AI for prediction & Earth system modelling

AI for environmental data, Uppsala University

Olof Mogren, RISE Research Institutes of Sweden

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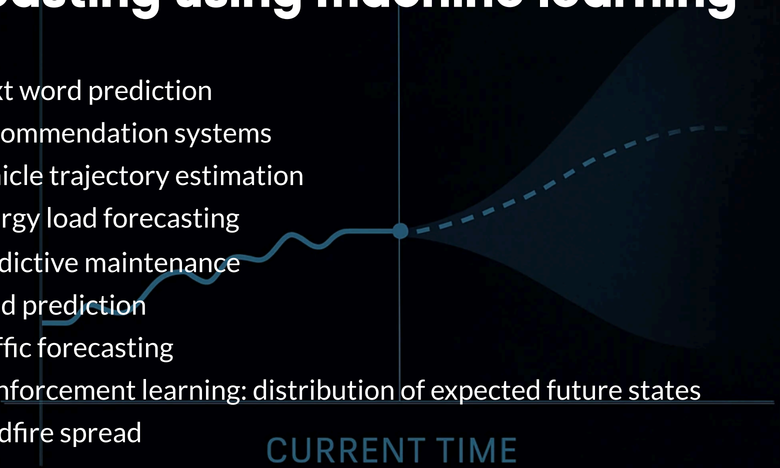
Forecasting

- Accurate weather forecasts prerequisite for some risk estimations
- Energy system planning
- Agriculture planning
- Disaster preparation
    - Drought, flooding, storms

Forecasting using machine learning

- Next word prediction
- Recommendation systems
- Vehicle trajectory estimation
- Energy load forecasting
- Predictive maintenance
- Yield prediction
- Traffic forecasting
- Reinforcement learning: distribution of expected future states
- Wildfire spread



Texas floods, July 2025

Photo: USA Today

Hydrological prediction

- Flood risk, drought forecasting
- Water management
- Decision support for adaptation planning

Flood risk estimation

https://sites.research.google/floods/

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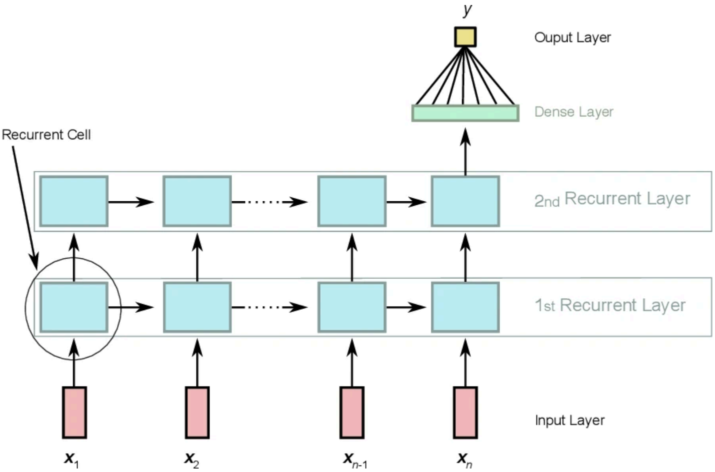
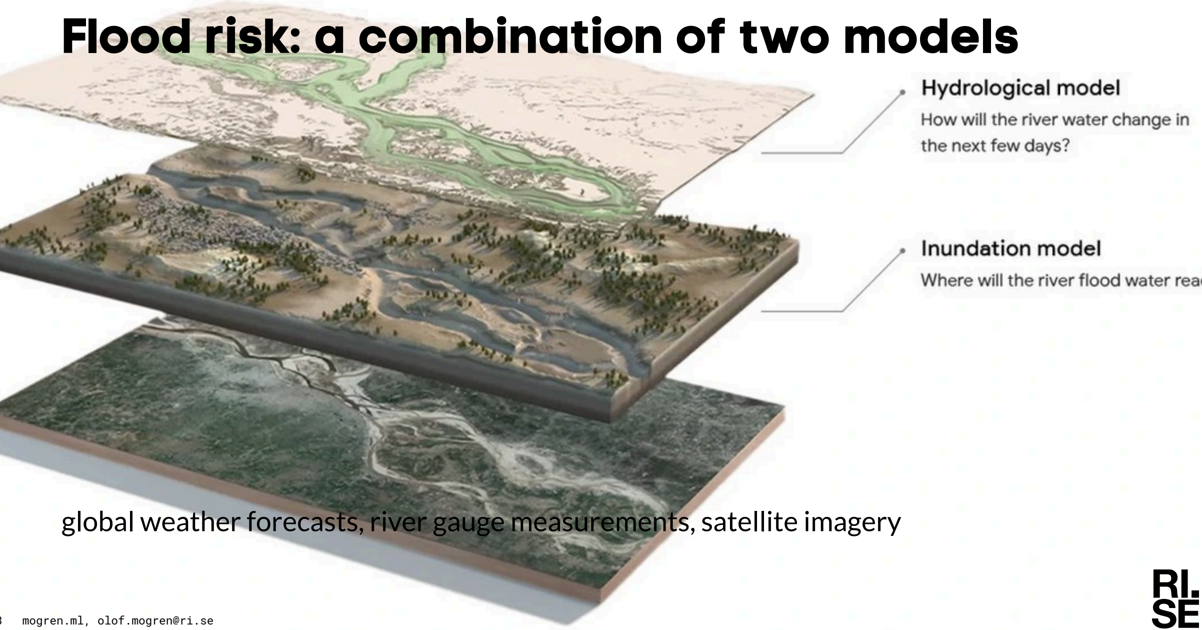
Recurrent neural networks



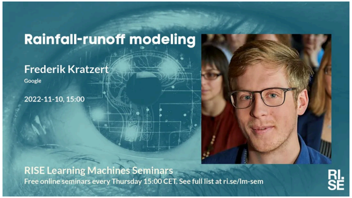
mogren.ml, olof.mogren@ri.se

Flood risk: a combination of two models



global weather forecasts, river gauge measurements, satellite imagery

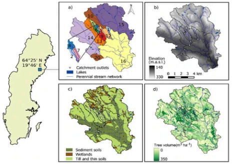
RISE Learning Machines Seminars

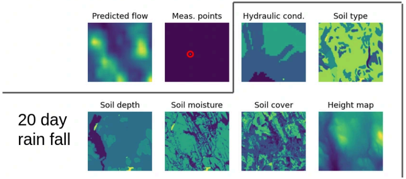


- Thursdays at 15
- [Recorded talk: Frederik Kratzert]
- Give me your email address to subscribe for invitations

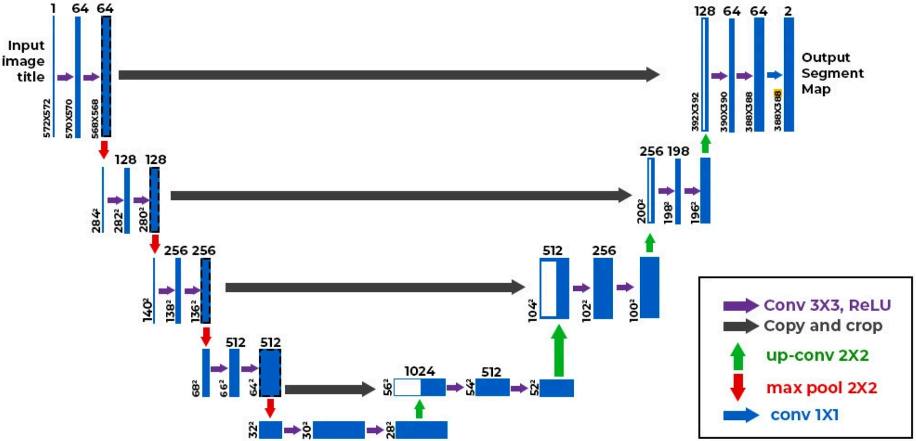
Stream flow forecasting

- Collaboration with University of São Paulo
    - Centro de Recursos Hídricos e Estudos Ambientais (CRHEA) - EESC - USP
- Dense predictions of water flow



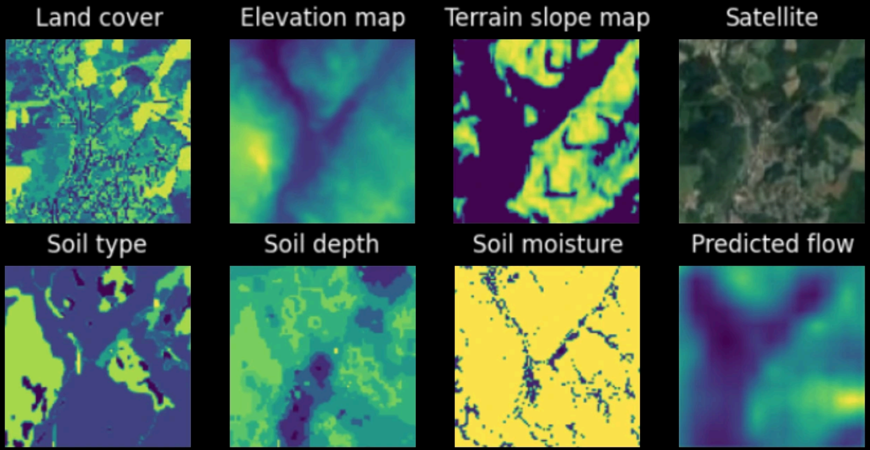


The UNet architecture



1 Ronneberger et al., 2015

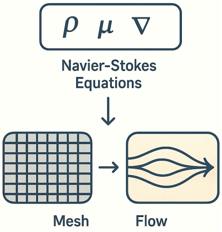
Dense stream flow prediction



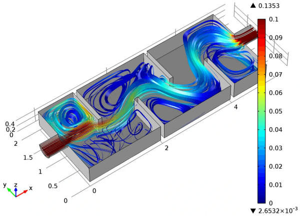
Earth system modeling

Process-based physical modeling

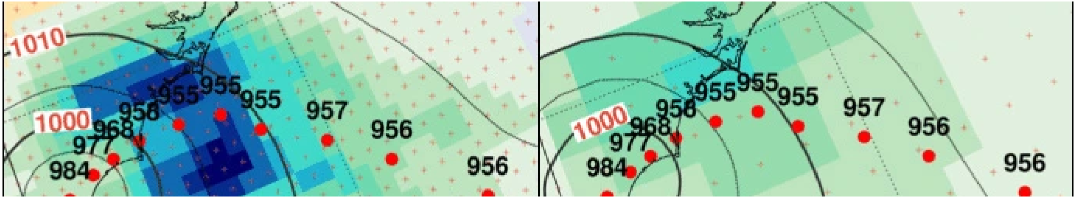
- Navier-Stokes equations
- Particle-based or mesh-based
- Computationally heavy



Streamlines colored by velocity. Width proportional to turbulent viscosity.

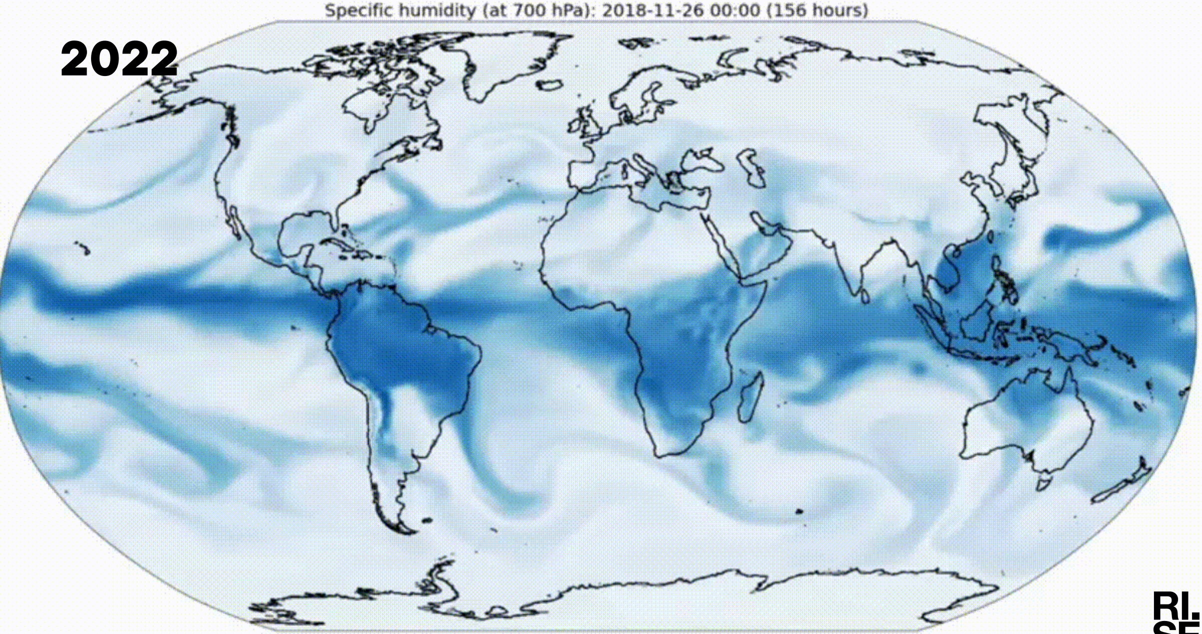


ERA5 dataset



- Reanalysis
- 1940-2022
- First part released 2019
- Extended 2023 (1940-1978)

2022



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FourCastNet, Pangu-Weather, GraphCast

TECHNICAL REPORT 1

Pangu-Weather: A 3D High-Resolution System for Fast and Accurate Global Weather Forecast

Kaifeng Bi, Lingxi Xie, Hengheng Zhang, Xin Chen, Xiaotao Gu, and Qi Tian✉, *Fellow, IEEE*

Abstract—In this paper, we present Pangu-Weather, this purpose, we establish a data-driven environment ECMWF reanalysis (ERA5) data and train a few deep of forecast is $0.25° \times 0.25°$, comparable to the ECMW AI-based method outperforms state-of-the-art numeric RMSE and ACC) of all factors (*e.g.*, geopotential, spe hour to one week). There are two key strategies to im (3DEST) architecture that formulates the height (pres aggregation algorithm to alleviate cumulative forecast short to medium-range forecast (*i.e.*, forecast time ra downstream forecast scenarios, including extreme we forecast in real-time. Pangu-Weather not only ends th but also reveals novel directions for improving deep le

Index Terms—Numerical Weather Prediction, Deep L

Forecasting Global Weather with Graph Neural Networks

Ryan Keisler
rkeisler@gmail.com

Abstract

We present a data-driven approach for forecasting global weather using gra neural networks. The system learns to step forward the current 3D atmosphe state by six hours, and multiple steps are chained together to produce skill forecasts going out several days into the future. The underlying model is train on reanalysis data from ERA5 or forecast data from GFS. Test performance metrics such as $Z500$ (geopotential height) and $T850$ (temperature) improves up previous data-driven approaches and is comparable to operational, full-resolution, physical models from GFS and ECMWF, at least when evaluated on 1-degree scales and when using reanalysis initial conditions. We also show results from connecting this data-driven model to live, operational forecasts from GFS.

FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators

A Preprint

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Pedram Hassanzadeh, Rice University, Houston, TX 77005

FourCastNet, short for Fourier ForeCast casting model that provides accurate sho FourCastNet accurately forecasts high-re speed, precipitation, and atmospheric wat energy resources, predicting extreme weat and atmospheric rivers. FourCastNet mat Forecasting System (IFS), a state-of-the-ar times for large-scale variables, while outpe tion. FourCastNet generates a week-long than IFS. The speed of FourCastNet enab forecasts with thousands of ensemble-me how data-driven deep learning models suc toolkit to aid and augment NWP models.

GraphCast: Learning skillful medium-range global weather forecasting

Remi Lam[*,1], Alvaro Sanchez-Gonzalez[*,1], Matthew Willson[*,1], Peter Wirnsberger[*,1], Meire Fortunato[*,1], Alexander Pritzel[*,1], Suman Ravuri[1], Timo Ewalds[1], Ferran Alet[1], Zach Eaton-Rosen[1], Weihua Hu[1], Alexander Merose[2], Stephan Hoyer[2], George Holland[1], Jacklynn Stott[1], Oriol Vinyals[1], Shakir Mohamed[1] and Peter Battaglia[1]
[*]equal contribution, [1]DeepMind, [2]Google

We introduce a machine-learning (ML)-based weather simulator—called "GraphCast"—which outperforms the most accurate deterministic operational medium-range weather forecasting system in the world, as well as all previous ML baselines. GraphCast is an autoregressive model, based on graph neural networks and a novel high-resolution multi-scale mesh representation, which we trained on historical weather data from the European Centre for Medium-Range Weather Forecasts (ECMWF)'s ERA5 reanalysis archive. It can make 10-day forecasts, at 6-hour time intervals, of five surface variables and six atmospheric variables, each at 37 vertical pressure levels, on a 0.25° latitude-longitude grid, which corresponds to roughly 25×25 kilometer resolution at the equator. Our results show GraphCast is more accurate than ECMWF's deterministic operational forecasting system, HRES, on 90.0% of the 2760 variable and lead time combinations we evaluated. GraphCast also outperforms the most accurate previous ML-based weather forecasting model on 99.2% of the 252 targets it reported. GraphCast can generate a 10-day forecast (35 gigabytes of data) in under 60 seconds on Cloud TPU v4 hardware. Unlike traditional forecasting methods, ML-based forecasting scales well with data: by training on bigger, higher quality, and more recent data, the skill of the forecasts can improve. Together these results represent a key step forward in complementing and improving weather modeling with ML, open new opportunities for fast, accurate forecasting, and help realize the promise of ML-based simulation in the physical sciences.

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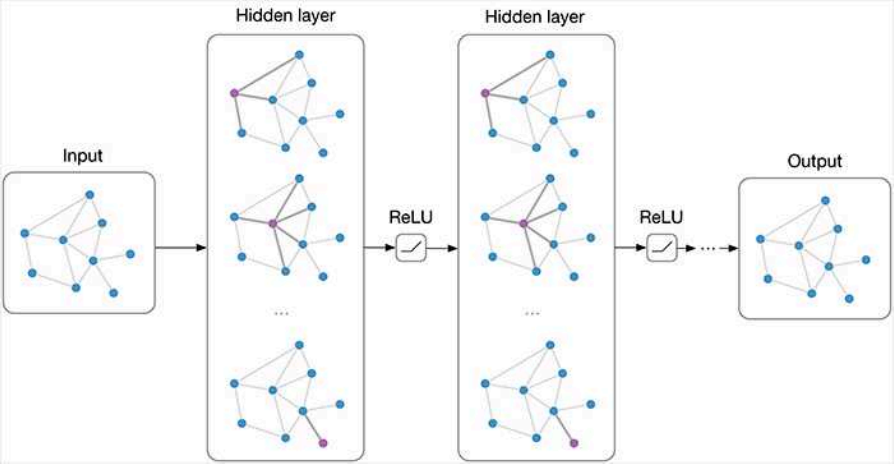
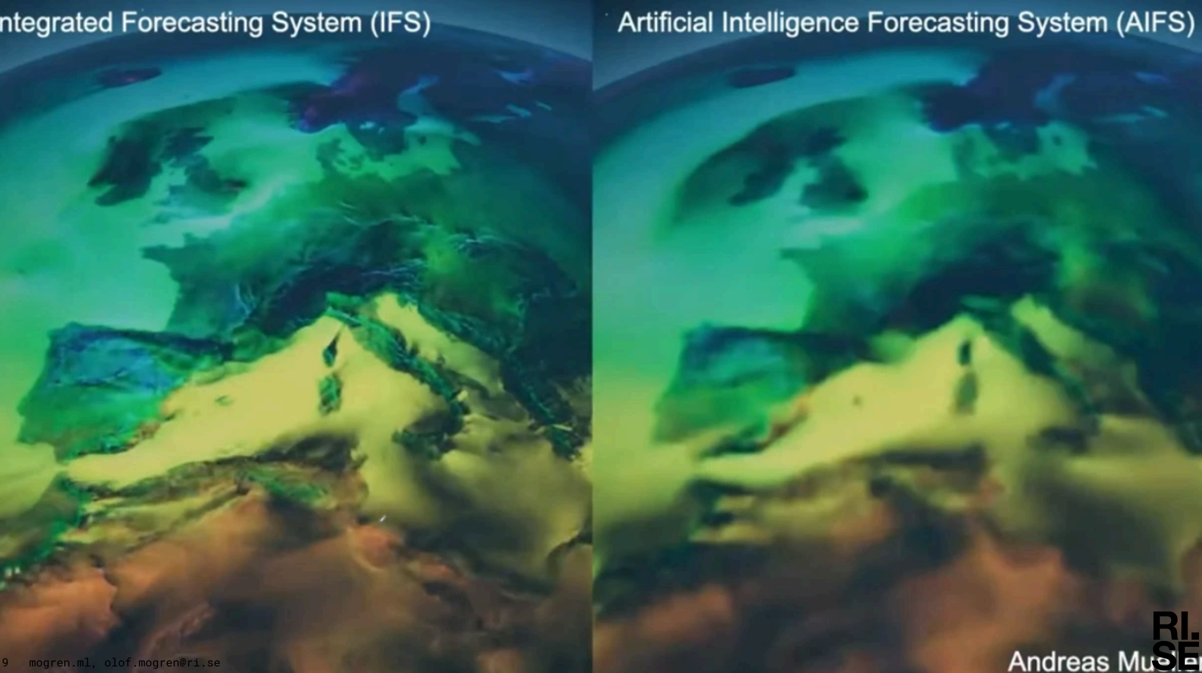
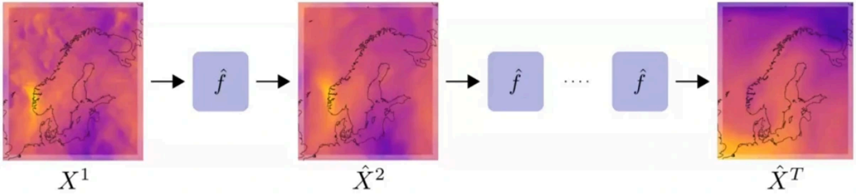
Graph neural networks
for physical modeling



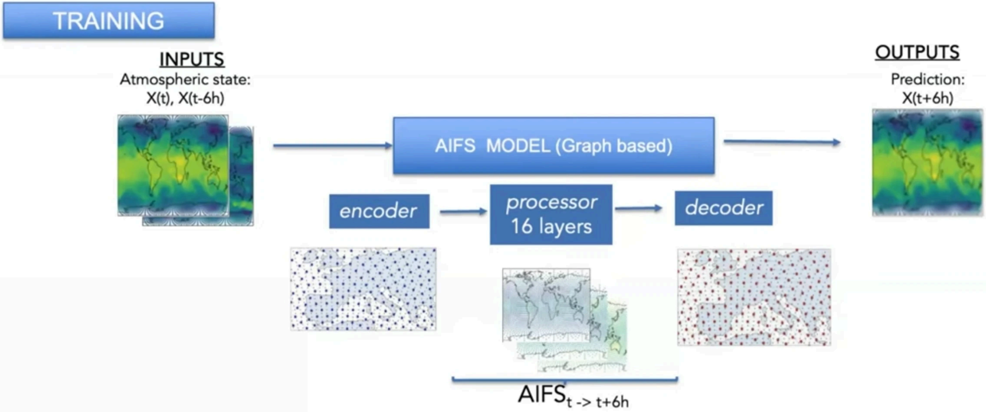

ntegrated Forecasting System (IFS)
Artificial Intelligence Forecasting System (AIFS)
Andreas Mu

The MLWP framework



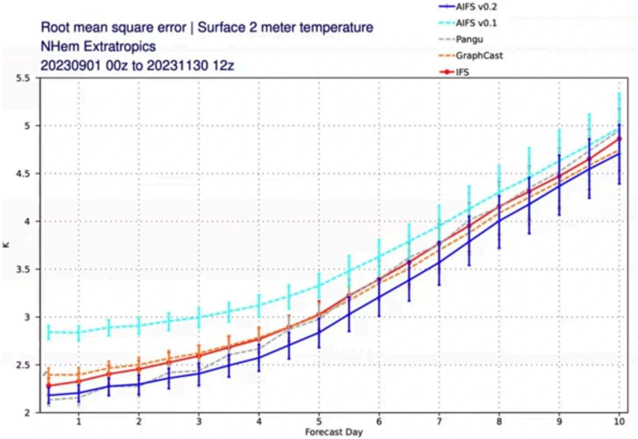
- Weather state X^t, forcing F^t
- Assumed dynamics model $X^t = f(X^{t-2:t-1}, F^t)$
- Approximate with ML model $\hat{f} \approx f$
- Encode - process - decode

ECMWF AI Forecasting System



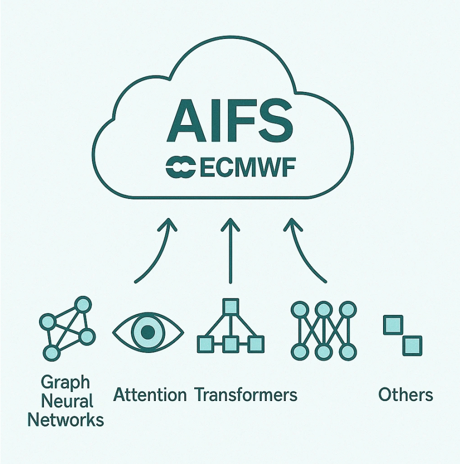
Lots of neural network architectures successful.
All share weights across space to some extent.

AIFS vs IFS



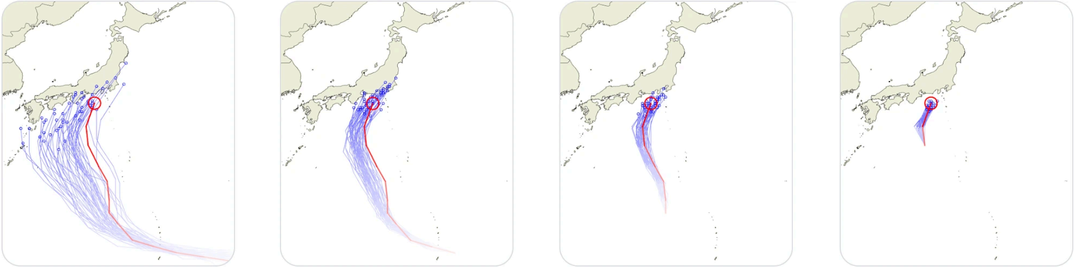
Lang et al. ECMWF Newsletter 2024 and the AIFS team

Solutions build on years of progress



- Graph neural networks
- Transformer (attention) architecture
- Diffusion models

Diffusion models: Gencast



7-day forecast | 5-day forecast | 3-day forecast | 1-day forecast

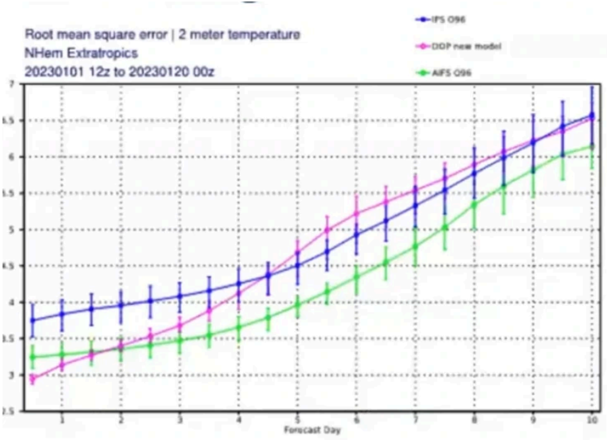
Cyclone track up to October 12, 2019, at 0600 UTC

Possible paths predicted by GenCast

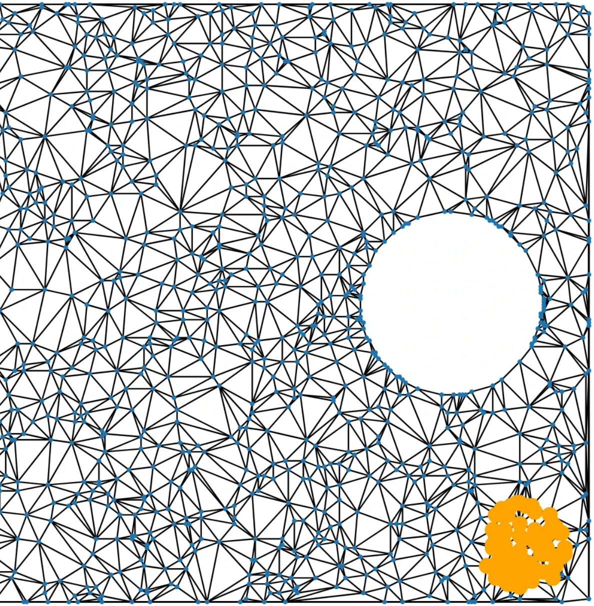
Image from Google DeepMind. Typhoon Hagibis, 2019-10-12

Data assimilation

- From observations to estimate of Earth system state
- Work ongoing on how to use ML for this



 Alexe et al., 2024



Equivariant
graph neural networks

- GNN respecting rotations and translations in 2D space
- Resulting equivariant model that learn more efficiently

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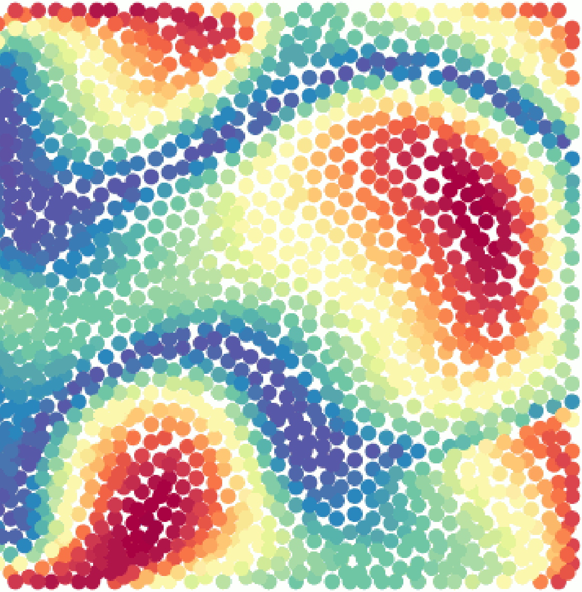
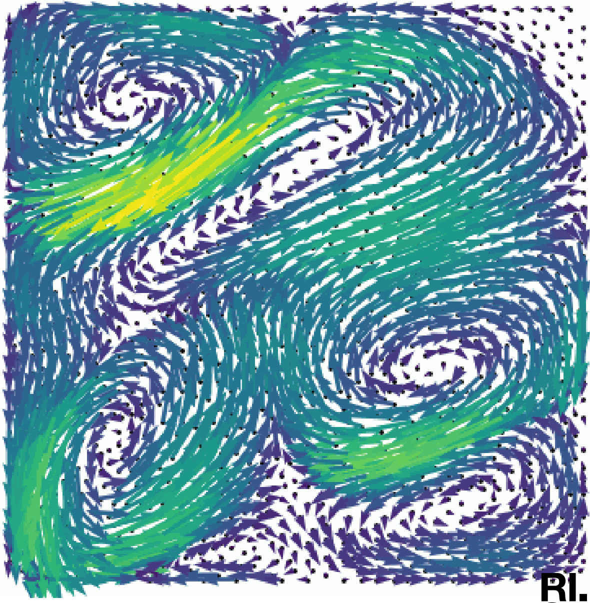




Why equivariance

- Translation, rotation built-in
- Data effiency
- Consistency with physical symmetries
- Accuracy, scalability

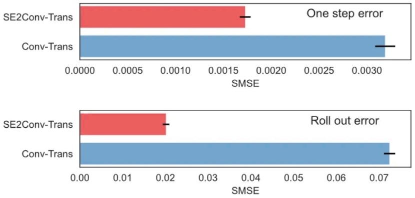
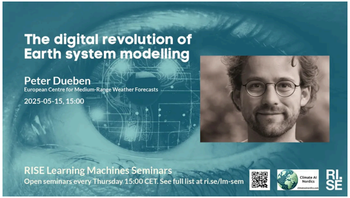


Figure 8. Our approach (red) obtains significantly lower one-step as well as rollout errors compared to the non-invariant counterpart (blue). The rollout error is, however, even more reduced, which showcases the ability of our model to maintain accurate prediction accuracy even over longer time horizons.

AI for weather extreme estimation

Learn more



- Recording of Peter Dueben (ECMWF)'s talk, 2025-05-15
- Recording of Joel Oskarsson (Linköping University)'s talk, 2024-11-07

Thank you!

Yesterday:

- 10: Introduction to AI and Machine Learning
  - Olof Mogren
- 11: Introduction and Brief History of Natural Language Processing (NLP)
  - Murathan Kurfalı
- 13: AI for Climate Adaptation and Mitigation
  - Olof Mogren
- 14: Exercises

Today:

- 10: AI for Environmental Monitoring
  - Olof Mogren
- 11: AI for Prediction and Earth System Modelling
  - Olof Mogren
- **13: Using NLP and Large Language Models: General Concepts and Climate Applications**
  - Murathan Kurfalı
- 14: **Coffee, then** exercises