

AI for prediction & Earth system modelling

AI for environmental data, Uppsala University

Olof Mogren, RISE Research Institutes of Sweden

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

CURRENT TIME

Texas floods, July 2025



Hydrological prediction

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



View options

Map

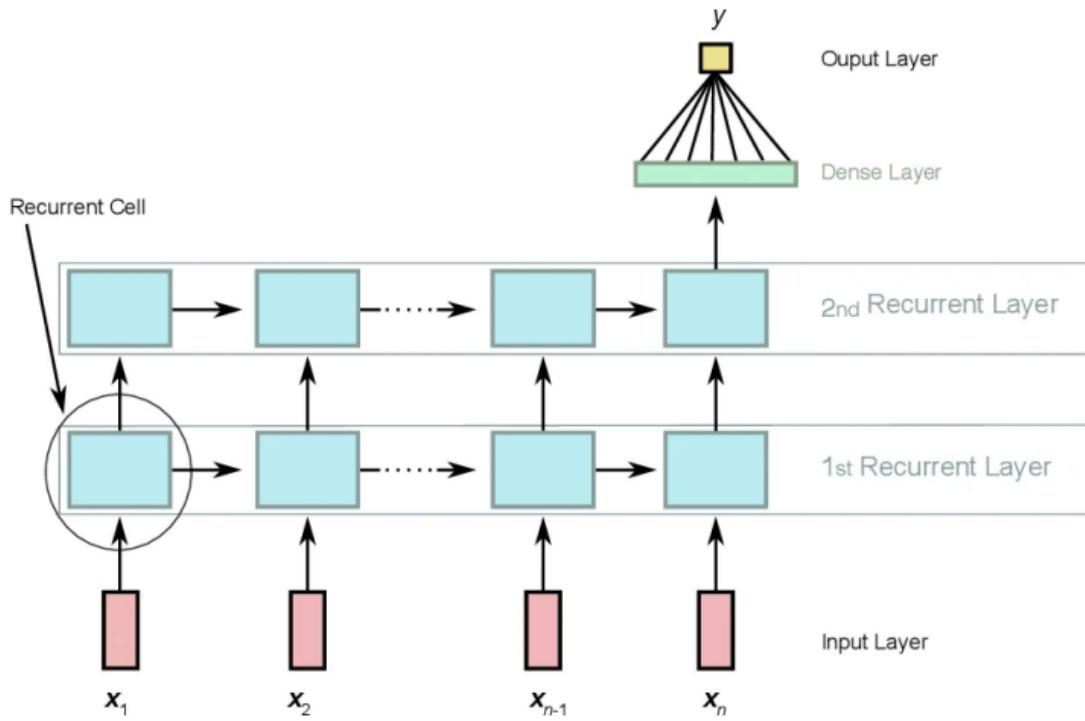
Hybrid

Flood risk estimation

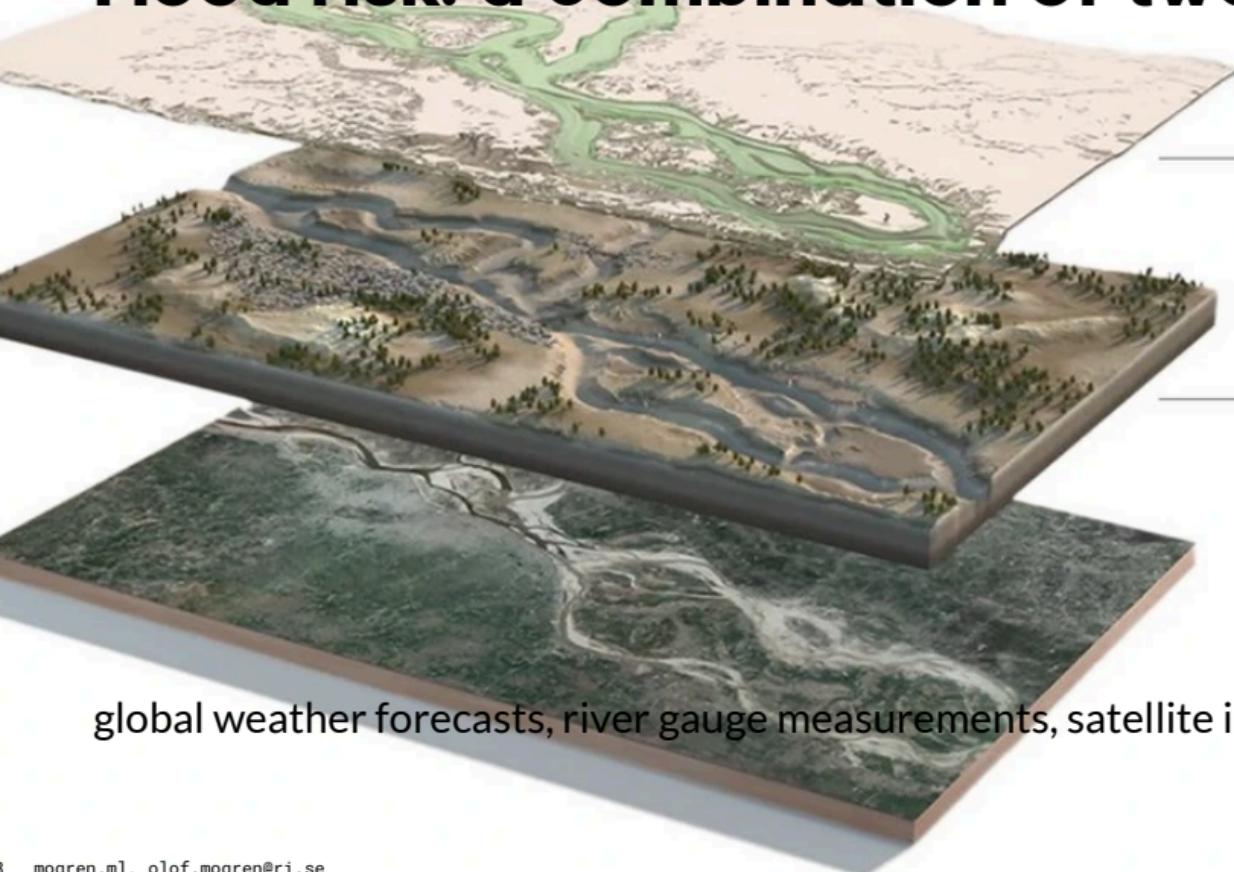


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Recurrent neural networks



Flood risk: a combination of two models



Hydrological model

How will the river water change in the next few days?

Inundation model

Where will the river flood water reach?

global weather forecasts, river gauge measurements, satellite imagery

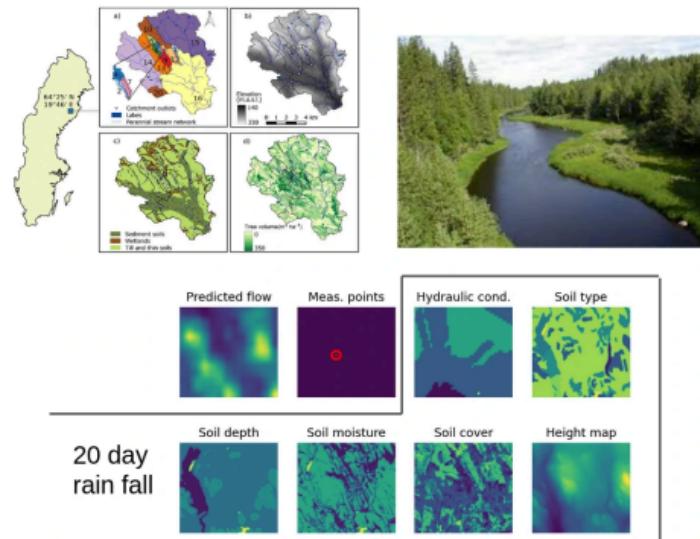
RISE Learning Machines Seminars



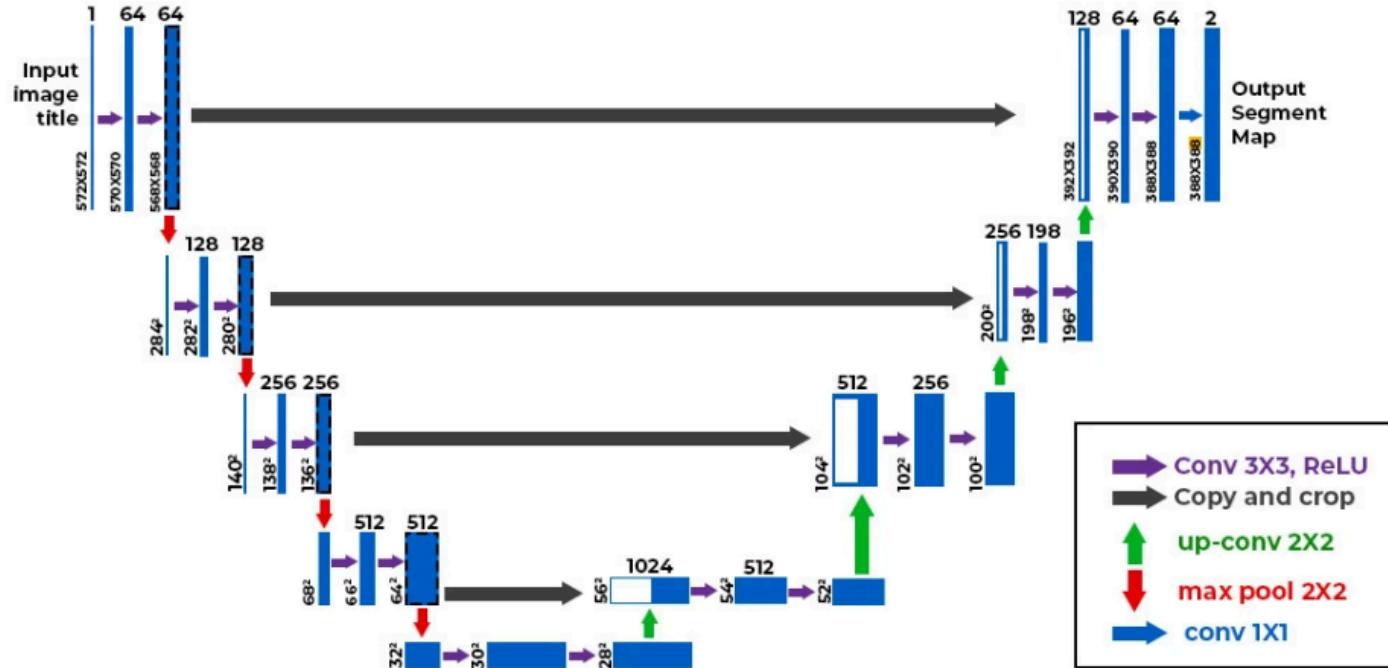
- Thursdays at 15
- [Recorded talk: Frederik Kratzert](#)
- Give me your email address to subscribe for invitations

Stream flow forecasting

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

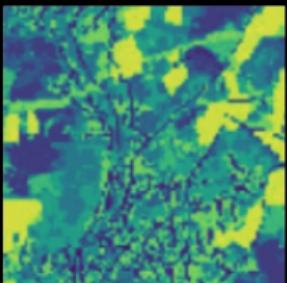


The UNet architecture

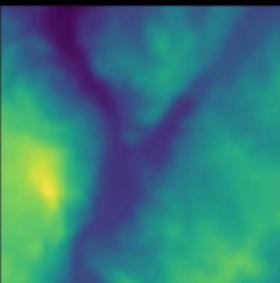


Dense stream flow prediction

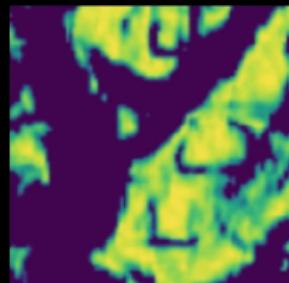
Land cover



Elevation map



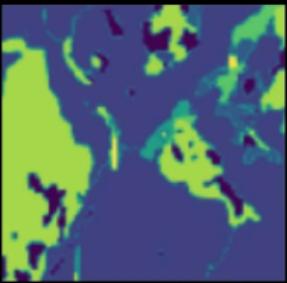
Terrain slope map



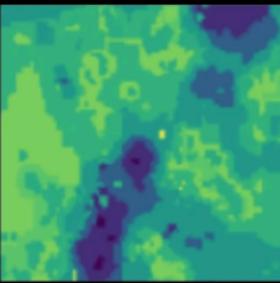
Satellite



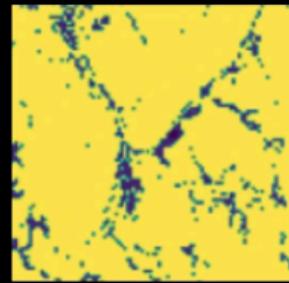
Soil type



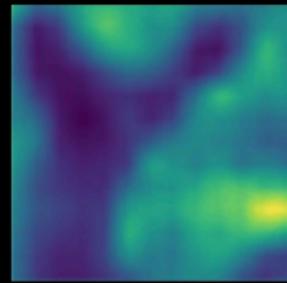
Soil depth



Soil moisture



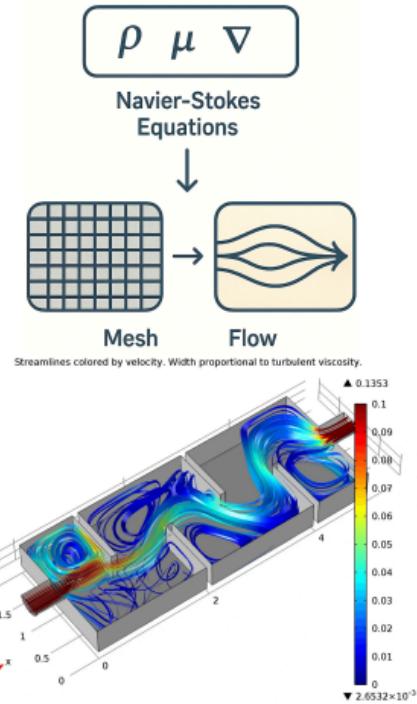
Predicted flow



Earth system modeling

Process-based physical modeling

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



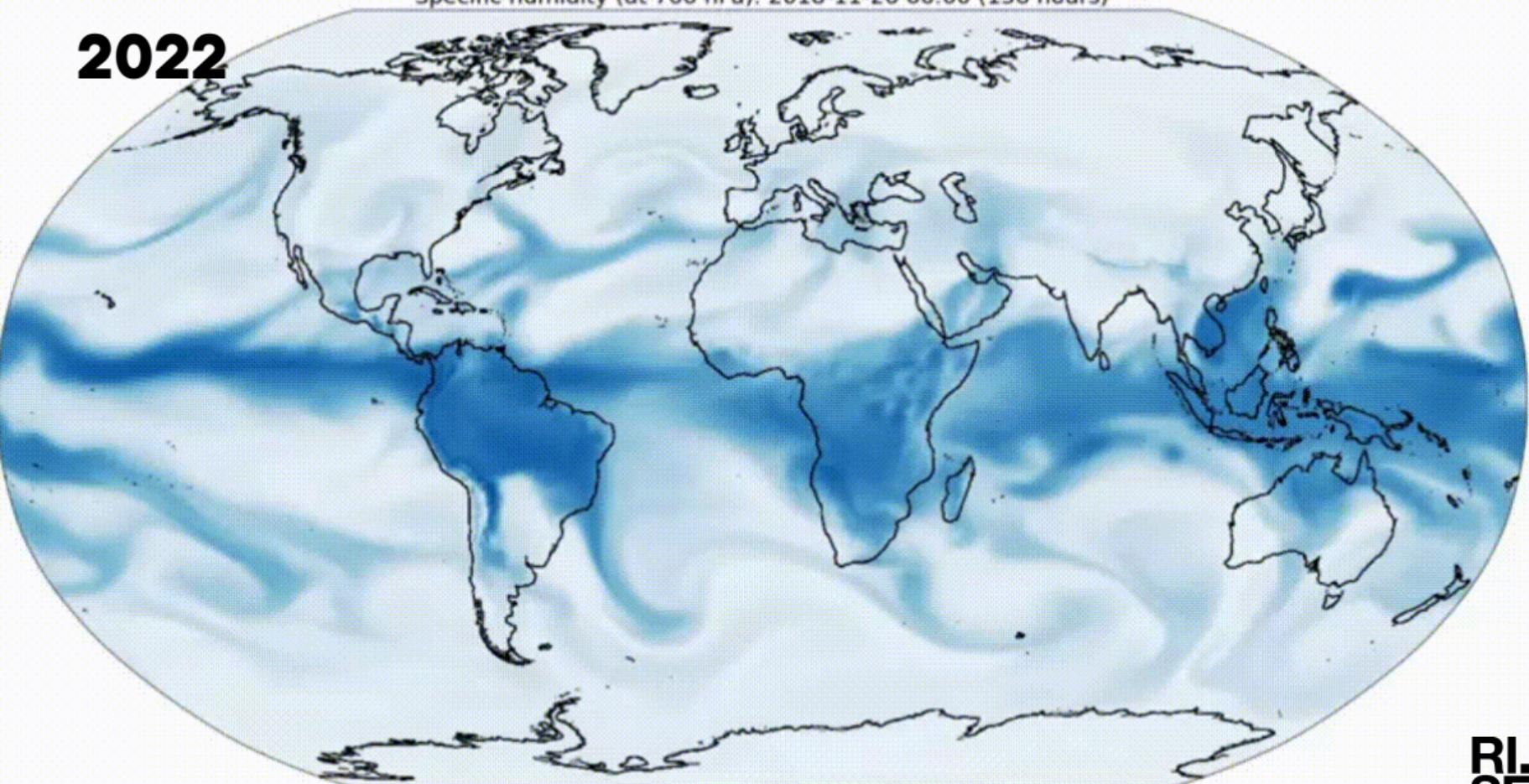
ERA5 dataset



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

Specific humidity (at 700 hPa): 2018-11-26 00:00 (156 hours)

2022



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I.
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FourCastNet, Pangu-Weather, GraphCast

TECHNICAL REPORT

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, for this purpose, we establish a data-driven environment ECMWF reanalysis (ERA5) data and train a few deep of forecast is $0.25^\circ \times 0.25^\circ$, comparable to the ECMWF **AI-based method outperforms state-of-the-art numerical RMSE and ACC** of all factors (e.g., geopotential, speed hour to one week). There are two key strategies to implement (3DEST) architecture that formulates the height (pressure) aggregation algorithm to alleviate cumulative forecast short to medium-range forecast (*i.e.*, forecast time range downstream forecast scenarios, including extreme weather forecast in real-time. Pangu-Weather not only ends the forecast but also reveals novel directions for improving deep learning methods.

Index Terms—Numerical Weather Prediction, Deep Learning, Weather Forecasting.

Forecasting Global Weather with Graph Neural Networks

Ryan Keisler
rkeisler@gmail.com

Abstract

We present a data-driven approach for forecasting global weather using graph neural networks. The system learns to step forward the current 3D atmospheric state by six hours, and multiple steps are chained together to produce skillful forecasts going out several days into the future. The underlying model is trained on reanalysis data from ERA5 or forecast data from GFS. Test performance metrics such as Z750 (geopotential height) and T850 (temperature) improves upon 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

Jasdeep Pathak
NVIDIA Corporation
Santa Clara, CA 95051

Shashank Subramanian
Lawrence Berkeley National Laboratory
Berkeley, CA 94720

Peter Harrington
Lawrence Berkeley National Laboratory
Berkeley, CA 94720

Sanjeev Raju
University of Michigan
Ann Arbor, MI 48109

Adesh Chittipeddy
Rice University
Houston, TX 77005

Ni Sun
NVIDIA Corporation
Santa Clara, CA 95051

David Hall
NVIDIA Corporation
Santa Clara, CA 95051

California
NVIDIA
Santa Clara, CA 95051

Pedram Hassanzadeh
Rice University
Houston, TX 77005

Kartik
NVIDIA
Santa Clara, CA 95051

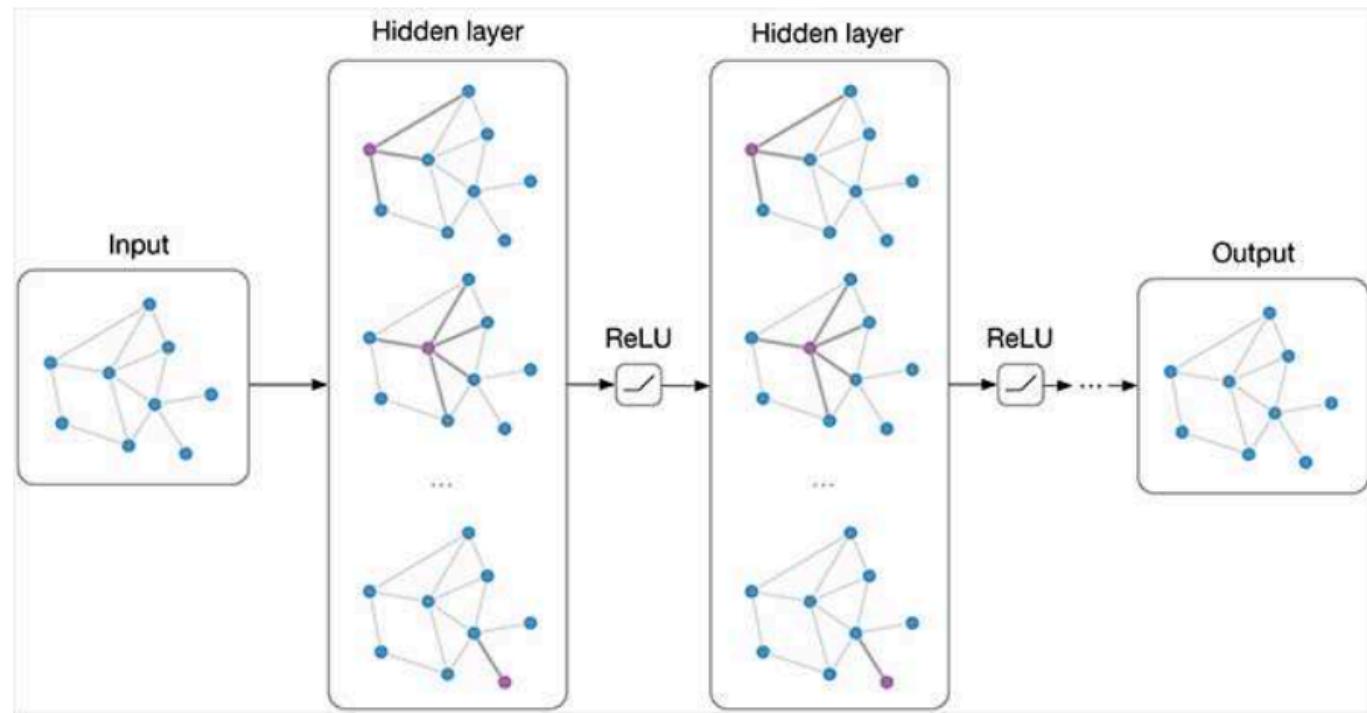
GraphCast: Learning skillful medium-range global weather forecasting

Remi Lam^{✉,1}, Alvaro Sanchez-Gonzalez^{2,1}, Matthew Willison^{3,1}, Peter Wirsberger^{3,1}, Meire Fortunato^{3,1}, Alexander Prizel¹, Suman Ravuri¹, Timo Ewalds¹, Ferran Aleix¹, Zach Eaton-Rosen¹, Weihua Hu¹, Alexander Meroze², Stephan Hoyer², George Holland¹, Jacklyn Stott¹, Oriol Vinyals¹, Shakir Mohamed¹ and Peter Battaglia¹

¹equal contribution, ²DeepMind, ³Google

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.

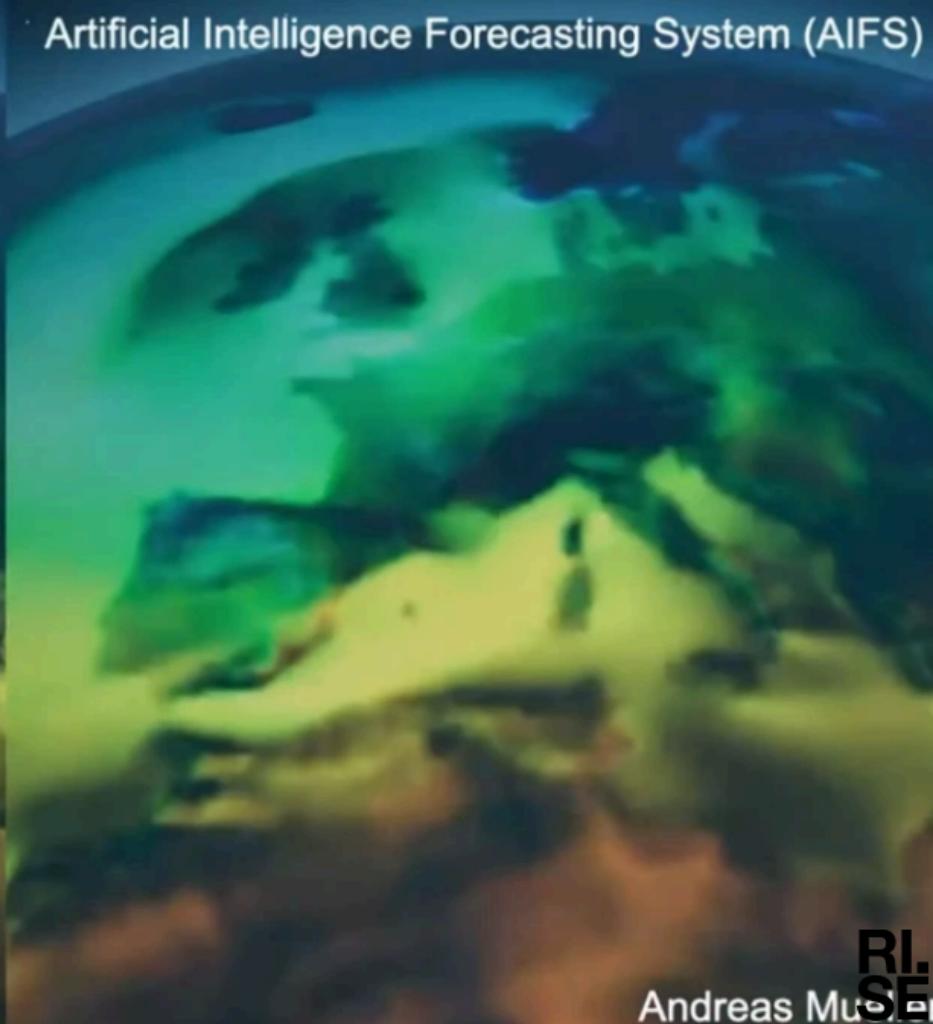
Graph neural networks for physical modeling



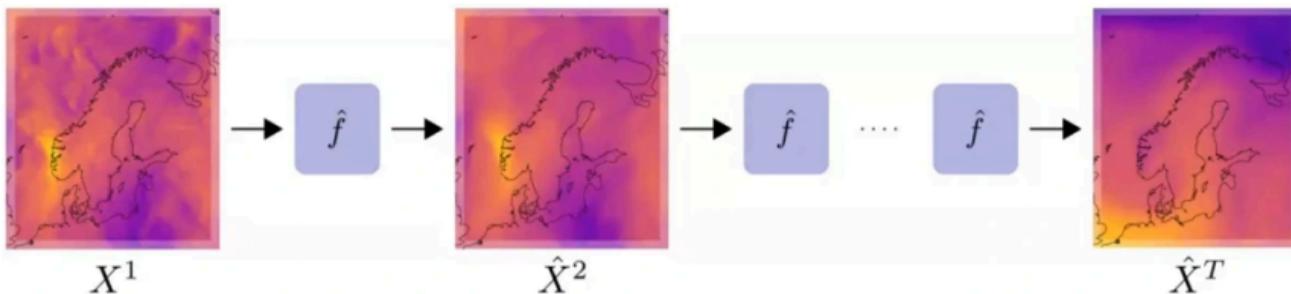
Integrated Forecasting System (IFS)



Artificial Intelligence Forecasting System (AIFS)



The MLWP framework



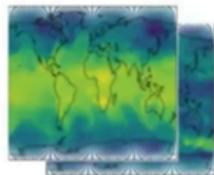
- Weather state X^t , forcing F^t
- Assumed dynamics model $X^t = f(X^{t-2:t-1}, F^t)$
- Approximate with ML model $\hat{f} \approx f$
- Encode - process - decode

ECMWF AI Forecasting System

TRAINING

INPUTS

Atmospheric state:
 $X(t), X(t-6h)$



AIFS MODEL (Graph based)

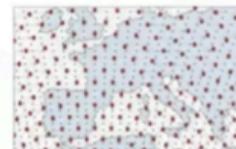
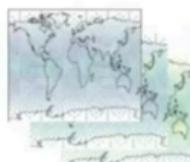
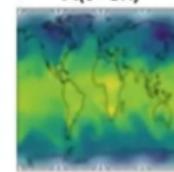
encoder

processor
16 layers

decoder

OUTPUTS

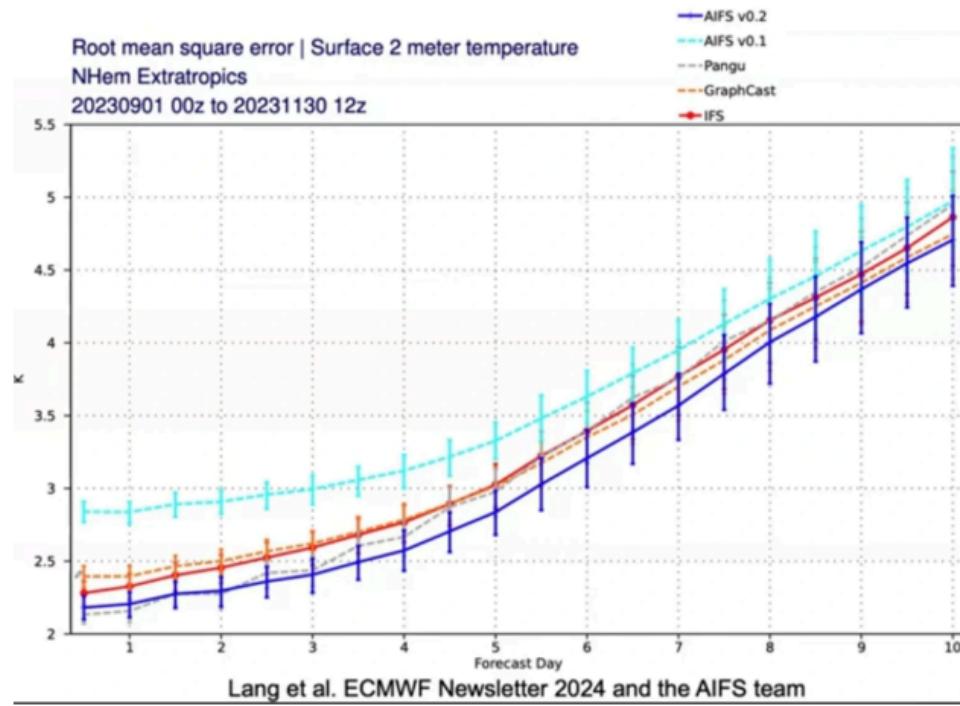
Prediction:
 $X(t+6h)$



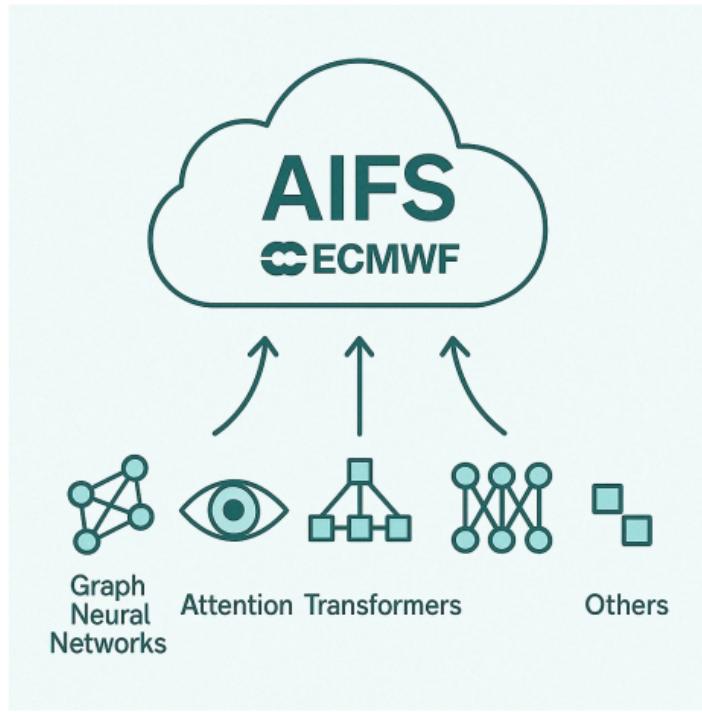
AIFS_{t -> t+6h}

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

AIFS vs IFS

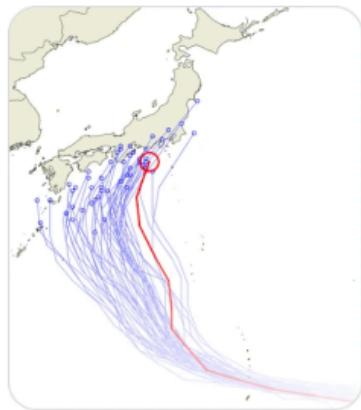


Solutions build on years of progress

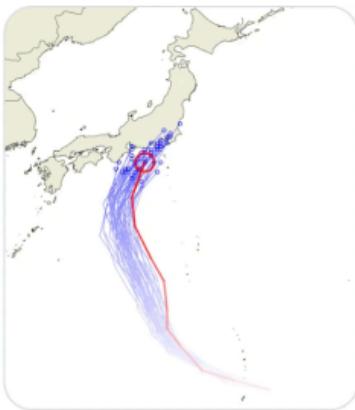


- Graph neural networks
- Transformer (attention) architecture
- Diffusion models

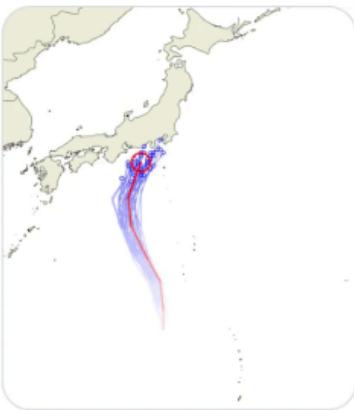
Diffusion models: Gencast



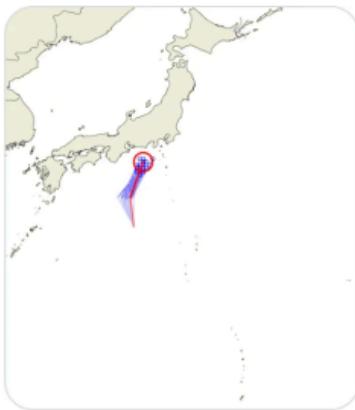
7-day forecast



5-day forecast



3-day forecast



1-day forecast



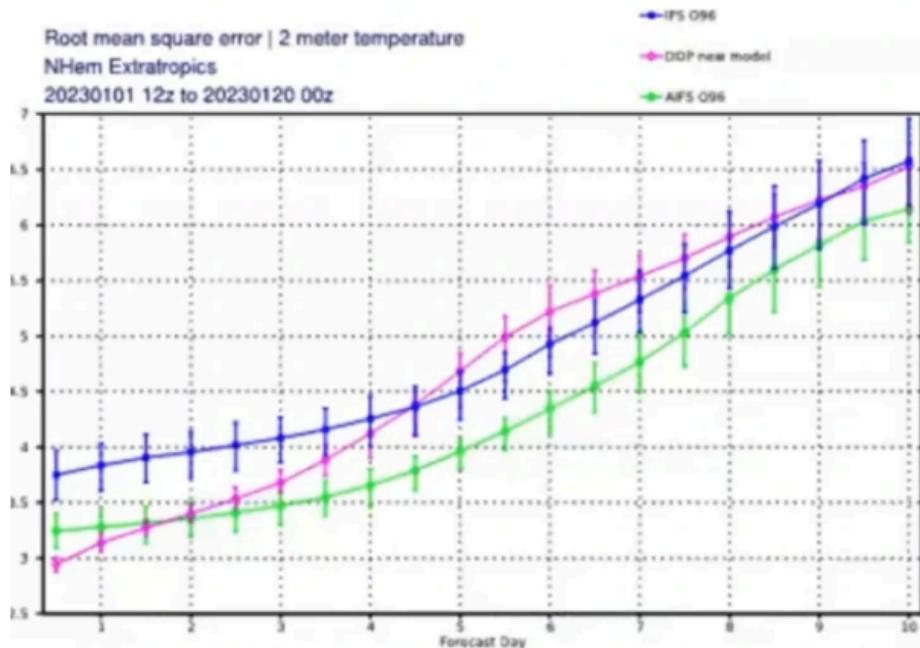
Cyclone track up to October 12, 2019, at 0600 UTC

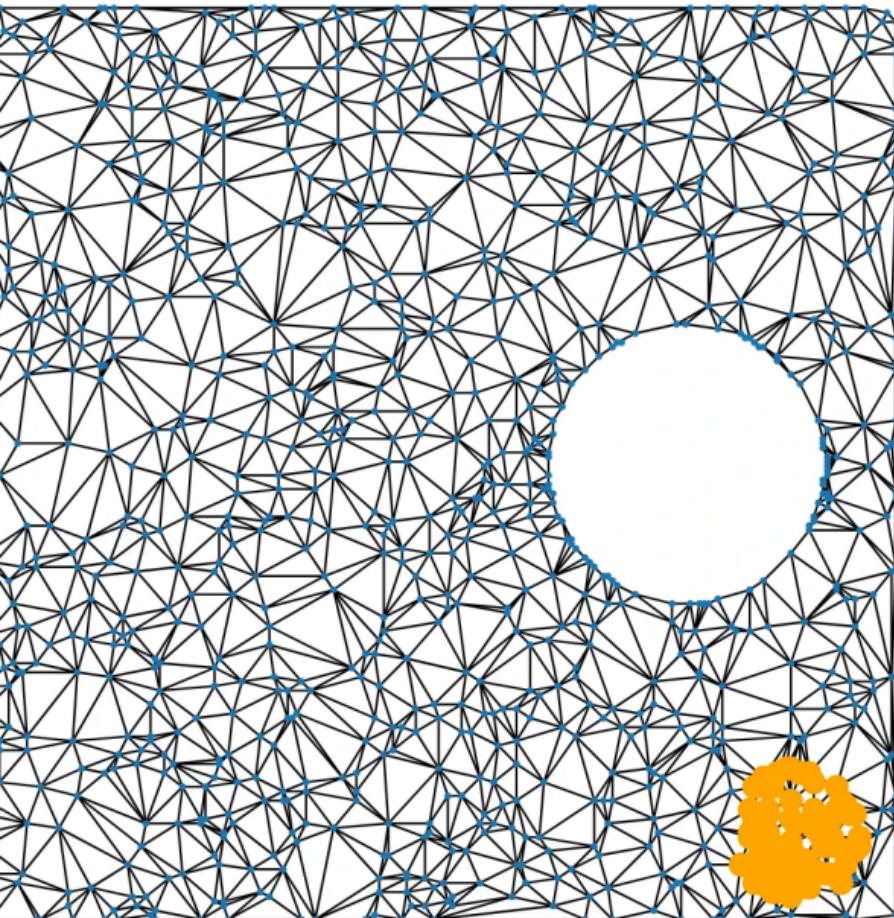


Possible paths predicted by GenCast

Data assimilation

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

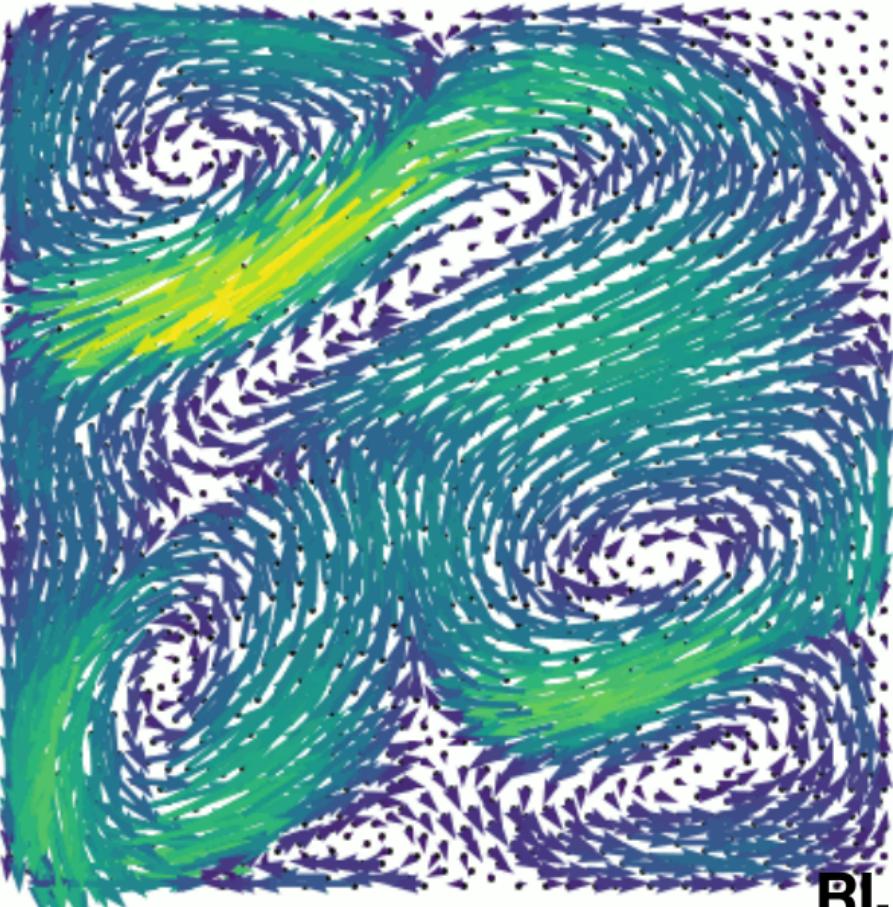
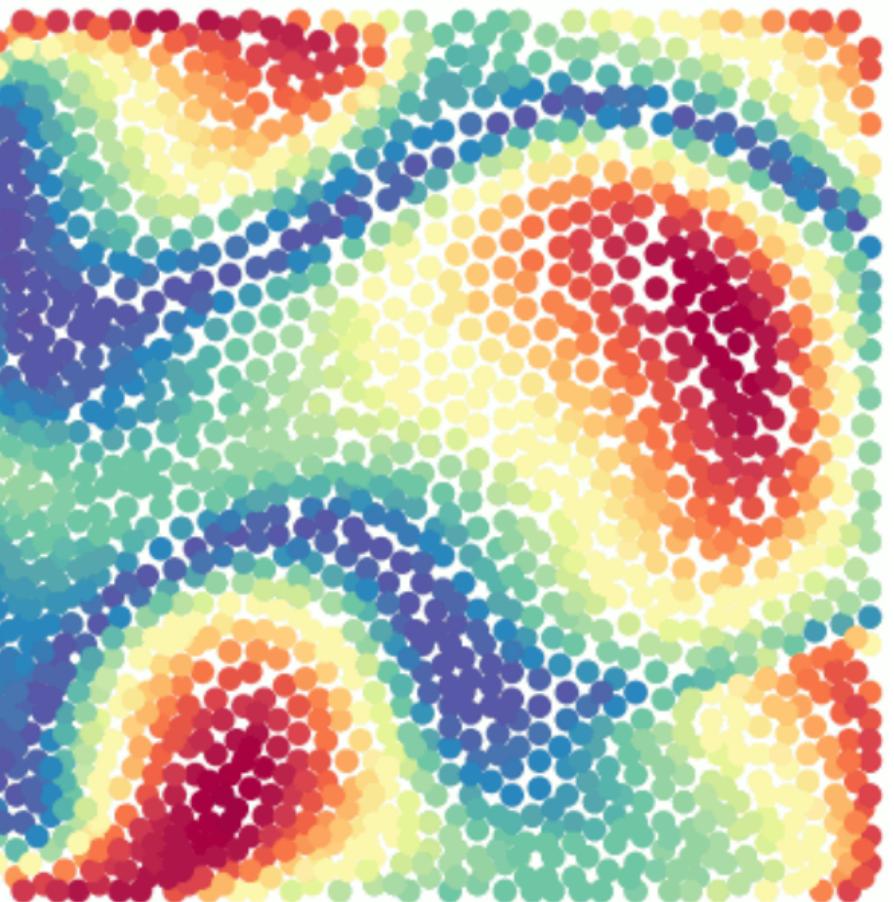




Equivariant graph neural networks

- 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 efficiency
- Consistency with physical symmetries
- Accuracy, scalability

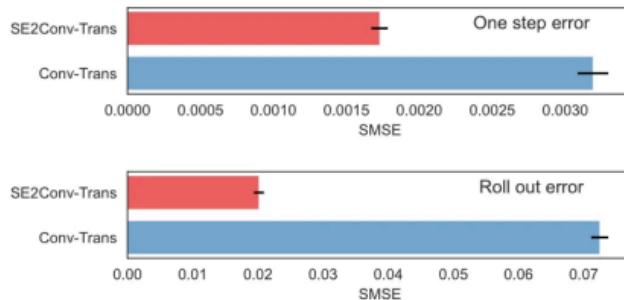


Figure 8. Our approach (red) obtains significantly lower one-step as well as rollout errors compared to the non-invariant counterpart (blue). The rollout error is, however, even more reduced, which showcases the ability of our model to maintain accurate prediction accuracy even over longer time horizons.

AI for weather extreme estimation

Geophysical Research Letters*
RESEARCH LETTER
INTERDISCIPLINARY STUDIES

Regional Heatwave Prediction Using Graph Neural Network and Weather Station Data
Pétronin L^a, Yu Xu^a, Jiaxin Wang^b, and Aishah Sharmin^{c,d}

^aUniversity of Science and Technology of China, Hefei, Anhui, China; ^bUniversity of Chinese Academy of Sciences, Beijing, China; ^cDepartment of Aerospace Engineering, University of Southern California, Los Angeles, CA, USA; ^dDepartment of Electrical and Computer Engineering, University of Southern California, Los Angeles, CA, USA

Abstract Short-term prediction of short-term heatwaves is a novel, long-term heatwave forecasting problem. This paper proposes a novel graph neural network (GNN) model to predict short-term heatwaves and long-term heatwaves. The GNN model is trained with a heatwave dataset from the National Centers for Environmental Prediction (NCEP) and the National Centers for Atmospheric Research (NCAR). The results show that the GNN model can predict short-term heatwaves and long-term heatwaves with a better accuracy than the baseline models.

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frontiers in Climate

Deep Learning-Based Extreme Heatwave Forecast
Mariano, Jeanine-Dumas^a, Francesco Ragone^{a,b}, Pierre Dognin^a, and Frédéric Bouchal^a

^aCNRS, Institut Jean le Rond d'Allemand, CNRS Laboratoire de Physique Lyon, Lyon Université de Lyon, Villeurbanne, France; ^bUniversité Grenoble Alpes, Grenoble, France

Abstract Due to the impact of extreme heat waves and heat biodiversity, this study is a key challenge. We specifically study extremes, which are among the most important for climate impact because they are associated with significant social and economic costs. Their probability. This present work explores the use of deep learning using outputs of a climatic model, as an alternative strategy of extreme long-lasting heatwaves. This new approach is assessed by comparing it with a traditional statistical proxy for estimating rare events in climate records, which should eventually be useful for forecasting. Fitting addressing issues such as class size imbalance that is often encountered in extreme events. In this article, we first used a nested nature of extreme events initially introduced a Convolutional Neural Network, using 1,000 years large class undersampling and transfer learning. For testing, we used a climatic model (IPSL-CM5A-LR) to generate synthetic data. The results show that the proposed approach achieves significant performance in forecasting the heatwaves. We are able to predict them at three days, as 15 days ahead of the start of the event (20 day lead).

frontiers in Climate

Extreme Heat Prediction through Deep Learning and Explainable AI
Faria, Daniel^a, Arash Zare^a, Mohammad Hassan Ghani Alzahr^a, Sajid Iqbal^a, and Ahmadullah Shahzad Asghar^a

^aDepartment of Civil and Structural Engineering, University of Nottingham Malaysia Campus, Semenyih, Selangor, Malaysia

Abstract Extreme heat waves are causing widespread concern for comprehensive studies on their occurrence and societal implications. With the ongoing rise in global temperatures, the frequency and intensity of heatwaves have increasingly changed. Predictive planning and assessing safety, timely intervention, and effective adaptation are critical for mitigating the negative impacts of extreme heat waves. Deep learning and explainable AI (XAI) have emerged as promising tools for improving the performance of extreme heat wave prediction. In this study, we performed data pre-processing and collected datasets from Princeton Long-Short Term Memory (LSTM), using the Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models. Instead of using a single model, we integrated Explainable AI (XAI) to provide transparency and accountability. Although Weather Explainable AI (WEA) has advanced in predicting extreme heat waves, its performance is still limited. Therefore, we propose a hybrid model to enhance the performance of WEA. Our study addresses the issue of extreme heat wave prediction by using adaptive transfer learning, which largely improves the performance of the proposed model. The model is evaluated using a comprehensive metric for collecting five years of historical data and studying the results. Our study demonstrates that the LSTM model performs well, and the proposed model outperforms the baseline methods. The results indicate that the performance of the proposed model is improved compared to the baseline methods. The results also show that the proposed model is more accurate than the baseline methods. Overall, the study emphasizes how important it is to use XAI to interpret the results of extreme heat prediction. This study also highlights the importance of XAI in improving the performance of extreme heat wave prediction.

PLOS ONE

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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 Kurfali
- 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 Kurfali
- 14: Coffee, then exercises

