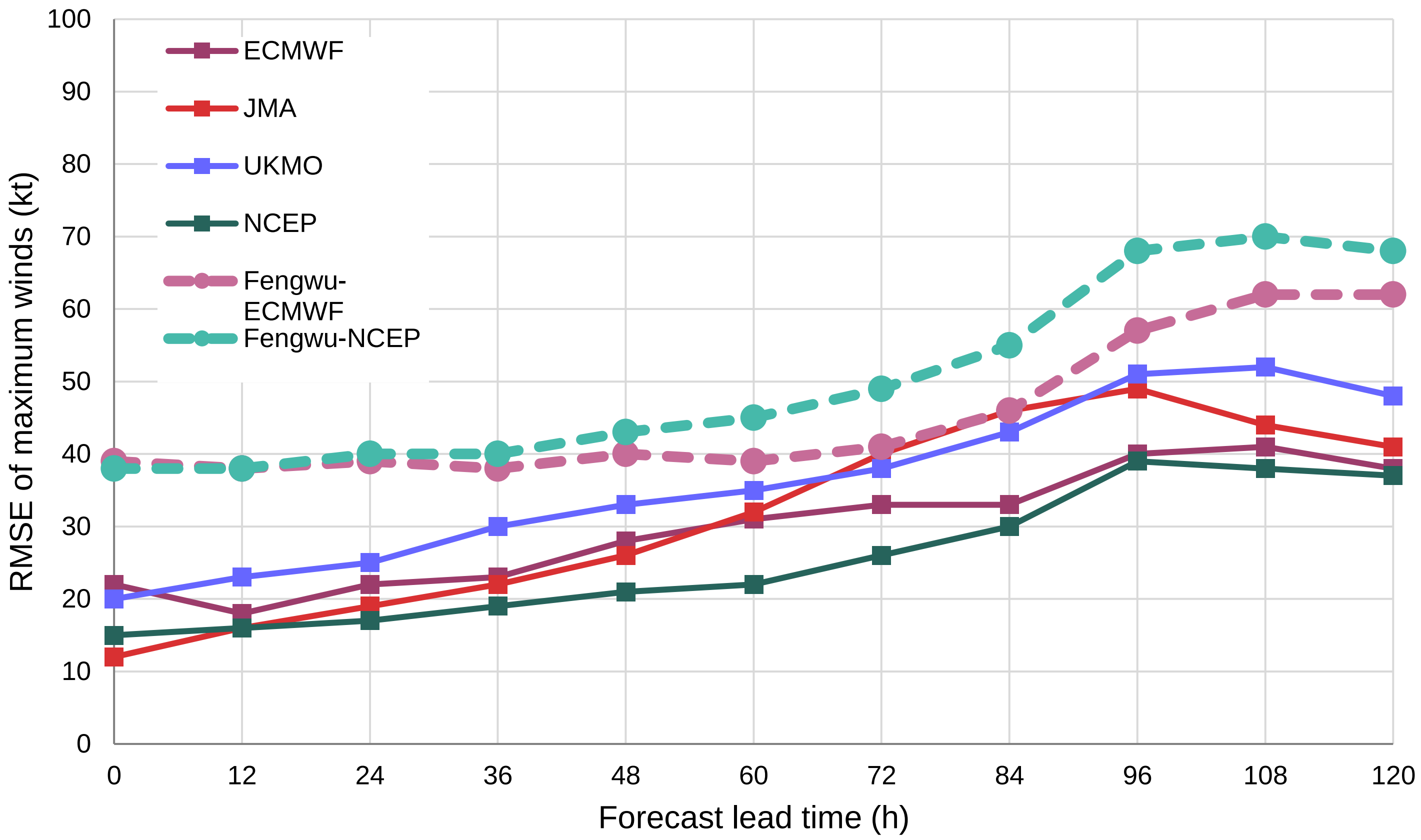
Performance of FengWu on Tropical Cyclone Track

- Verification of TC tracks since Sep 2023 (larger sample size), including
- Saola 蘇拉
- Haikui 海葵
- Kirogi 鴻雁
- Yun-yeung 鴛鴦
- 2324 nameless
- Koinu 小犬
- Bolaven 布拉萬



Performance of FengWu on Tropical Cyclone Intensity

- Verification of TC intensity since Sep 2023, including
- Saola 蘇拉
- Haikui 海葵
- Kirogi 鴻雁
- Yun-yeung 鴛鴦
- 2324 nameless
- Koinu 小犬
- Bolaven 布拉萬
- Similar to other AI models, Fengwu forecast the tropical cyclones persistently too weak.



FengWu-GHR

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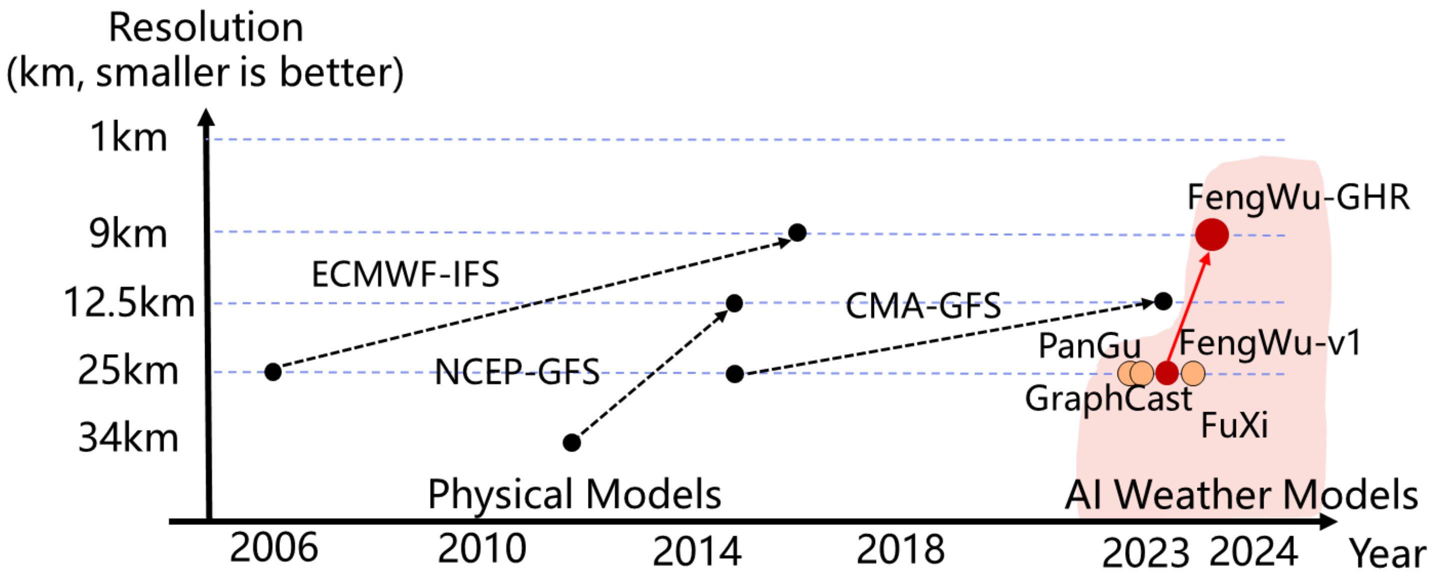
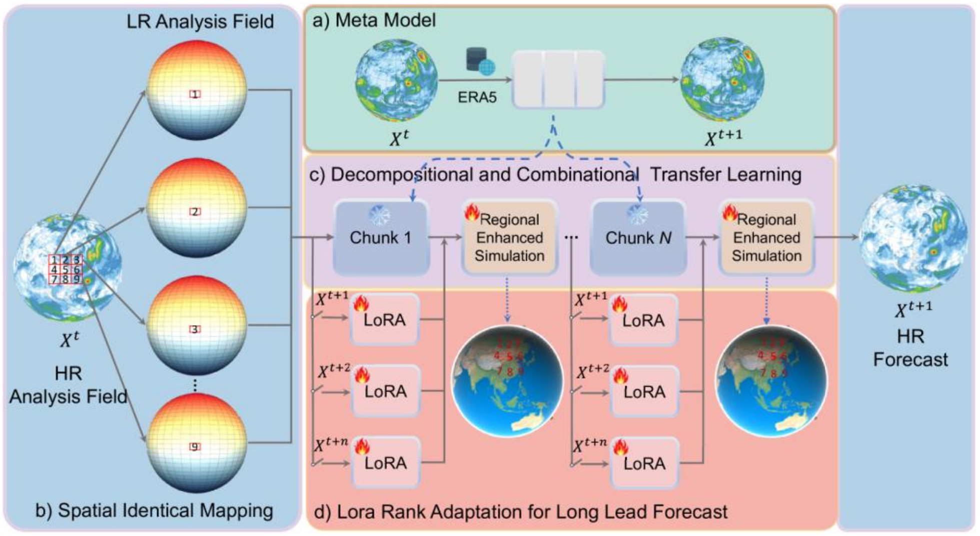
- Collaborated with CMA, FengWu-GHR is developed which is the first data-driven global medium range weather forecasting model that **works on the 0.09 degree spatial resolution**.
- Propose the **Decompositional and Combinational Transfer Learning**, which opens the door for learning higher resolution weather models with limited data and computational resources by utilizing lower resolution data (e.g., ERA5) for pretraining and higher resolution data (operational analysis data from ECMWF) for fine-tuning.

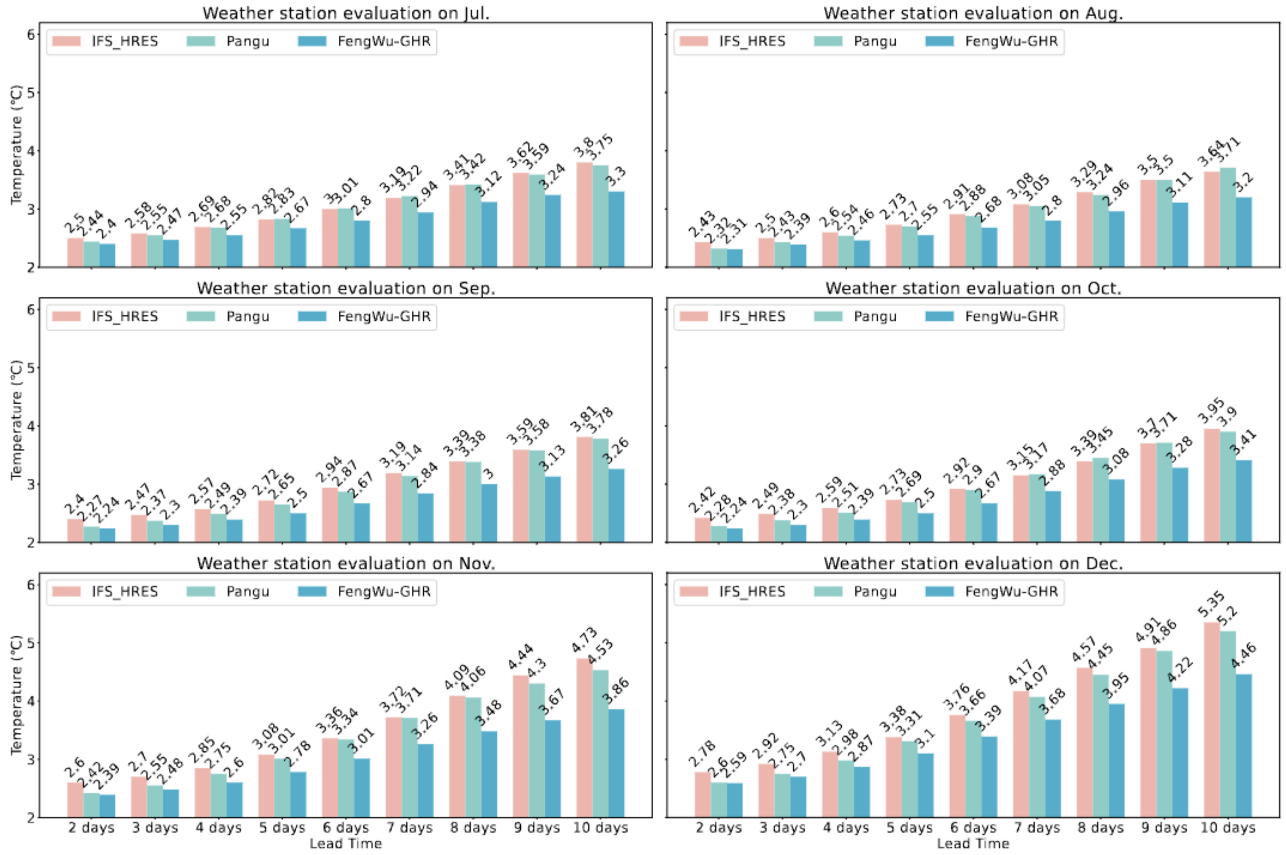




Han, T., et al. (2024) FengWu-GHR: Learning the Kilometer-scale Medium-range Global Weather Forecasting. arXiv:2402.00059 DOI: 10.48550/arXiv.2402.00059

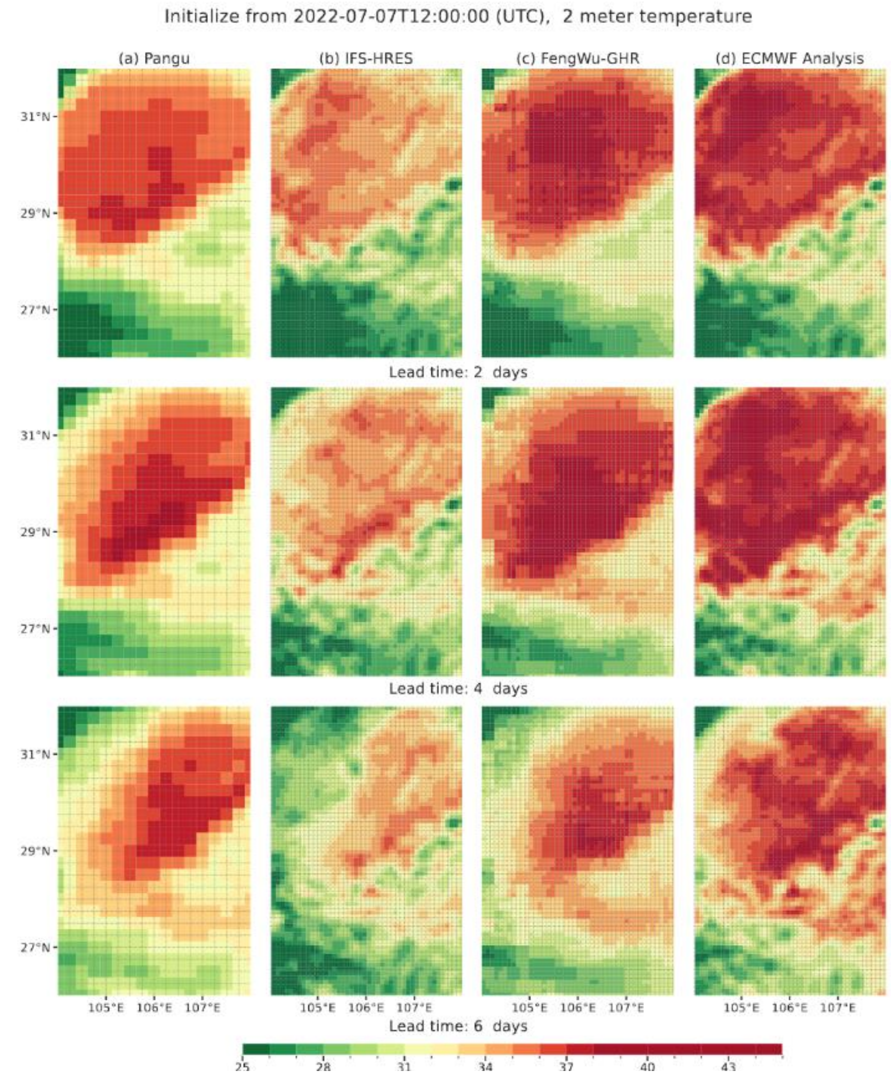
FengWu-GHR

- Evaluations with 18150 stations from NCEI



We conducted evaluations on 18 thousands staions from NCEI and evaluate the model from July to December of 2022. This evalution further confirm that FengWu-GHR significantly improves the prediction performances at all lead times.

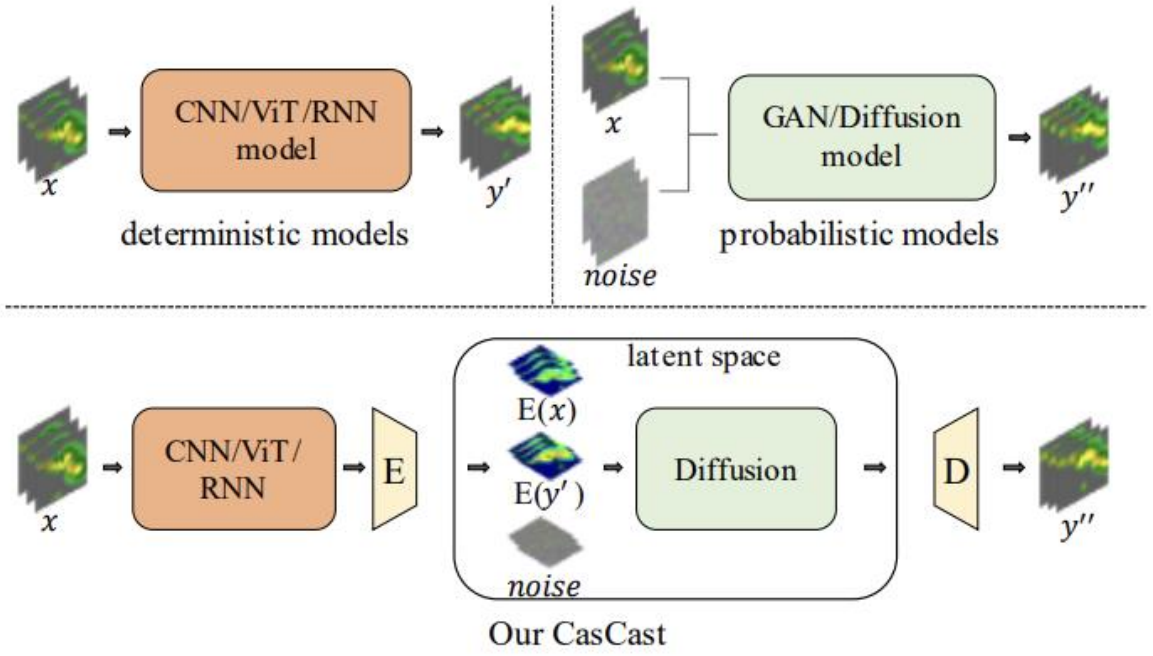
- Heat waves happened in the summer of 2022 in Chongqing

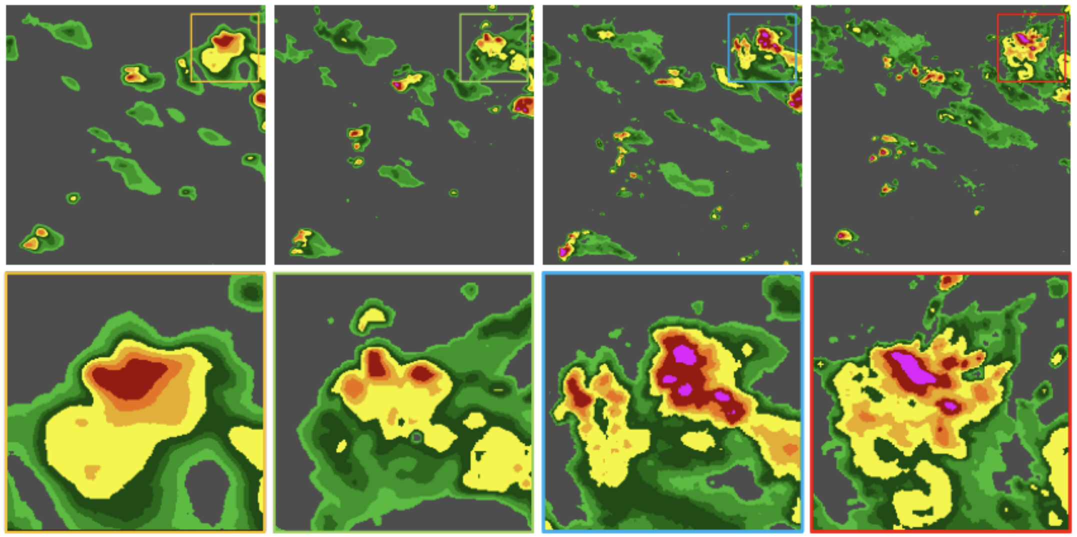


FengWu-Cascast for Precipitation Nowcasting

Challenges: Deterministic methods (e.g., Earthformer) can model meso-scale systems but **lack of fine-grained details**. Generative methods (e.g., PreDiff) can capture small-scale phenomena but face challenges in **accurately predicting large-scale distributions**.

Core idea: decompose the weather dynamics into meso-scale and small-scale systems, and generate them with deterministic models and latent diffusion transformers separately.





FengWu-Cascast for Precipitation Nowcasting

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Comprehensive experiments are conducted on three large scale datasets and demonstrate the superity of the proposed scheme. (**The model is now runing at Shanghai Meteorological Bureau**)

model	CRPS↓	SSIM↑	HSS↑	CSI-M↑			CSI-181↑			CSI-219↑		
				POOL1	POOL4	POOL16	POOL1	POOL4	POOL16	POOL1	POOL4	POOL16
ConvLSTM (Shi et al., 2015)	0.0264	0.7749	0.5232	0.4102	0.4163	0.4475	0.2453	0.2525	0.2977	0.1322	0.1380	0.1734
PredRNN (Wang et al., 2017)	0.0271	0.7497	0.5192	0.4045	0.4161	0.4623	0.2416	0.2567	0.3214	0.1331	0.1447	0.1909
PhyDNet (Guen & Thome, 2020)	0.0253	0.7649	0.5311	0.4198	0.4226	0.4410	0.2526	0.2532	0.2782	0.1362	0.1359	0.1526
SimVP (Gao et al., 2022b)	0.0259	0.7772	0.5280	0.4153	0.4226	0.4530	0.2532	0.2604	0.3000	0.1338	0.1394	0.1685
EarthFormer† (Gao et al., 2022a)	0.0251	0.7756	0.5411	0.4310	0.4319	0.4351	0.2622	0.2542	0.2562	0.1448	0.1409	0.1481
NowcastNet (Zhang et al., 2023)	0.0283	0.5696	0.5365	0.4152	0.4452	0.5024	0.2495	0.2935	0.3725	0.1422	0.1874	0.2700
LDM⋆ (Rombach et al., 2022)	0.0208	0.7495	0.4386	0.3465	0.3442	0.3520	0.1470	0.1391	0.1432	0.0671	0.0655	0.0717
PreDiff⋆ (Gao et al., 2023)	0.0202	0.7648	0.4914	0.3875	0.3918	0.4157	0.2076	0.2069	0.2264	0.1032	0.1051	0.1213
CasCast(ours)	**0.0202**	**0.7797**	**0.5602**	**0.4401**	**0.4640**	**0.5225**	**0.2879**	**0.3179**	**0.3900**	**0.1851**	**0.2127**	**0.2841**

model	HKO-7							MeteoNet						
	CRPS↓	CSI-M↑			CSI-185↑			CRPS↓	CSI-M↑			CSI-47↑		
		POOL1	POOL4	POOL16	POOL1	POOL4	POOL16		POOL1	POOL4	POOL16	POOL1	POOL4	POOL16
ConvLSTM	0.0257	0.4000	0.4084	0.4280	0.1569	0.1843	0.2472	0.0218	0.3008	0.3050	0.3465	0.0982	0.1091	0.1588
PredRNN	0.0252	0.3996	0.4146	0.4398	0.1633	0.1981	0.2634	0.0214	0.2914	0.3003	0.3402	0.0823	0.0990	0.1462
PhyDNet	0.0245	0.4213	0.4121	0.3846	0.1807	0.1768	0.1913	0.0216	0.3120	0.3124	0.3356	0.1106	0.1157	0.1482
SimVP	0.0248	0.4236	0.4195	0.4134	0.1881	0.1953	0.2233	0.0218	0.3017	0.3143	0.3577	0.0997	0.1134	0.1599
EarthFormer	0.0251	0.4096	0.4003	0.3950	0.1729	0.1731	0.1935	0.0224	0.2831	0.2855	0.3154	0.0787	0.0872	0.1208
NowcastNet	0.0296	0.4234	0.4518	0.4724	0.2025	0.2607	0.3601	0.0277	0.2955	0.3232	0.3734	0.1236	0.1521	0.2115
LDM⋆	0.0260	0.3045	0.2738	0.2764	0.0517	0.0605	0.0928	0.0209	0.2131	0.2191	0.2369	0.0359	0.0407	0.0552
PreDiff⋆	0.0244	0.3221	0.3152	0.3046	0.0788	0.0852	0.1113	0.0197	0.2546	0.2668	0.2935	0.0490	0.0594	0.0867
CasCast(ours)	**0.0205**	**0.4267**	**0.4608**	**0.4938**	**0.2158**	**0.2772**	**0.3653**	**0.0180**	**0.3156**	**0.3650**	**0.4420**	**0.1204**	**0.1563**	**0.2357**

Fengwu-GFM: Generalist Foundation Model

Modeling Earth weather systems involves a series of complex subprocesses that are intended to transform intricate Earth observation data into applications like **weather forecasting, downscaling, assimilation, re-trieval, and bias correction.**

Significant trend in AI research is the development of foundation models, shifting towards large-scale pre-training and in-context learning.

This poses a **challenge**: *Is it possible to design a universal foundation model capable of handling the variety of complex weather understanding tasks and data modalities?*

GPT-3 OpenAI
Jul. 22th, 2020

Climax Microsoft
Dec. 18,2023

Flamingo DeepMind
Apr. 29th, 2022

Aurora Microsoft
May. 28,2024

4M EPFL
Dec. 11th, 2023

Prithvi IBM NASA
Sep. 20,2024

Chameleon Meta
May. 17th, 2024

Fengwu-GFM: Generalist Foundation Model

Challenges:

- Designing a new specific model for a single-task scenario is time-consuming, and labor-intensive.
- Weather understanding tasks face an intrinsic bottleneck in data scale due to restrictions on individual scenes and single observation devices

Category	Method	Data Acquisition Difficulty	Supported Tasks	Multi-tasks support?	Multi-modal support?	Generalist support?
Computer Vision	HAT (Chen et al., 2023d)	Low-cost	Image super-resolution (SR)	✗	✗	✗
	IPT (Chen et al., 2021)	Low-cost	Image restoration, Derain, Dehaze	✓	✗	Requires fine-tuning
	Painter (Wang et al., 2023a)	Low-cost	Image restoration Segmentation, Keypoint detection	✓	✗	✓
	PromptGIP (Liu et al., 2023a)	Low-cost	Image restoration, Derain, Dehaze	✓	✗	✓
	GenLV (Chen et al., 2024a)	Low-cost	Image restoration, enhancement, translation	✓	✗	✓
Earth Science	Prediff (Gao et al., 2024)	High-cost	Weather forecasting	✗	✗	✗
	Cascast (Gong et al., 2024)	High-cost	Post-processing	✗	✗	✗
	Climax (Nguyen et al., 2023)	High-cost	Weather forecasting, Super-resolution	✓	✗	Requires fine-tuning
	Aurora (Bodnar et al., 2024)	High-cost	Weather forecasting Atmospheric chemistry prediction	✗	✓	Requires fine-tuning
	WeatherGFM (ours)	High-cost	Weather forecasting, Weather image SR Weather image translation, Post-processing	✓	✓	✓

Fengwu-GFM: Generalist Foundation Model

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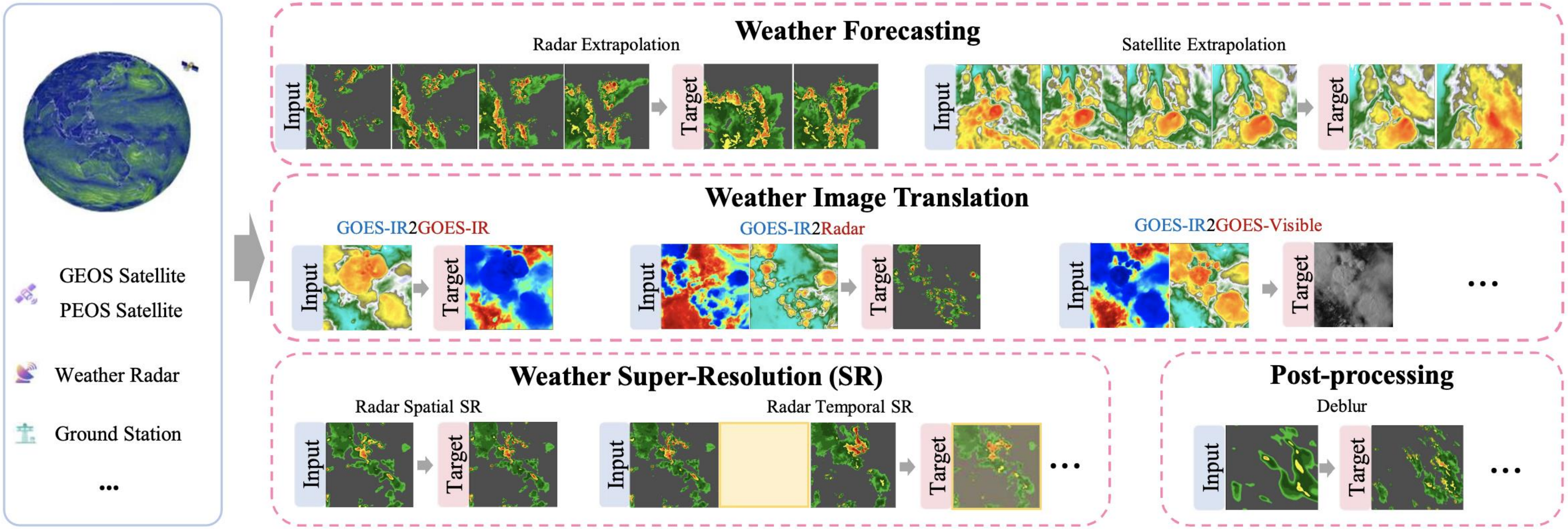
Weather understanding tasks involve processing **multi-source observational data**, such as geostationary satellites (GEOS), polar-orbiting satellites (POES), weather radars, and ground observation stations. Each task (e.g., weather forecasting, spatial and temporal super-resolution, weather image translation, and post-processing) utilizes **different types of input and output data**.



How to unify these tasks and data modalities into a general foundation model?

Fengwu-GFM: Generalist Foundation Model

Prompt learning

Vision and language prompt designing

Task prompts commonly provide specific task-related input-output pairs.

Weather prompt designing

we proposed three prompts to handle different modalities of input. Support single variable (super-resolution), multiple variables (e.g., image translation), and time-series variables(e.g., weather forecasting).

Text Prompt:	{example: sea otter, loutre de merr}	query: cheese	output: fromage
Visual Prompt:	{example: image1, image2}	query: image3	output: image4

Weather Prompts

Weather Prompt1:	{example: image1, image2}	query: image3	output: image4
Weather Prompt2:	{example: image1,image2, image3}	query: image4,image5	output: image6
Weather Prompt3:	{example: sequence1, sequence2}	query: sequence3	output: sequence4

Fengwu-GFM: Generalist Foundation Model

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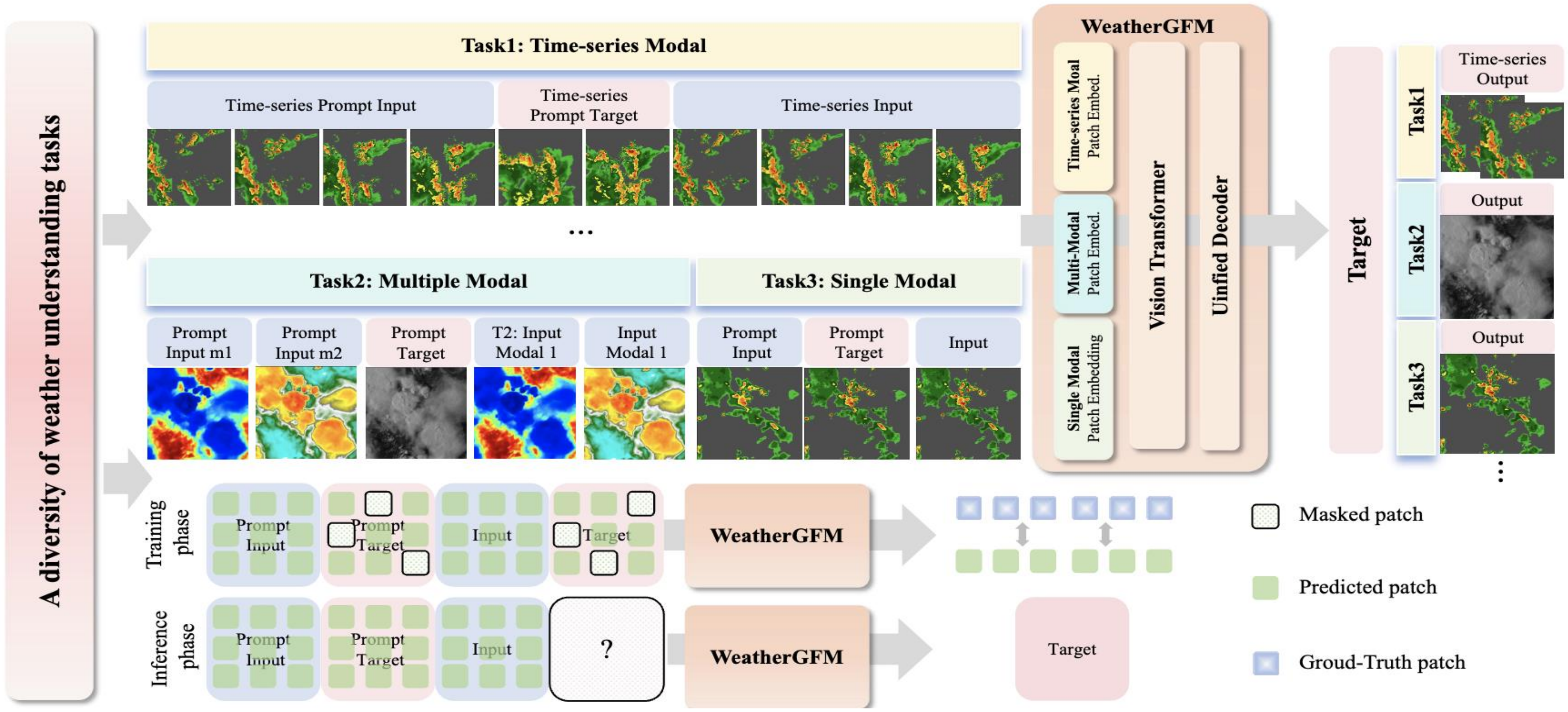
Weather in-context learning: Unify the weather understanding problem as the visual prompting question-answer paradigm by ***mask modeling***.



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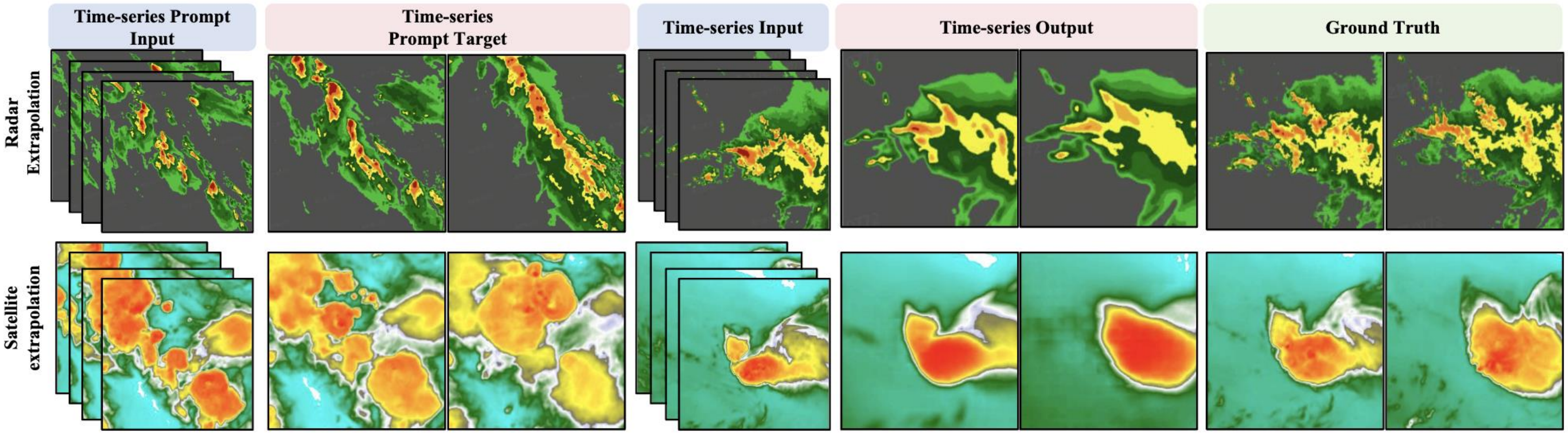
Time-series modal

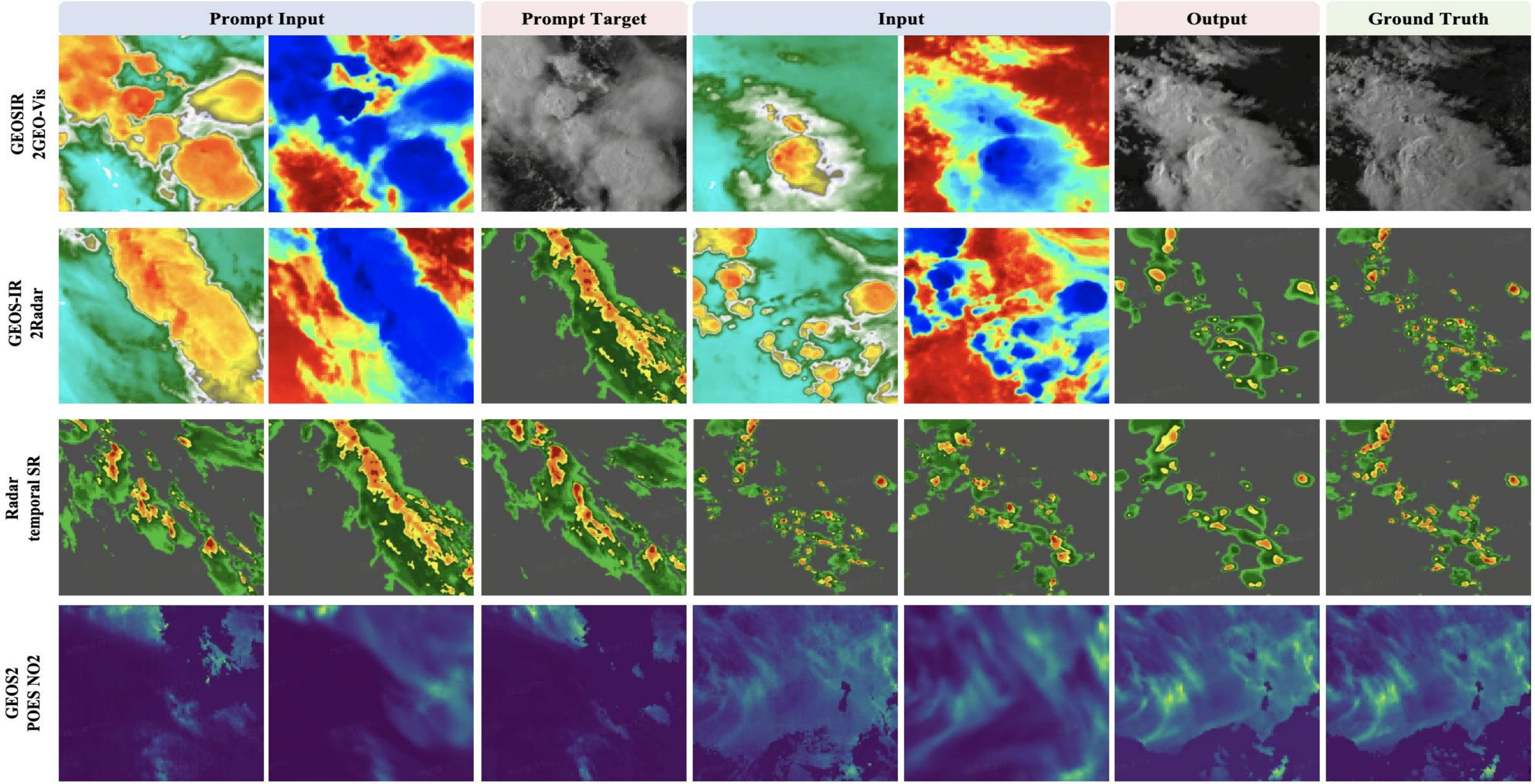
Weather Generalist foundation model can achieve strong universal capabilities



Fengwu-GFM: Generalist Foundation Model

Multi-modal

Weather Generalist foundation model can achieve strong universal capabilities



Fengwu-GFM: Generalist Foundation Model

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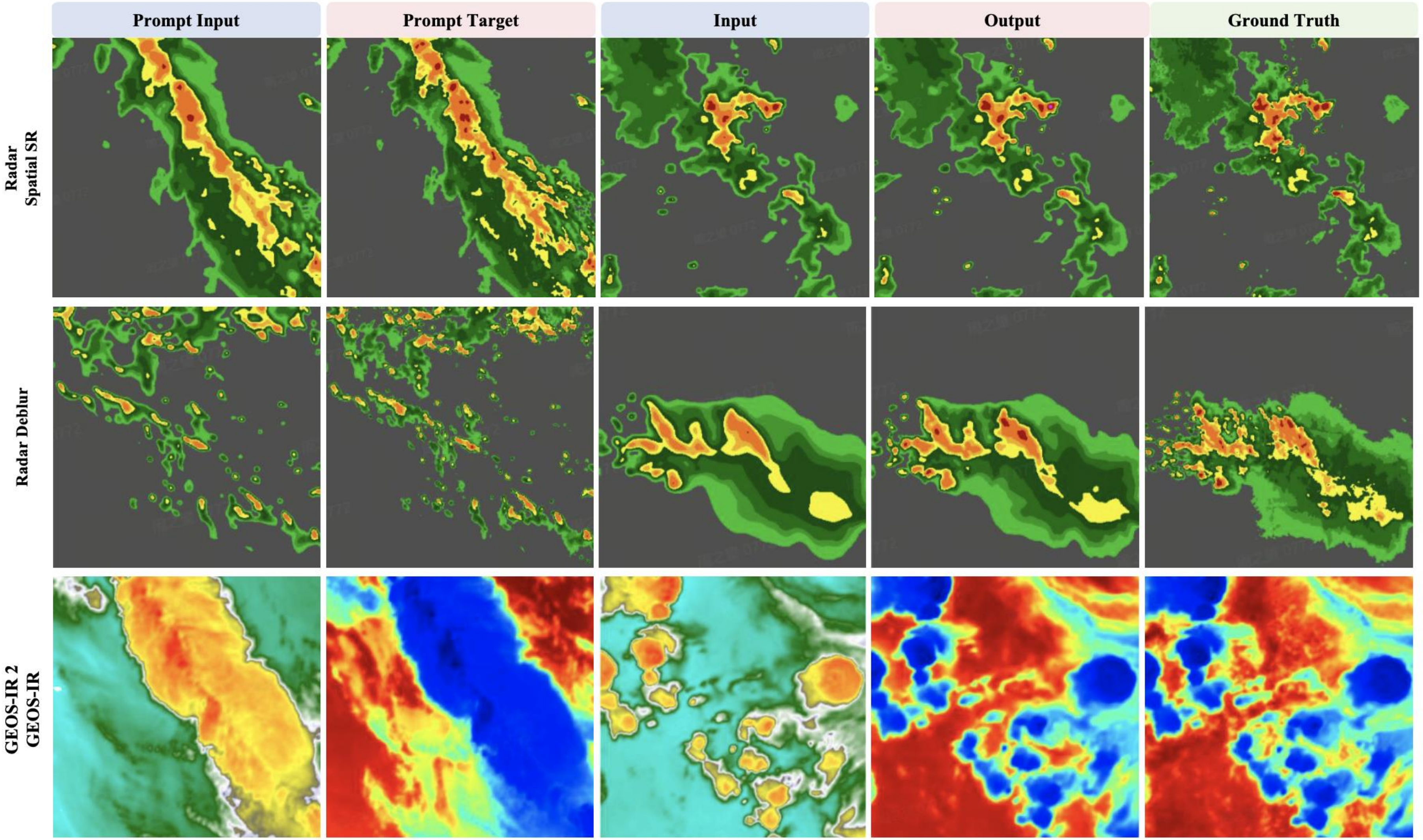
Single modal

Weather Generalist foundation model can achieve strong universal capabilities



Fengwu-GFM: Generalist Foundation Model

Weather Generalist foundation model outperforms the performance of the single-task model.

Task name	Weather super-resolution (SR)										
	Satellite Spatial SR			Radar Temporal SR				Radar Spatial SR			
Metrics	RMSE	CSI/-4000	CSI/-6000	RMSE	CSI/74	CSI/160	CSI/219	RMSE	CSI/74	CSI/160	CSI/219
UNet$^{\#}$	0.932	0.650	0.912	0.739	0.485	0.182	0.034	0.650	0.675	0.400	0.184
ViT$^{\#}$	0.047	0.987	0.990	0.333	0.591	0.285	0.061	**0.120**	0.830	0.637	0.358
WeatherGFM†	**0.042**	**0.988**	**0.996**	**0.327**	**0.597**	**0.287**	**0.073**	0.121	**0.831**	**0.644**	**0.375**

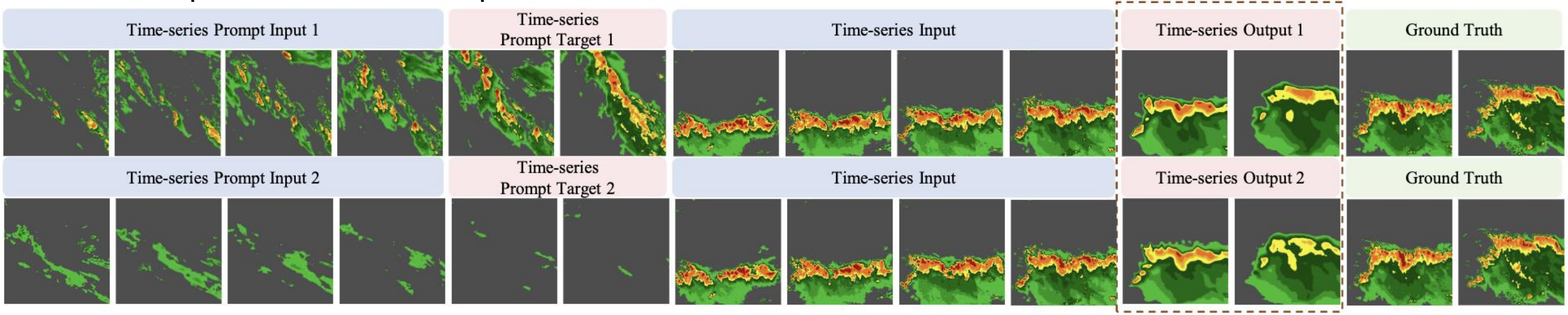
Task name	Weather Forecasting							Post-processing			
	Satellite extrapolation			Radar extrapolation				Deblur			
Metrics	RMSE	CSI/-4000	CSI/-6000	RMSE	CSI/74	CSI/160	CSI/219	RMSE	CSI/74	CSI/160	CSI/219
UNet$^{\#}$	1.033	0.617	0.900	0.815	0.353	0.082	0.007	0.713	0.457	0.145	0.027
ViT$^{\#}$	0.408	0.840	0.943	0.490	0.440	0.079	0.007	**0.163**	**0.594**	**0.291**	**0.104**
WeatherGFM†	**0.347**	**0.863**	**0.951**	**0.467**	**0.465**	**0.128**	**0.021**	0.244	0.607	0.243	0.074

Task name	Weather image translation										
	GOES2Radar						GOES-IR2GOES-IR				
Metrics	RMSE	CSI/16	CSI/74	CSI/160	CSI/181	CSI/219	RMSE	CSI/-6000	CSI/-4000	CSI/0	CSI/2000
UNet$^{\#}$	0.821	0.222	0.370	0.180	0.153	**0.079**	0.915	0.929	0.741	0.638	0.078
ViT$^{\#}$	0.445	0.602	0.436	0.180	0.131	0.042	**0.257**	0.987	**0.972**	**0.809**	0.136
WeatherGFM†	**0.436**	**0.619**	**0.447**	**0.208**	**0.157**	0.053	0.310	**0.993**	0.968	0.808	**0.222**

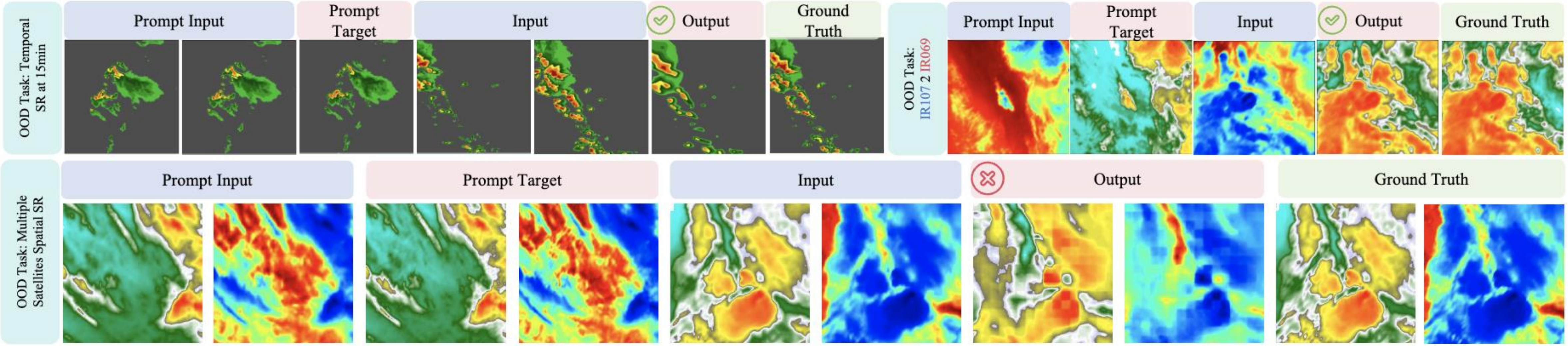
Task name	GOES-IR2GOES-Visible						GOES2POES-NO_2				
Metrics	RMSE	CSI/2000	CSI/3200	CSI/4400	CSI/5600	CSI/6800	RMSE	CSI/1	CSI/5	CSI/10	CSI/15
UNet$^{\#}$	0.915	0.422	0.285	0.179	0.100	0.040	0.866	0.799	0.360	0.274	0.202
ViT$^{\#}$	**0.448**	**0.574**	**0.437**	**0.303**	**0.184**	**0.071**	0.549	**0.841**	0.432	0.328	**0.253**
WeatherGFM†	0.858	0.386	0.272	0.168	0.081	0.027	**0.302**	0.682	**0.562**	**0.382**	0.197

Fengwu-GFM: Generalist Foundation Model

Our method can **comprehend specific weather cases** based on weather prompts rather than being a black box model incapable of interactive operations.



OOD tests demonstrate the model’s ability to identify tasks outside the training distribution from new prompts, showcasing a degree of **generalization**.



Summary

Generalist Model is an emerging paradigm that seamlessly integrates AI with Earth Science.

Generative models plays a key role in the whole process of earth modeling, including data processing, data fusion, forecasting, and support specific application.

We have conducted a set of works in the domain that have been proved effective through **real-world deployments**.

Looking forward to more discussions

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THANK YOU