Foundation models of ocean and atmosphere in 2025: milestones and perspectives.

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We do:

Developing and analyzing ML/DL/AI algorithms for fundamemental and applied problems in Earth Sciences

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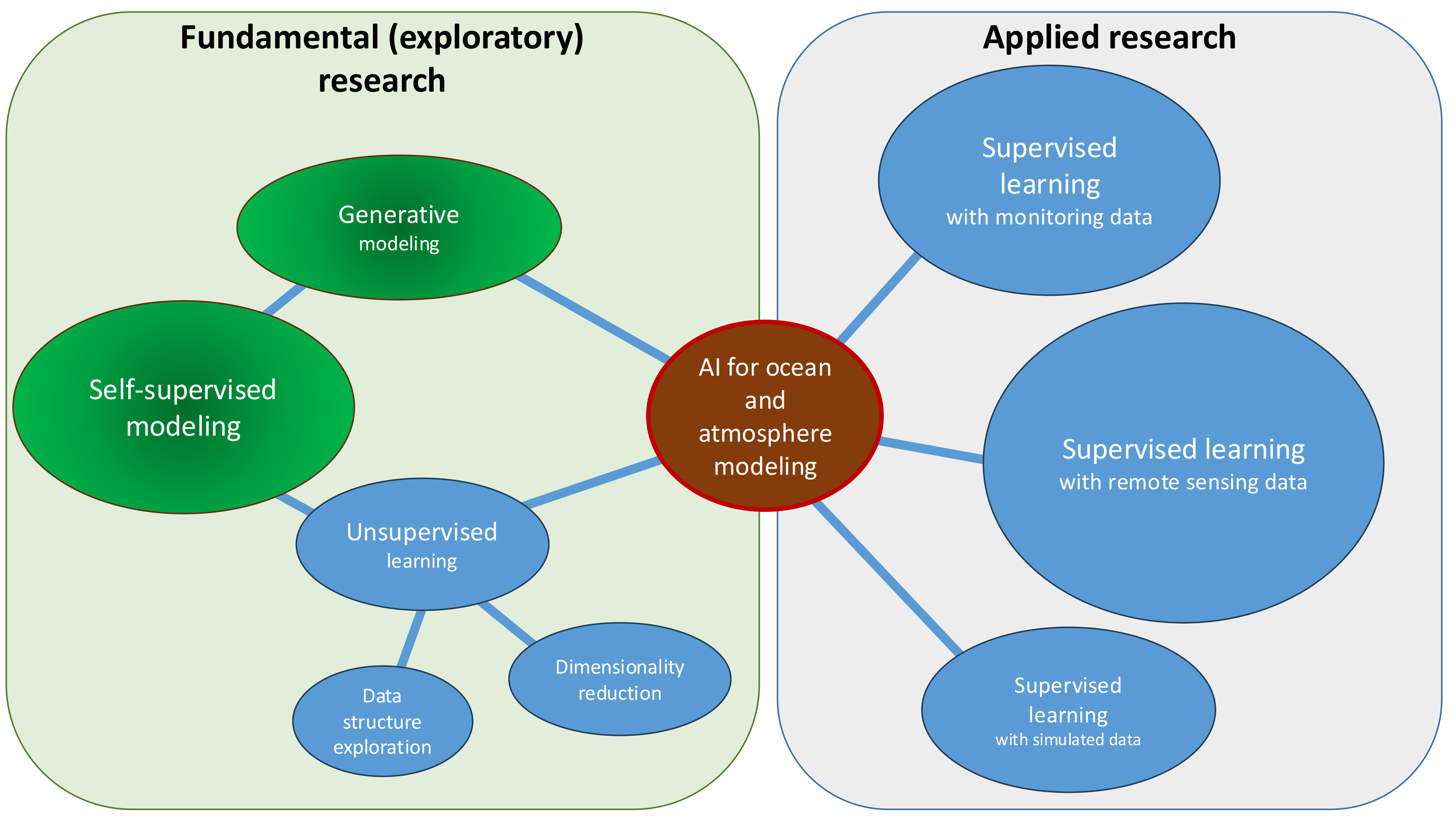
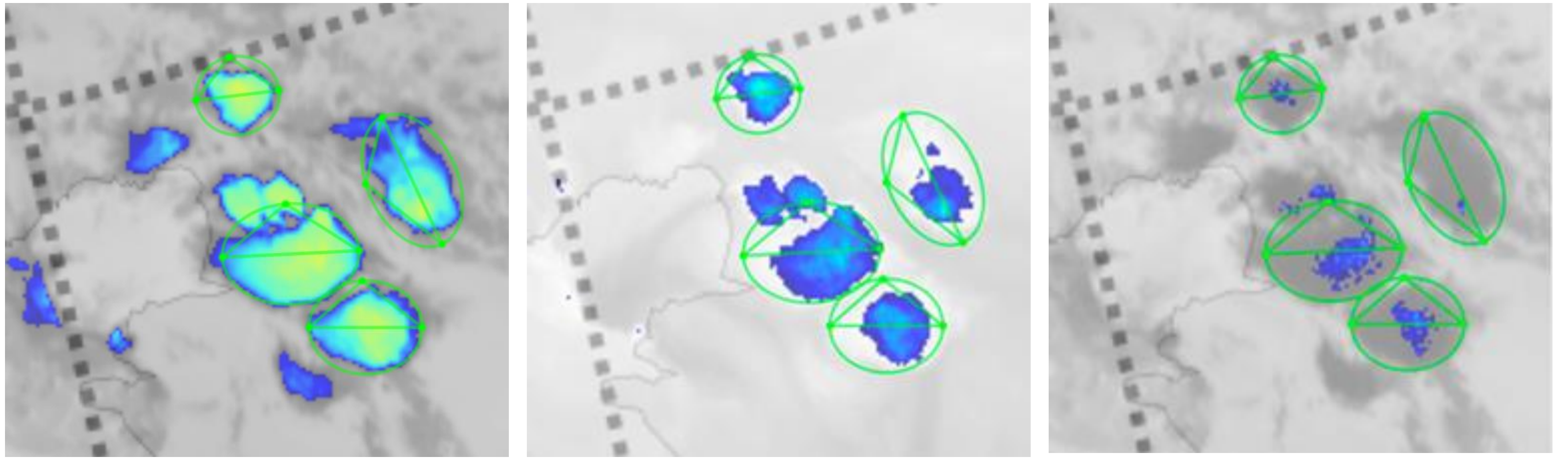

Fundamental (exploratory) research
Applied research
Generative modeling
Self-supervised modeling
Unsupervised learning
Data structure exploration
Dimensionality reduction
AI for ocean and atmosphere modeling
Supervised learning with monitoring data
Supervised learning with remote sensing data
Supervised learning with simulated data

AI for phenomena detection

Mesoscale convective systems detection

$ch9$ (10.8 μm) $ch5$ (6.25 μm) $ch5 - ch9$



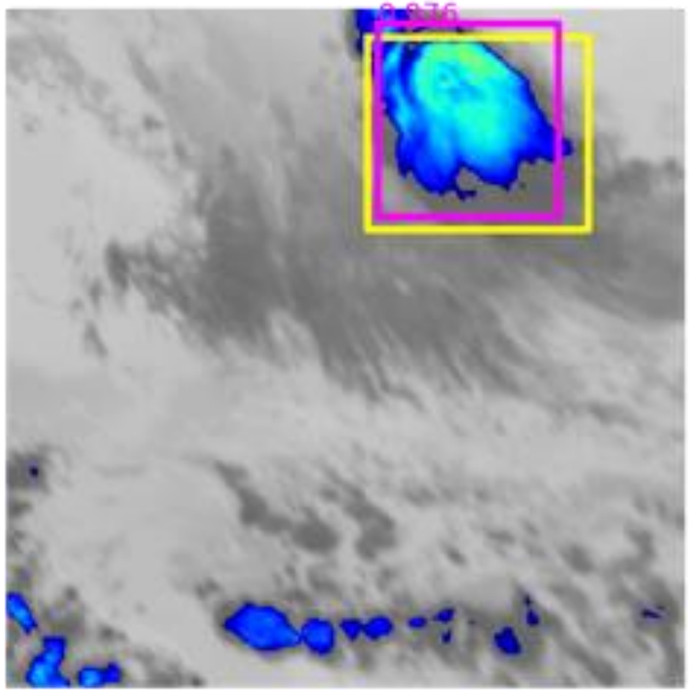
Meteosat (MSG4) data,
European territory of Russia

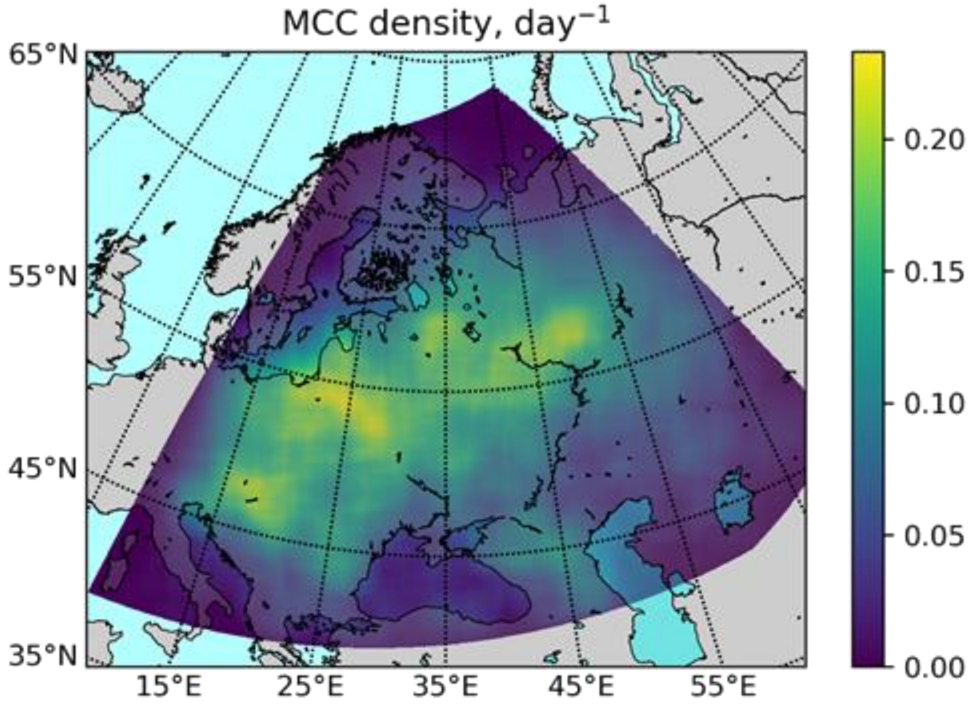
Krinitskiy, M.; Sprygin, A.; Elizarov, S.; Narizhnaya, A.; Shikhov, A.; Chernokulsky, A. Towards the Accurate Automatic Detection of Mesoscale Convective Systems in Remote Sensing Data: From Data Mining to Deep Learning Models and Their Applications. *Remote Sens.* **2023**, *15*, 3493. https://doi.org/10.3390/rs15143493

AI for phenomena detection

Mesoscale convective systems detection

$ch9$ (10.8 μm)





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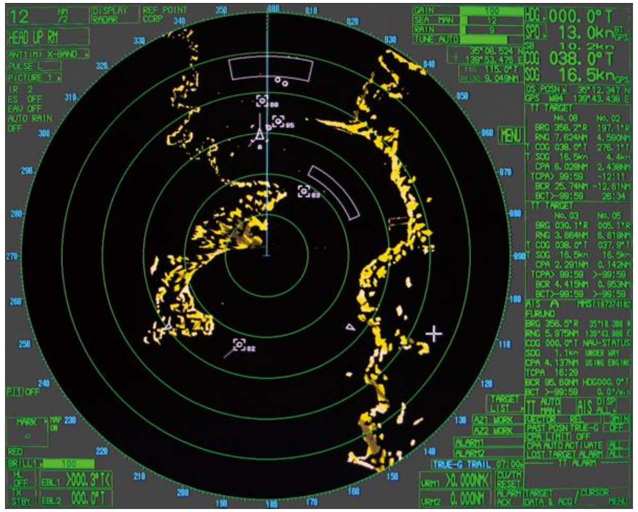
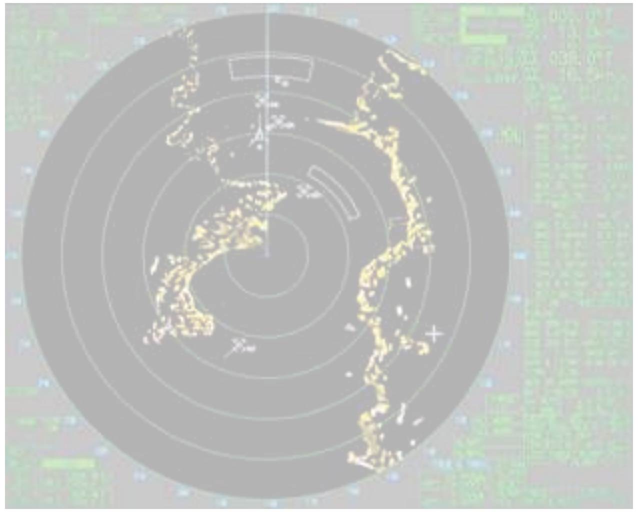
AI for field measurements

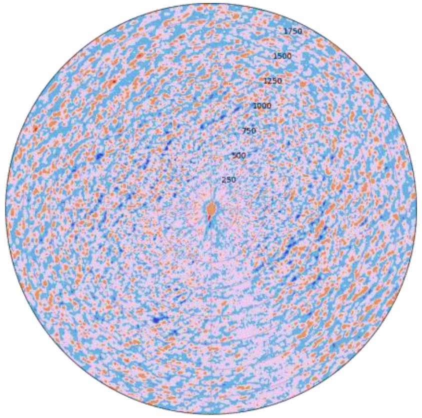
Wind waves characteristics acquisition using marine navigation radar data

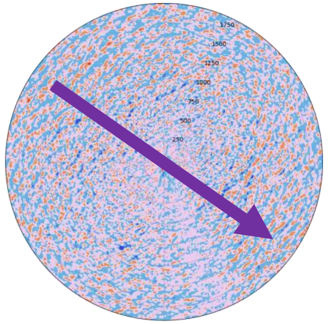


AI for field measurements

Wind waves characteristics acquisition using marine navigation radar data







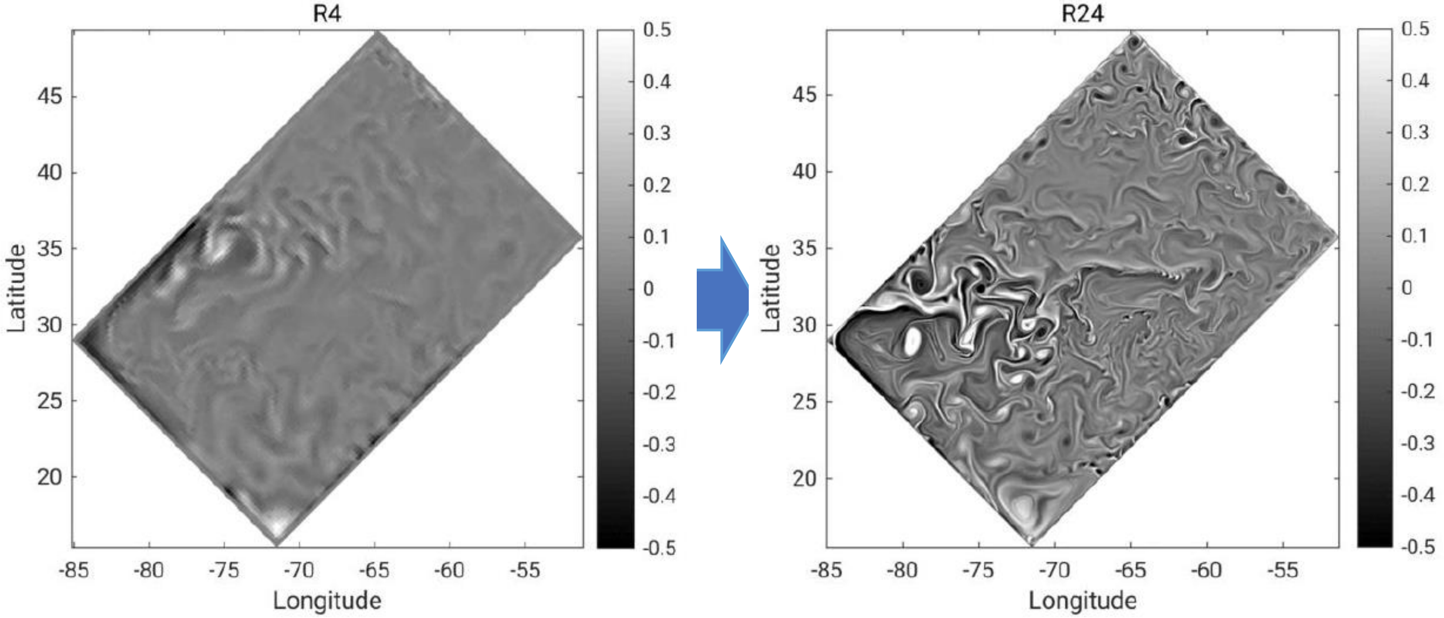
Supervised tasks

There is a vast array of other supervised tasks in Earth Sciences that can be enhanced, automated, or made less reliant on human intervention

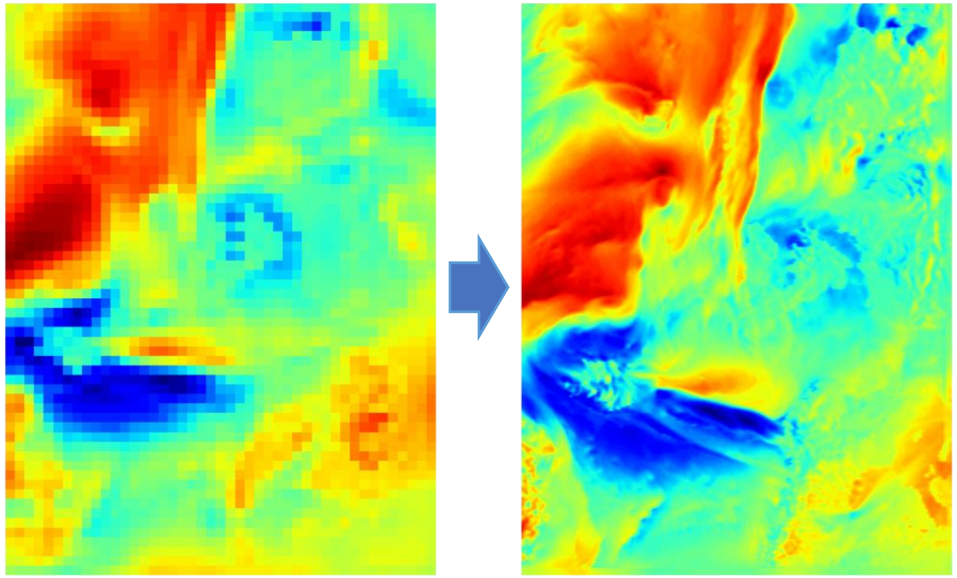
Atmosphere and Ocean modeling tasks are different (in some sense):

- There is governing physics, thus, it should be Physics-Informed AI
- Training data is huge
- There are a number of challenges for the statstical approach

AI for statistical downscaling



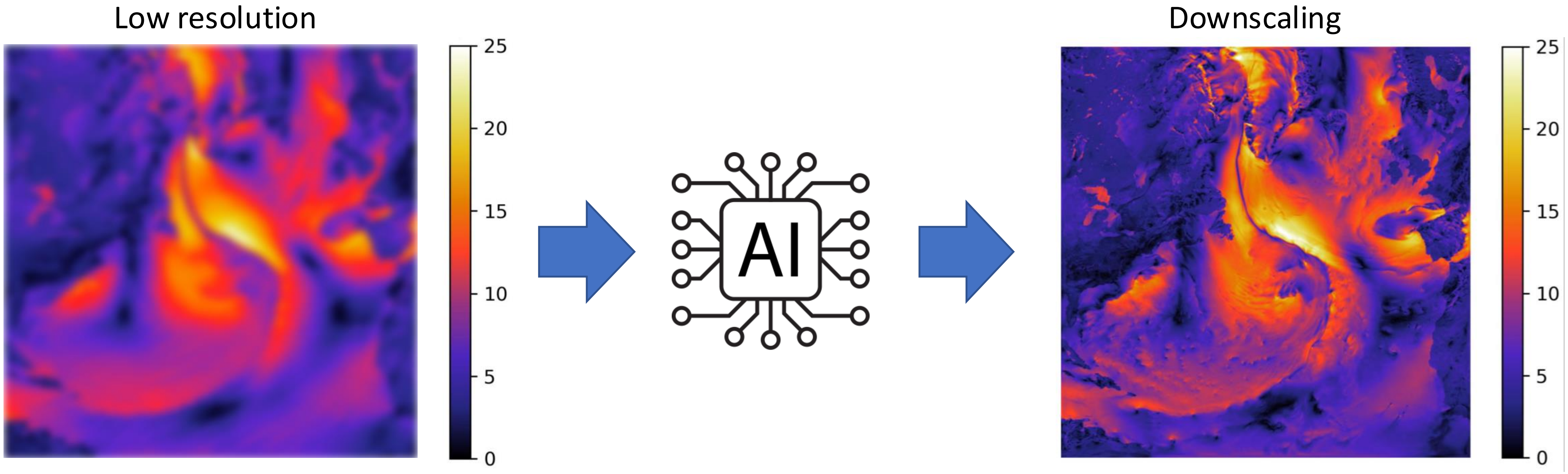
Ocean currents downscaling



Wind downscaling

AI for statistical downscaling

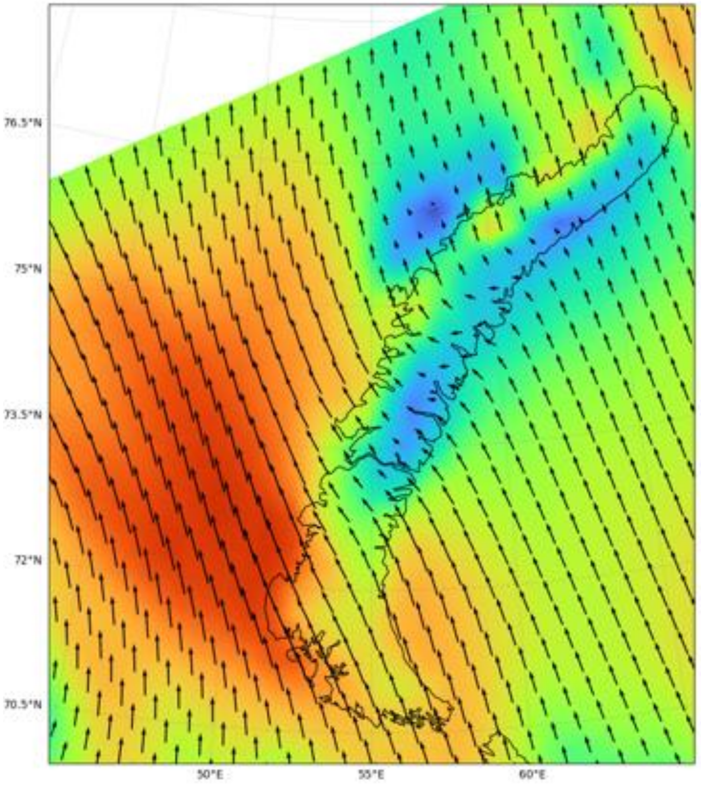
- Neural downscaling of surface wind



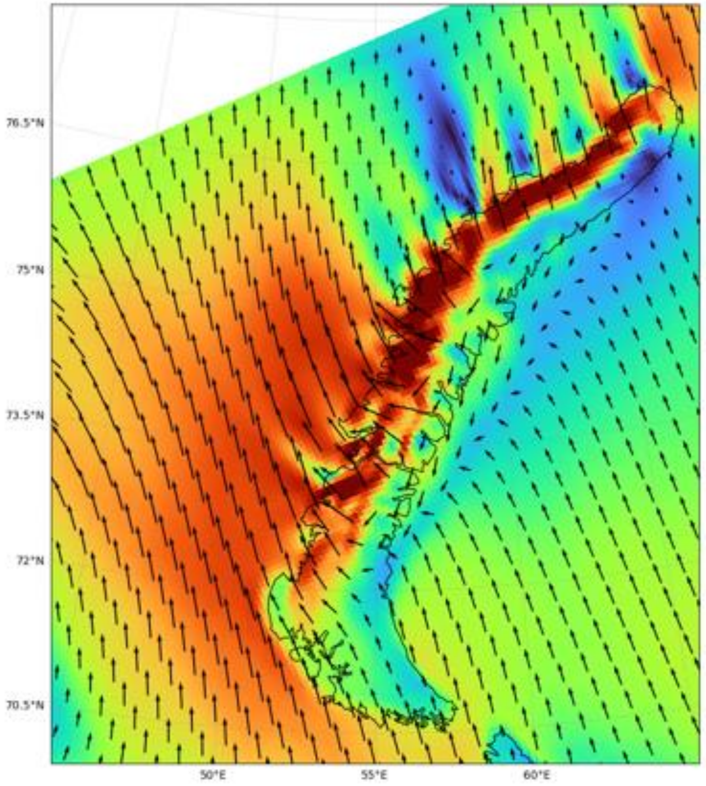
* Rezvov, V. Y., M. Krinitskiy, and S. Gulev. "Approximation of high-resolution surface wind speed in the North Atlantic using discriminative and generative neural models based on RAS-NAAD 40-year hindcast." *The 6th International Workshop on Deep Learning in Computational Physics*. 2022.

AI for statistical downscaling

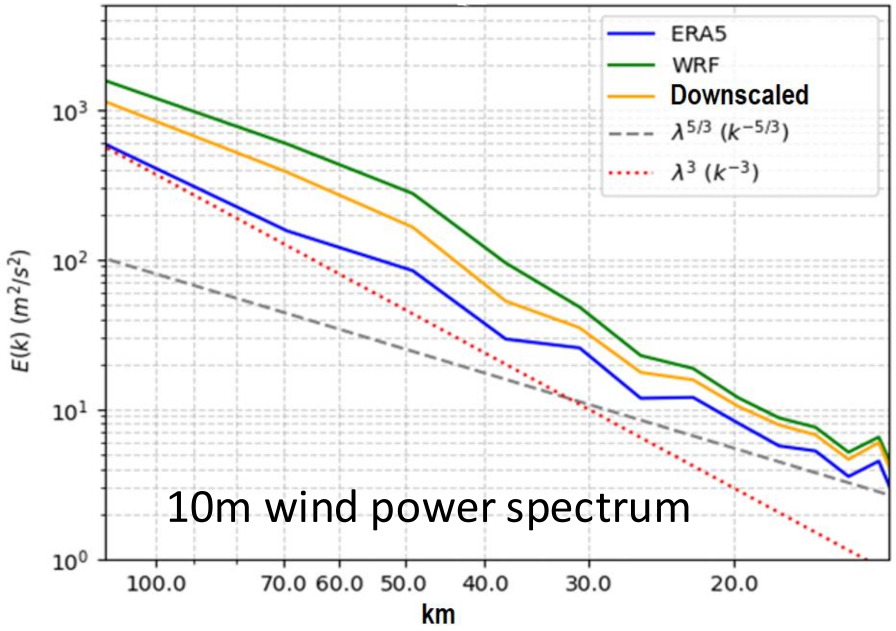
Wind at Novaya Zemlya during bora event
08:00UTC 15 Feb 2022



ERA5



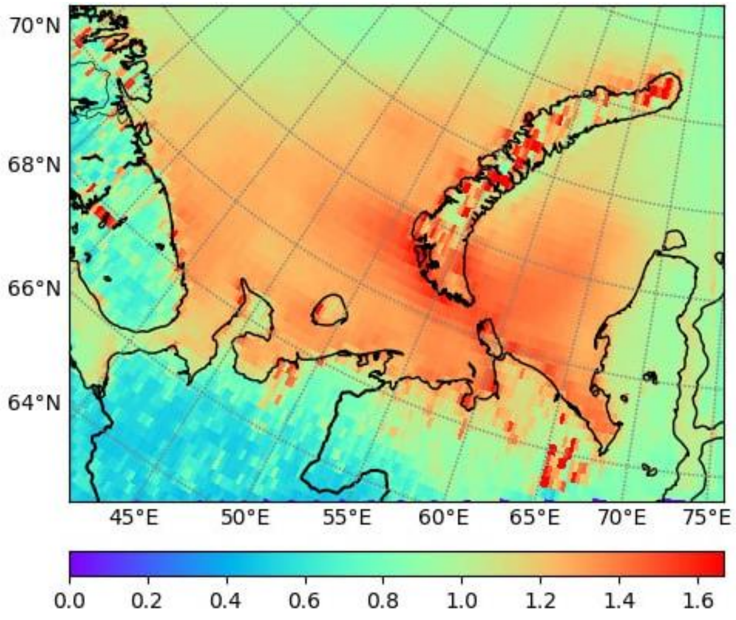
Downscaled

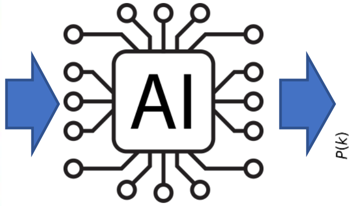


Supervised learning

- Neural correction

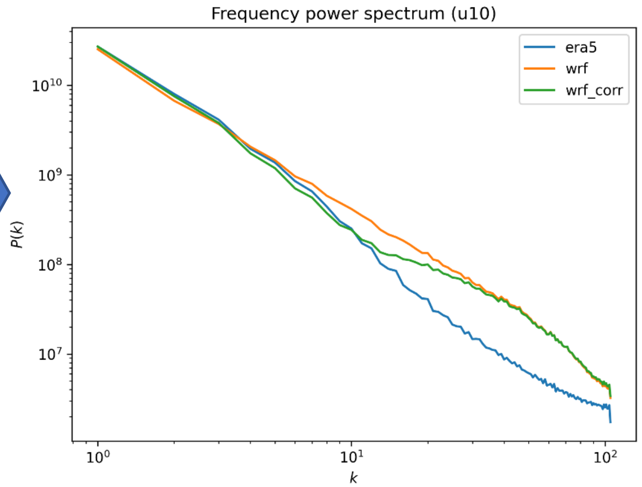
Wind modeling errors (v10)



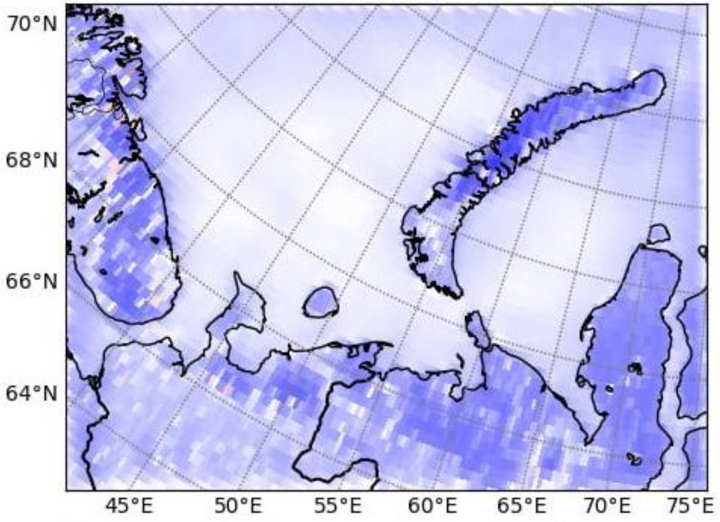


Corrected result

wind spectrum



errors decrease



Neural modeling of climate components

Statistical (neural) modeling of the atmosphere and the ocean

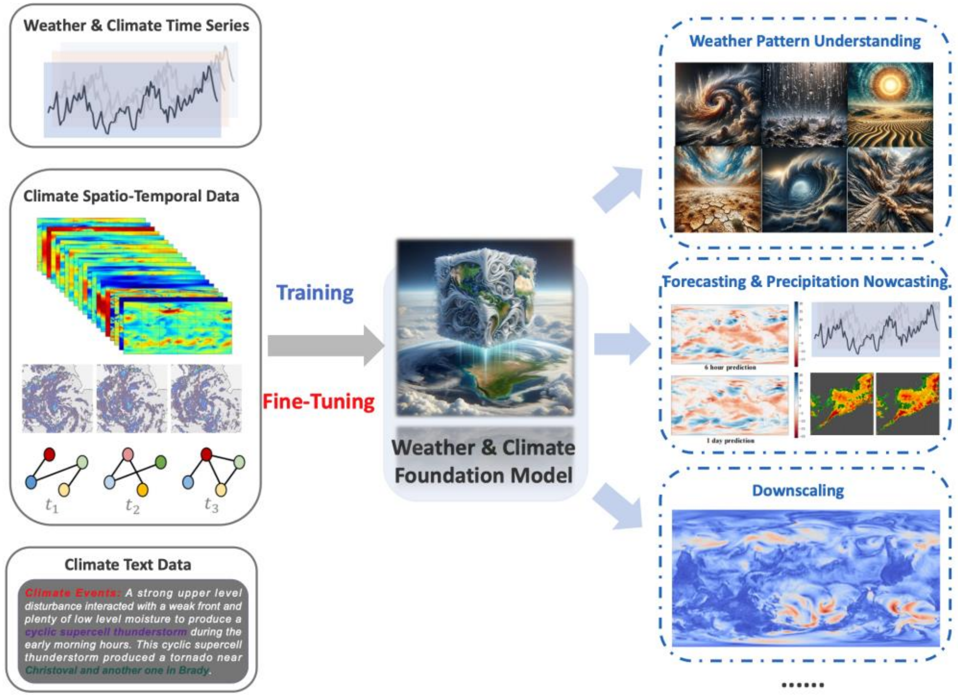
Supervised learning, «Routine» AI, specific modeling	Self-supervised learning, «Generative» AI foundation modeling

- **Requires paired** climate **data “source-outcome”**:
  - low-resolution <–> high-resolution
  - modeling result <–> corrected result
  - time series <-> N-day forecast
- **Requires TONS of paired data**
- A neural model learns the specific mapping source->outcome
- **Each downstream task requires its own** paired dataset, its own model, its own training

- **Only requires source unpaired data** representing valid atmospheric/ocean physics
- A neural model learns the “behaviour” (distribution, physics) of the data;
- A downstream task (downscaling, forecast, correction) then requires **much less paired data**
- Each downstream task is solved **using the same foundation model** with finetuning

Foundation models of the atmosphere

Foundation neural models of weather/climate – «ChatGPT» for the atmosphere



Model	resolution
Microsoft ClimaX[1,*] – Jan’2023, UCLA (USA)	1.40625˚
FengWu[2,*] – Apr’2023, China (6 организаций)	0.25°
PanGu[3,*] – July’2023, Huawei (China)	0.25°
FuXi[4,*] – Jun’2023, Fudan University (China)	0.25°
FourCastNet[5,*] – Feb’2022, NVIDIA	0.25°
GraphCast[6,*] – Nov’2023, Google	0.25°
W-MAE[7,*] – Apr’2023, UEST (China)	0.25°
Prithvi WxC[8,*] – Sep’2024, IBM+NASA (USA)	0.625°
ECMWF AIFS[9]	0.25°
Russian foundation atmospheric model	**coming soon**

Foundation models of the atmosphere

Foundation neural models of weather/climate – «ChatGPT» for the atmosphere

Model	Resolution	Training data
Microsoft ClimaX[1,*] – Jan’2023, UCLA (USA)	1.40625°	CMIP6 (разнородные симуляции); ERA5 при дообучении
FengWu[2,*] – Apr’2023, China (6 организаций)	0.25°	ERA5, 0.25° → IFS+наблюдения на 0.09°
PanGu[3,*] – July’2023, Huawei (China)	0.25°	ERA5 (1979–2021), 0.25°
FuXi[4,*] – Jun’2023, Fudan University (China)	0.25°	ERA5 (1980–2018), 0.25°
FourCastNet[5,*] – Feb’2022, NVIDIA	0.25°	ERA5 (1979–2015), 0.25°
GraphCast[6,*] – Nov’2023, Google	0.25°	ERA5 (1979–2017), 0.25°
W-MAE[7,*] – Apr’2023, UEST (China)	0.25°	ERA5 (1979–2015), 0.25°
Prithvi WxC[8,*] – Sep’2024, IBM+NASA (USA)	0.625°	MERRA-2 (1980–2019), ~50 км
ECMWF AIFS[9]	0.25°	ERA5 (1979–2020)+IFS (2019-2020), 0.25°
Russian foundation atmospheric model	**Yet to come**	**High-resolution ocean and atmosphere simulations**

Foundation models of the atmosphere

Большие базисные модели атмосферы

ClimaX[1] FengWu[2] PanGu[3.] FuXi[4]

FourCastNet[5.] GraphCast[6] W-MAE[7] Prithvi WxC[8] ECMWF AIFS[9]

[1] Nguyen, T., Brandstetter, J., Kapoor, A., Gupta, J. K., & Grover, A. (2023). Climax: A foundation model for weather and climate. *arXiv preprint arXiv:2301.10343*.

[2] Chen, K., Han, T., Gong, J., Bai, L., Ling, F., Luo, J. J. & Ouyang, W. (2023). Fengwu: Pushing the skillful global medium-range weather forecast beyond 10 days lead. arXiv preprint arXiv:2304.02948.

[3] Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2023). Accurate medium-range global weather forecasting with 3D neural networks. Nature, 619(7970), 533-538.

[4] Chen, L., Zhong, X., Zhang, F., Cheng, Y., Xu, Y., Qi, Y., & Li, H. (2023). FuXi: a cascade machine learning forecasting system for 15-day global weather forecast. npj Climate and Atmospheric Science, 6(1), 190.

[5] Pathak, J., Subramanian, S., Harrington, P., Raja, S., Chattopadhyay, A., Mardani, M., ... & Anandkumar, A. (2022). Fourcastnet: A global data-driven high-resolution weather model using adaptive fourier neural operators. arXiv preprint arXiv:2202.11214.

[6] Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Alet, F., ... & Battaglia, P. (2023). Learning skillful medium-range global weather forecasting. Science, 382(6677), 1416-1421.

[7] Man, X., Zhang, C., Feng, J., Li, C., & Shao, J. (2023). W-MAE: Pre-trained weather model with masked autoencoder for multi-variable weather forecasting. arXiv preprint arXiv:2304.08754.

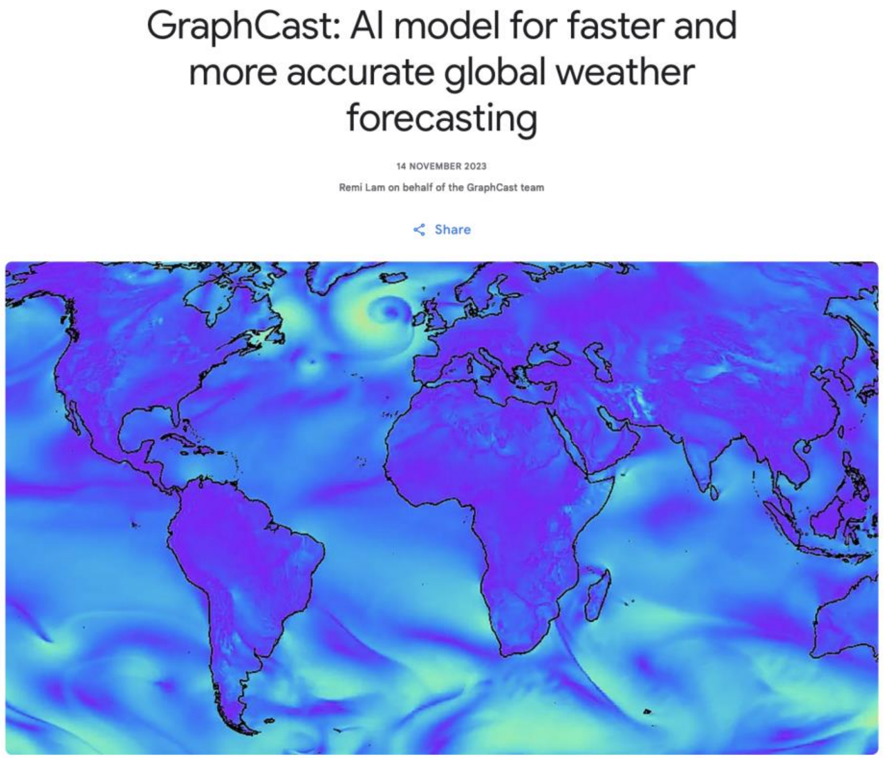
[8] Schmude, J.; Roy, S.; Trojak, W.; Jakubik, J.; Civitarese, D.S.; Singh, S.; Kuehnert, J.; Ankur, K.; Gupta, A.; Phillips, C.E.; et al. Prithvi WxC: Foundation Model for Weather and Climate 2024, arXiv preprint arXiv:2409.13598

[9] Lang, S.; Alexe, M.; Chantry, M.; Dramsch, J.; Pinault, F.; Raoult, B.; Clare, M.C.A.; Lessig, C.; Maier-Gerber, M.; Magnusson, L.; et al. AIFS -- ECMWF's Data-Driven Forecasting System 2024. arXiv:2406.01465

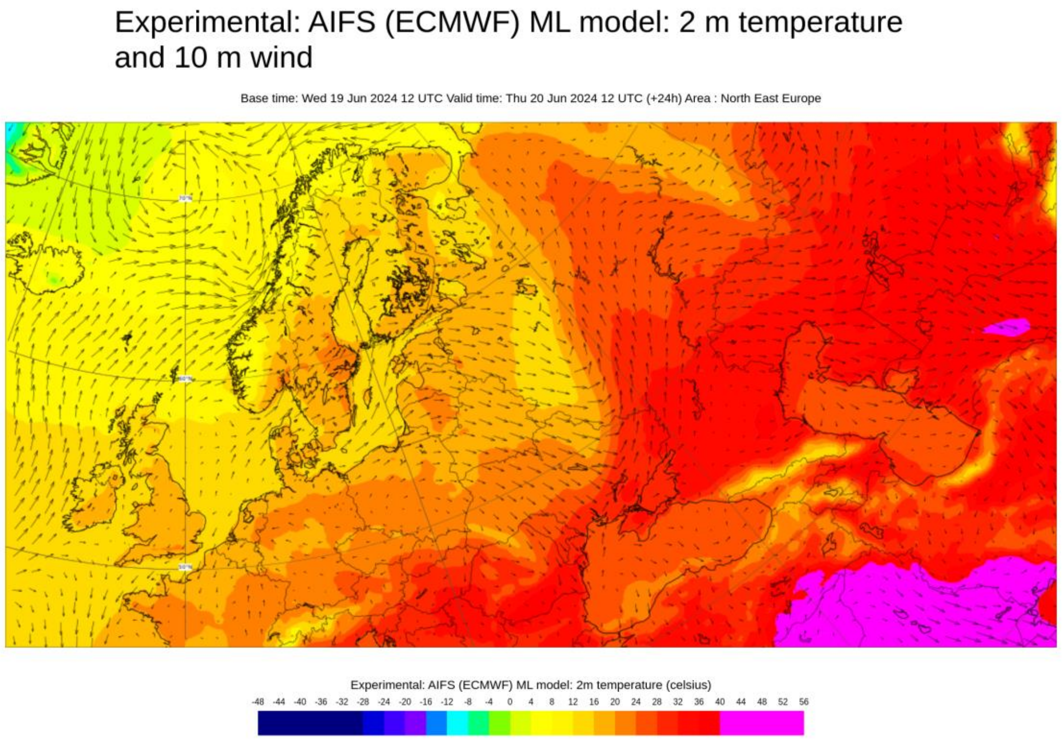
Foundation models applications

AI forecasts

GraphCast (Google)



AIFS (ECMWF)



Foundation models applications

- Neural downscaling:
  - wind speed
  - precipitation
  - temperature
- Neural statistical correction
- Short-term forecasts
- Subseasonal/seasonal forecasts
- Climate projections
- Analogs discovery
- Risk assessment
- Probabilistic droughts, floods forecast
- Probabilistic wildfires forecast

Foundation models of the ocean

Foundation models of the ocean?

Foundation models of the ocean

Foundation models of the ocean?

Model	Resolution	Training data
WenHai[1,*] – Mar'2025, China (3 организации)	1/12˚	GLORYS12, GLO12v4 (1993-2020) + ERA5
XiHe[2,*]	1/12˚	GLORYS12 (1993-2020) + ERA5 + satellite SST (OSTIA)
LangYa[3,*]	1/12˚	GLORYS12 (1993-2019) + ERA5
Russian foundation model of the ocean	**coming soon**	**High-resolution ocean and atmosphere simulations**

Foundation models of the ocean

Foundation models of the ocean

WenHai[1] XiHe[2] LangYa[3]

[1] 1. Cui, Y.; Wu, R.; Zhang, X.; Zhu, Z.; Liu, B.; Shi, J.; Chen, J.; Liu, H.; Zhou, S.; Su, L.; et al. Forecasting the Eddying Ocean with a Deep Neural Network. Nat Commun 2025, 16, 2268, doi:10.1038/s41467-025-57389-2.
[2] Wang, X.; Wang, R.; Hu, N.; Wang, P.; Huo, P.; Wang, G.; Wang, H.; Wang, S.; Zhu, J.; Xu, J.; et al. XiHe: A Data-Driven Model for Global Ocean Eddy-Resolving Forecasting 2024. arXiv:2402.02995
[3] Yang, N.; Wang, C.; Zhao, M.; Zhao, Z.; Zheng, H.; Zhang, B.; Wang, J.; Li, X. LangYa: Revolutionizing Cross-Spatiotemporal Ocean Forecasting 2024. arXiv:2412.18097

Foundation models of the ocean: perspectives

- Foundation models of the **Ocean**
  - Neural ocean downscaling
  - Analogs discovery
  - Short-term ocean forecacst
  - Subseasonal/seasonal forecasts
  - Uncertainties assessment for neural climate projections

LangYa: the training was conducted using a distributed data-parallel (DDP) strategy on a cluster of **16 NVIDIA A800 GPUs**, completed in just **14 days**.*

*Yang, N.; Wang, C.; Zhao, M.; Zhao, Z.; Zheng, H.; Zhang, B.; Wang, J.; Li, X. LangYa: Revolutionizing Cross-Spatiotemporal Ocean Forecasting 2024.

Thank you!

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