



Machine Learning Research for Climate Change and Environmental Sustainability

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December 2021: Boulder County, Colorado

- Snow drought conditions through fall and winter 2021 created dry land-cover
- 80-100 mph winds, combined with ignition, launched an uncontrollable “fire storm”
- Loss of 2 lives. 1000 homes and 20 businesses were destroyed, and more damaged



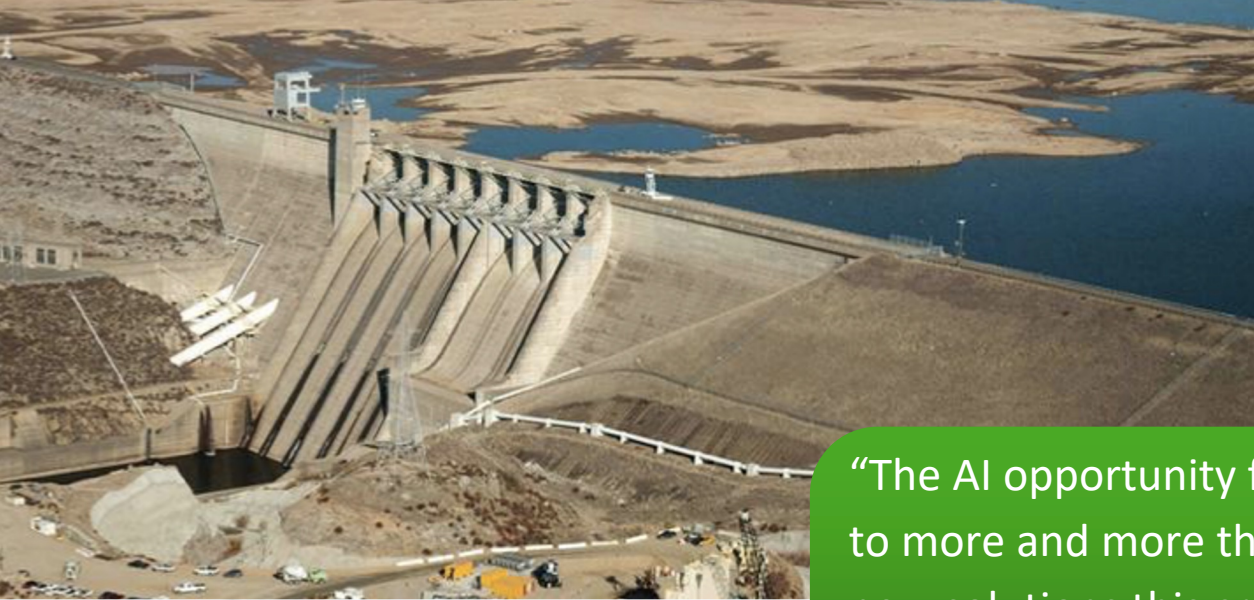
January 2018: Montecito, Santa Barbara County

- Thomas Fire destroyed 1063 structures and led to poor air quality
- Intense rainfall as the fire was nearing containment produced a debris flow
- 23 lives and over 130 homes were lost
- Damage to critical transportation and water resource infrastructure





Machine learning can shed light on climate change

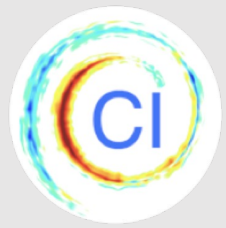


“The AI opportunity for the Earth is significant. Today’s AI explosion will see us add AI to more and more things every year.... As we think about the gains, efficiencies and new solutions this creates for nations, business and for everyday life, we must also think about how to maximize the gains for society and our environment at large.”

– The World Economic Forum: Harnessing Artificial Intelligence for the Earth. 2018



Climate Informatics is based on the vision that Machine learning can shed light on climate change

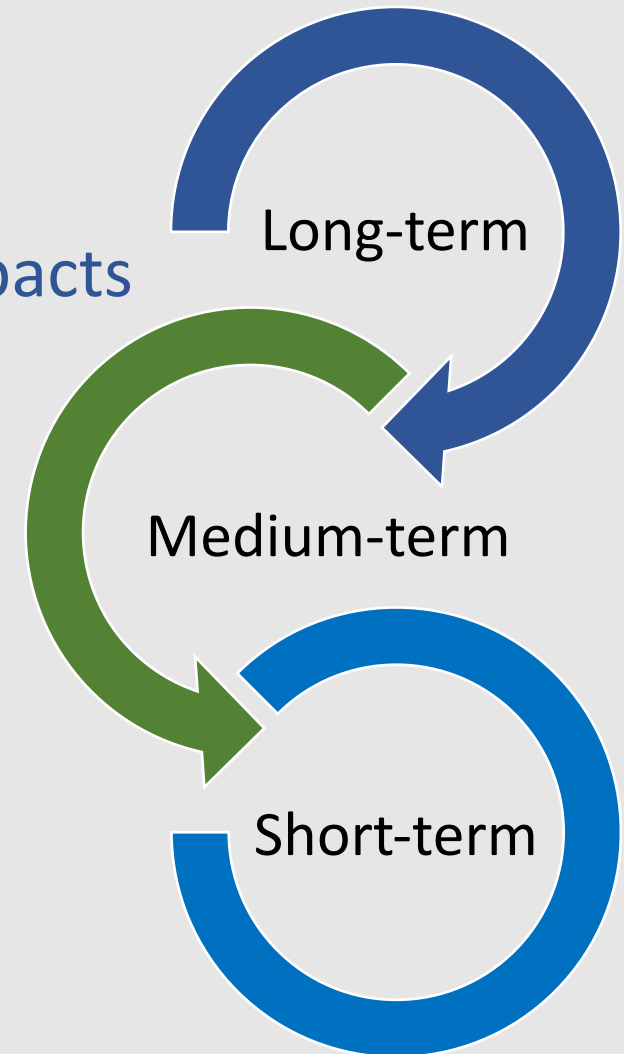


- 2008 Started research on Climate Informatics, with Gavin Schmidt, NASA
- 2010 “Tracking Climate Models” [Monteleoni et al., NASA CIDU, Best Application Paper Award]
- 2011 Launched International Workshop on Climate Informatics, New York Academy of Sciences
- 2012 Climate Informatics Workshop held at NCAR, Boulder, for next 7 years
- 2013 “Climate Informatics” book chapter [M et al., SAM]
- 2014 “Climate Change: Challenges for Machine Learning,” [M & Banerjee, NeurIPS Tutorial]
- 2015 Launched Climate Informatics Hackathon, Paris and Boulder
- 2018 World Economic Forum recognizes Climate Informatics as key priority**
- 2021 Computing Research for the Climate Crisis [Bliss, Bradley @ M, CCC white paper]
- 2022 First batch of articles published in Environmental Data Science, Cambridge University Press
- 2023 12th Conference on Climate Informatics and 9th Hackathon, Cambridge, UK
- 2024 13th Conference on Climate Informatics and 10th Hackathon, Turing Institute, London, APRIL



AI Research for Climate Change and Environmental Sustainability

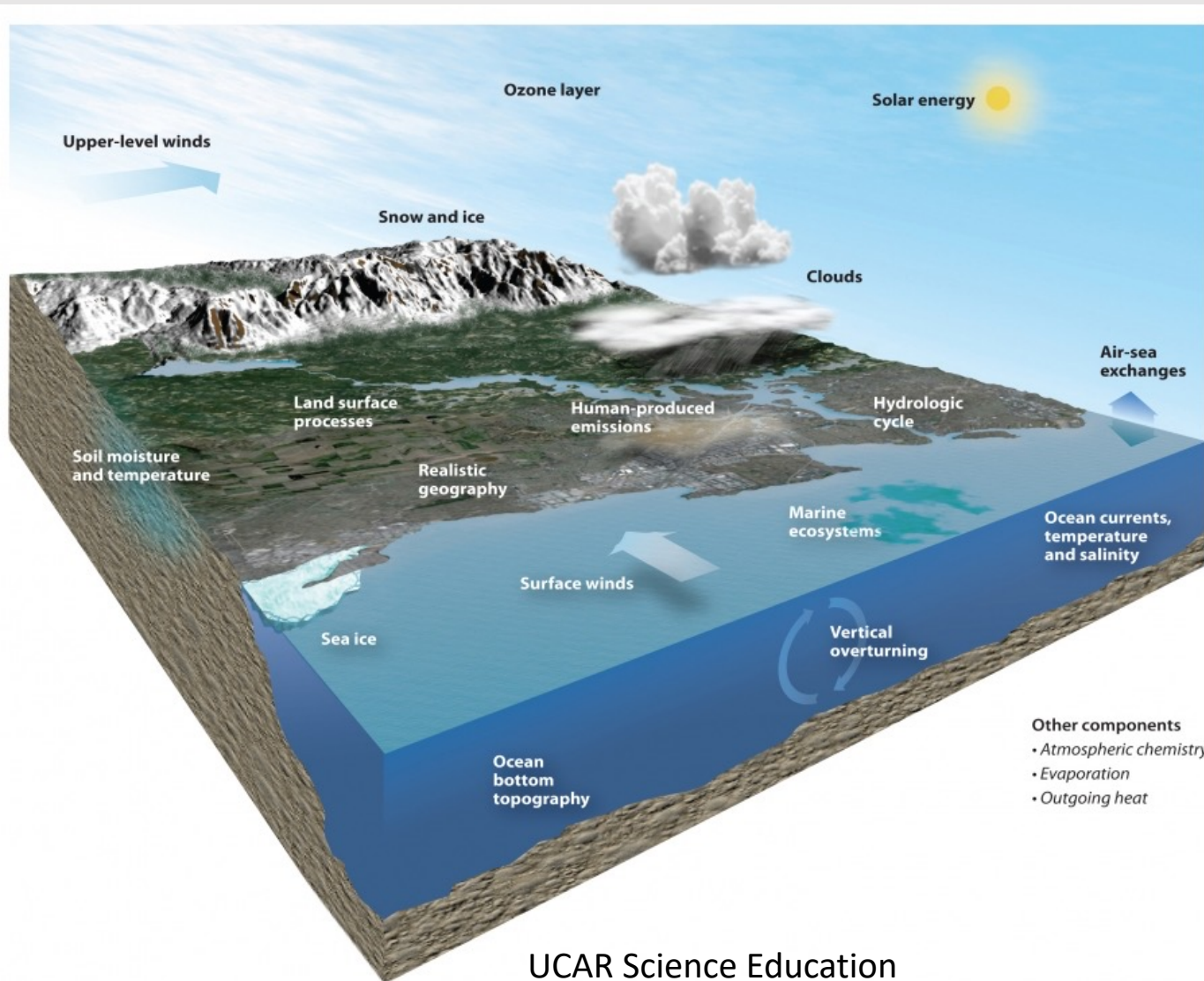
- Machine Learning for Climate Science
Understanding and Predicting Climate Change and Impacts
- Machine Learning for Climate Mitigation
Accelerating the Green Transition
- Machine Learning for Climate Adaptation
Extreme Weather and Cascading Hazards



Our Climate Informatics research also addresses **open problems** in Machine Learning

- ❑ Online learning with spatiotemporal non-stationarity
- ❑ Prediction at multiple timescales simultaneously
- ❑ Anomaly detection with limited supervision
- ❑ Tracking highly-deformable patterns

Machine Learning for Understanding and Predicting Climate Change



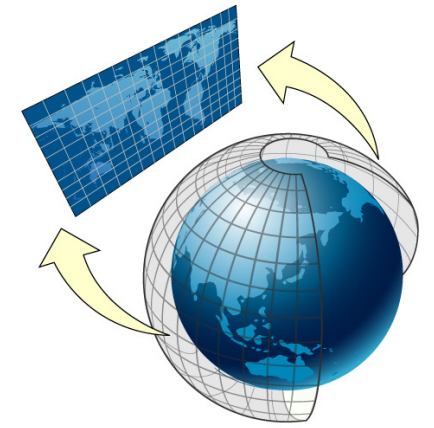
Robustify climate model ensemble forecasts using online learning for non-stationary spatiotemporal data [Multiple papers 2009-2020, e.g., AAAI 2012, ALT 2020]

Causal information hubs in Pacific ENSO region [Saha et al., Climate Informatics 2019]

Project long-term sea-level rise:

- NASA project using satellite altimetry [Sinha et al., AGU 2022, ICLR 2023 workshop] CU & NCAR
- NSF i-HARP project on ice-sheet contributions to sea-level rise

Online learning with spatiotemporal non-stationarity



Learning when the target concept can **vary over time**, and **multiple other dimensions** (e.g., latitude, longitude)

We can **exploit local structure in space and time**

We can **learn the level of non-stationarity in time and space**

[McQuade and Monteleoni, AAAI 2012] extended [Monteleoni & Jaakkola, NeurIPS 2003; Monteleoni et al. SAM 2011] to **multiple dimensions**

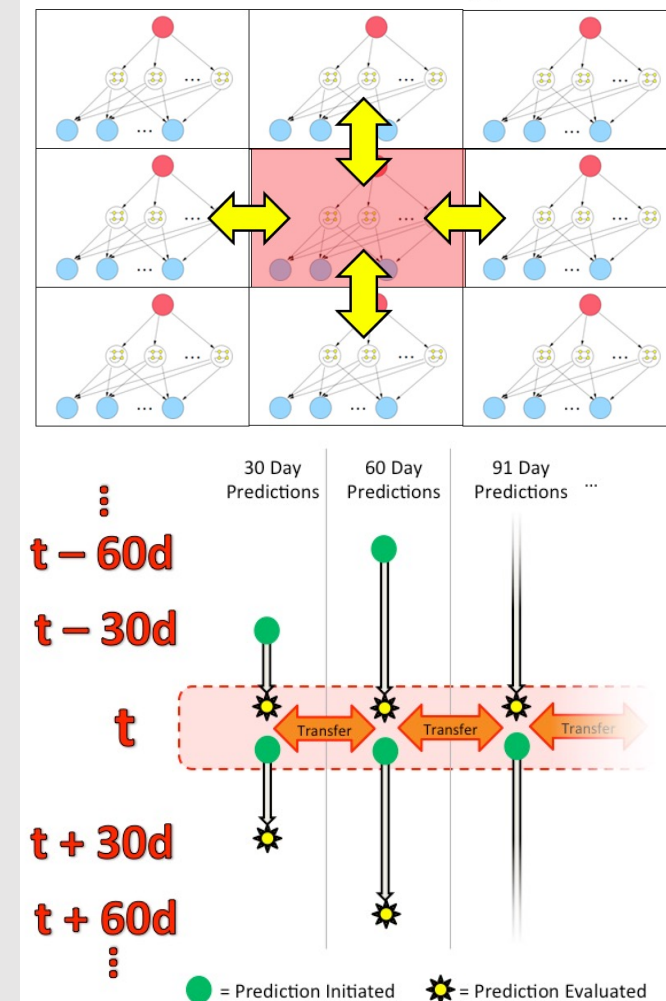
This framework for online learning was **open in machine learning**

New “regret” framework: [Cesa-Bianchi, Cesari, & Monteleoni, ALT 2020]

Prediction at **multiple timescales simultaneously**

Applications to both climate science, and financial volatility:

[McQuade and Monteleoni, CI 2015; SIGMOD DSMM 2016]



ML for the Green Transition

Accelerate the renewable energy transition

Week-ahead solar irradiance forecasting via deep sequence learning [Sinha et al., CI 2022] w/ NREL

ML to downscale climate model data for renewable energy planning:

- [Harilal et al., NeurIPS workshop 2022] Climate Change AI / Future Earth project w/ NREL, IIT-Roorkee
- INRIA Défis w/ Électricité de France

ML for modeling the effects of land-use change on CO₂ emissions

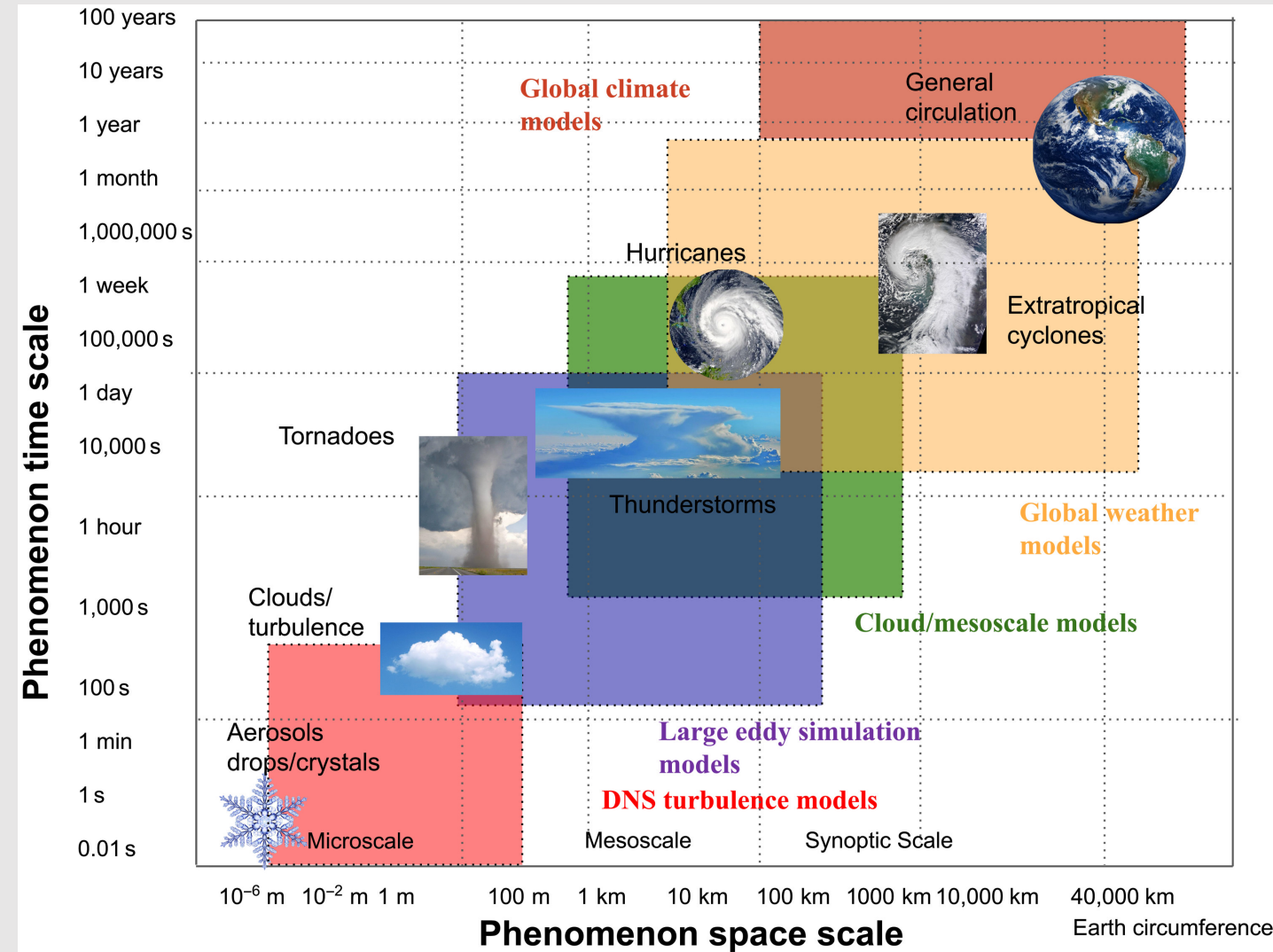


Downscaling climate model simulations

Global climate model simulations are coarser scale (in space and time) than needed for:

- Climate change mitigation
- Climate change adaptation

Approach: Use ML to **downscale** climate model data to relevant scales



[Gettelman, et al., Science Advances, 2022]

Semi/Unsupervised downscaling: Equity motivation

- Train models in **data-rich** regions and apply them in **data-poor** regions
 - Can evaluate them against supervised learning models in data-rich regions
 - Can fine-tune them using the limited data in the data-poor regions
- Contribution to climate data equity
 - Global scales:
 - Global North historically emitted more carbon; Meanwhile there's typically more data there
 - Global South is suffering the most severe effects of the resulting warming
 - Local scales (e.g. legacy of environmental injustice in USA)
 - Learn “virtual sensors”

Are Black Americans Underserved by the NWS Radar Network?

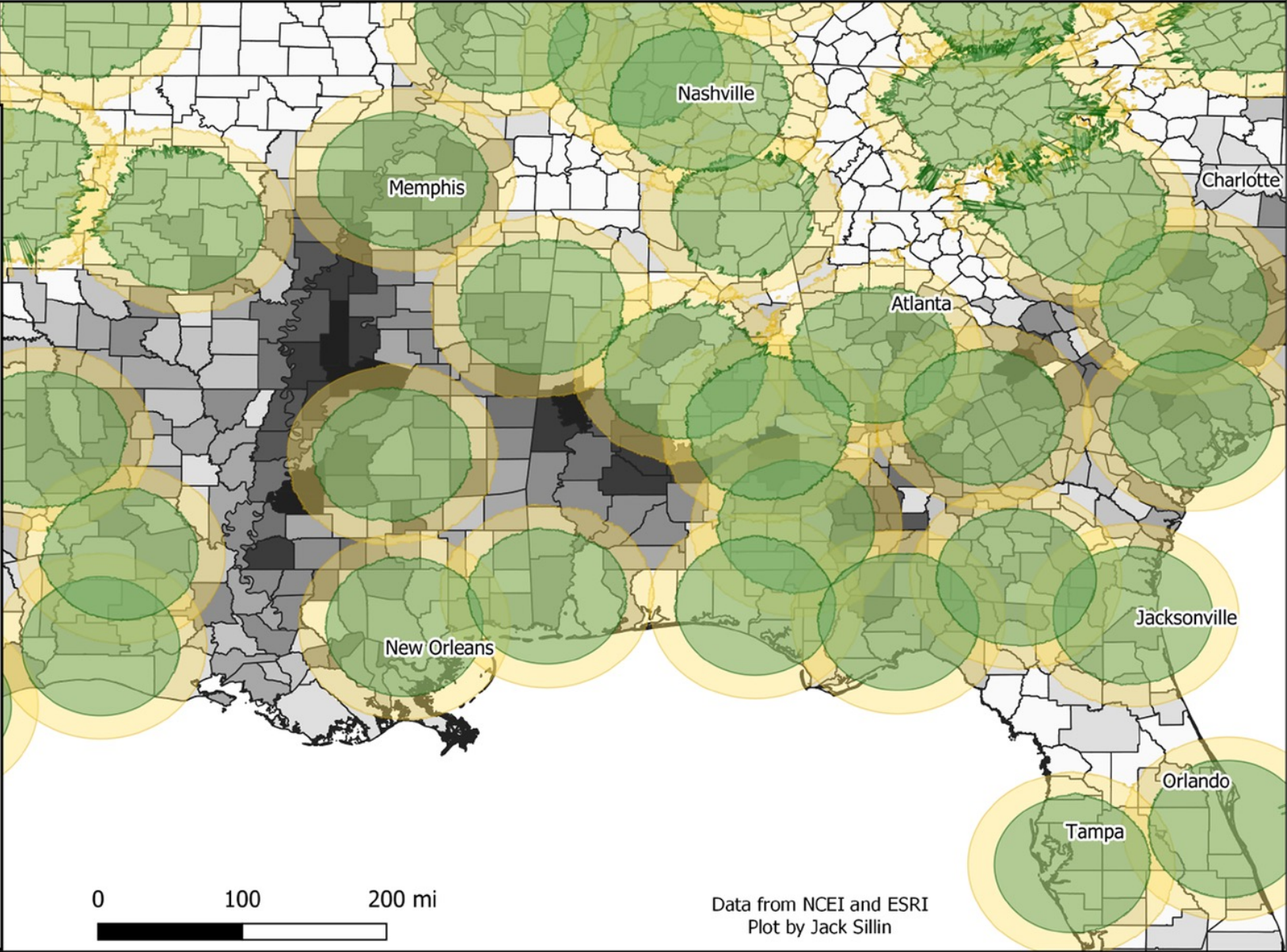
“Many majority-Black parts of the Southeast [USA] are relatively far from radar sites, meaning that it’s harder to gather information about storms impacting these areas.”

Weather radars detect storms by sending beams of energy out into the atmosphere and listening for energy that bounces back off rain, snow, hail, and anything else in the atmosphere.

The farther a storm is from a radar site, the less information we can get about it due to the beam height rising farther off the ground, and the beam width expanding leading to lower resolution.

High resolution radar data near the ground can be critical in many situations such as when severe thunderstorms and tornadoes threaten.

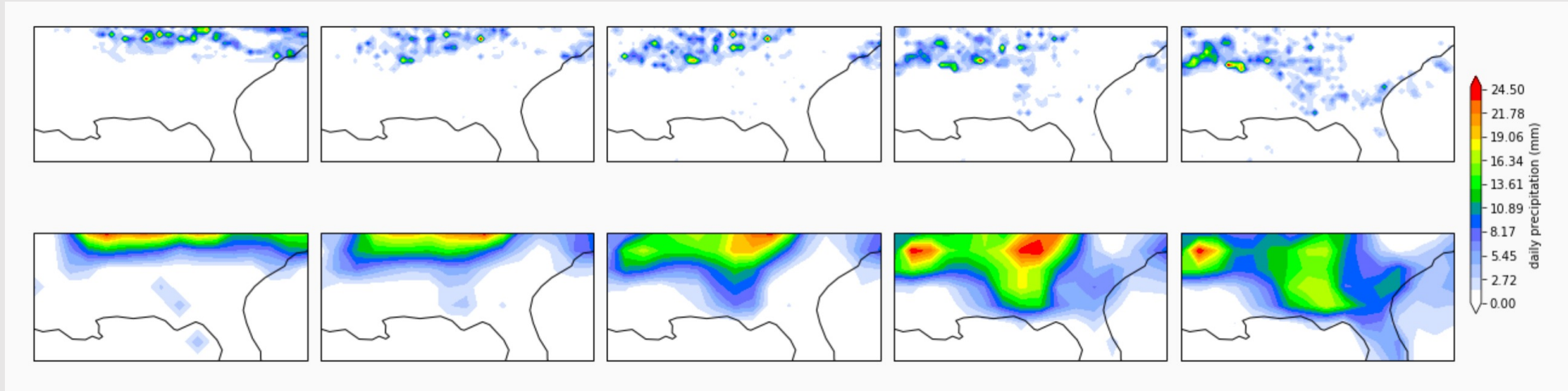
Many majority-Black parts of the Southeast are relatively far from radar sites, meaning that it's harder to gather information about storms impacting these areas.



Credit: Jack Sillin, in [McGovern et al., Environmental Data Science, 2022]



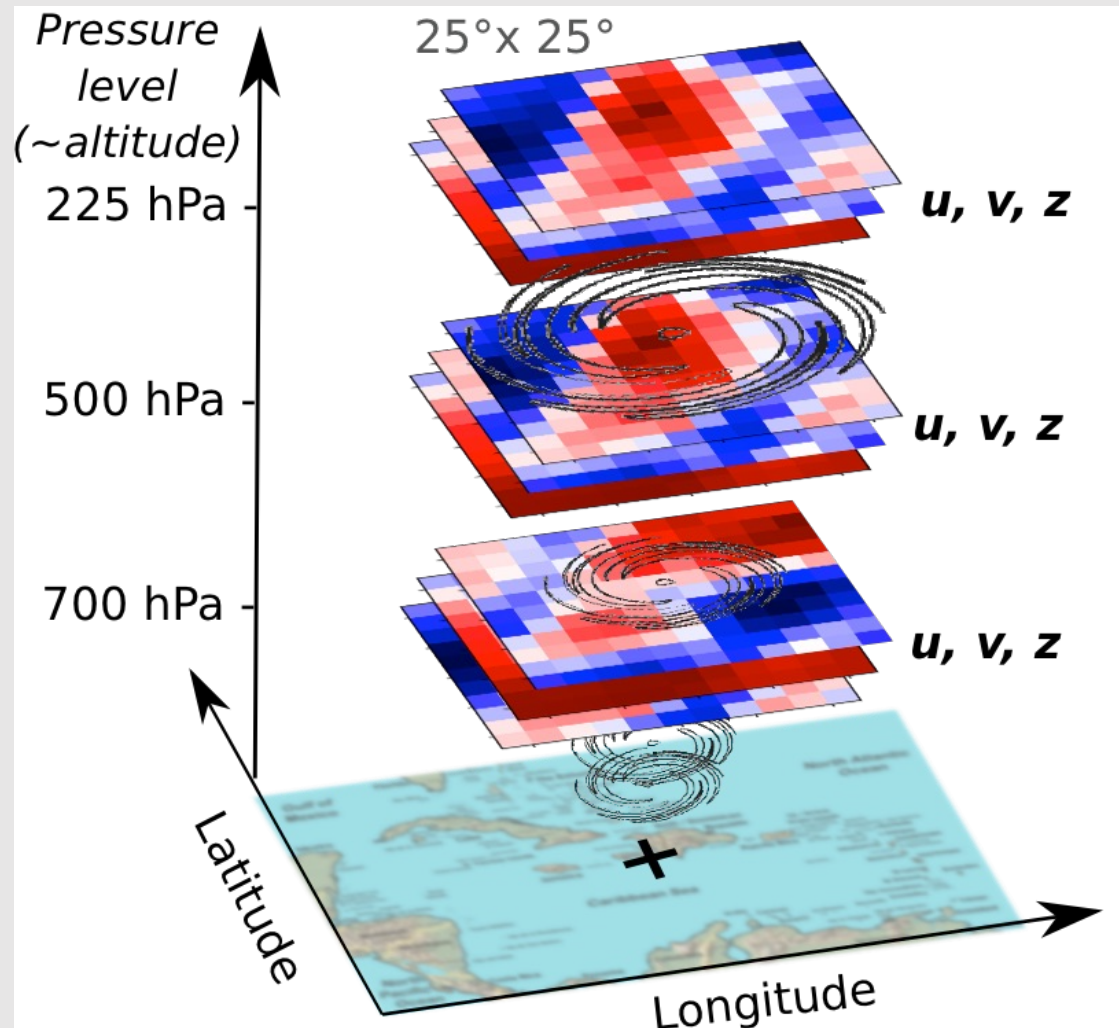
ClimAlign: Unsupervised, generative downscaling



General downscaling technique via domain alignment with normalizing flows
[AlignFlow: Grover et al., AAAI 2020][Glow: Kingma & Dhariwal, NeurIPS 2018]

- **Unsupervised**: do not need paired maps at low and high resolution
- **Generative**: can sample from posterior over latent representation OR sample conditioned on a low (or high!) resolution map
- **Intepretable**, e.g., via interpolation

Machine Learning for Extreme Weather and Cascading Hazards



Hurricane track prediction via fused CNNs
[Giffard-Roisin et al., Climate Informatics 2018; Frontiers 2020]

Forecasting Indian Summer Monsoon precipitation extremes

[Saha et al. Climate Informatics 2019; 2020] w/ India Meteorological Department (IMD)

Avalanche detection using CNN; VAE

[Sinha et al., Climate Informatics 2019; 2020] w/ Météo-France

How to use “ML foundation models for weather” to forecast extreme events?

The deep learning revolution in weather forecasting

Slides adapted from David Landry, INRIA Paris (formerly of Environment Canada)

- Starting in 2023, several tech-industry research teams used deep neural networks to perform medium-range weather forecasts (e.g., NVIDIA, Huawei, Google DeepMind)
- The best ML-models' skill became ~equivalent to the leading Numerical Weather Prediction (NWP) models

Forecasting Global Weather with Graph Neural Networks

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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 on metrics such as Z500 (geopotential height) and T550 (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.

1 Introduction

Numerical weather prediction (NWP), as part of the broader weather enterprise, has had an enormous and positive impact on society. Decades of steady improvements in the quantity and types of observational data, better modeling techniques, and more computational power have resulted in increasingly accurate weather forecasts and growing adoption of NWP in real-world applications. While statistical techniques have been used within NWP for decades, the core dynamical engines of these models continue to be based on the physical principles governing the atmosphere and ocean. More recently, spurred on by advancements in machine learning (ML), there has been a surge of interest in statistical, data-driven techniques for weather forecasting. The motivation for using ML is to improve upon an already extremely successful NWP program through some combination of better forecasts, faster forecasts, or more forecasts, i.e. larger ensembles. There may also be opportunities for using ML to advance our scientific understanding of the underlying physical processes [Kranke et al., 2020].

There is currently a very active hub of research at the intersection of NWP and ML. Example research areas include: faster or more accurate solving of relevant PDEs [Bischoff et al., 2019, Aliev et al., 2021, Kim et al., 2021, Li et al., 2021, Brandstätter et al., 2021], data assimilation [Herrera et al., 2021, Malik et al., 2021], hybrid parameterization [Bischoff and Bretherton, 2019, Chantry et al., 2021, Vivaldi et al., 2021, Meyer et al., 2021], nowcasting [Sundaresan et al., 2020, Aravali et al., 2019, Escholt et al., 2021, Kiseck et al., 2021, Ravari et al., 2021], modeling global NWP models [Bischoff et al., 2021], replacing global NWP models [Bischoff and Hariri, 2019, Aravali et al., 2020, Raspi and Thiery, 2021, Scher and Messer, 2021, Weyn et al., 2020, 2021, Clark et al., 2021], high-level proposals for end-to-end ML weather systems [Schulz et al., 2021], and decision making [Kranke et al., 2020].

FOURCASTNET: A GLOBAL DATA-DRIVEN HIGH-RESOLUTION WEATHER MODEL USING ADAPTIVE FOURIER NEURAL OPERATORS

A PREPRINT

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February 24, 2022

ABSTRACT

FourCastNet, short for *Fourier Forecasting Neural Network*, is a global data-driven weather forecasting model that provides accurate short to medium-range global predictions at 0.25° resolution. FourCastNet accurately forecasts high-resolution, fast-time-scale variables such as the surface wind speed, precipitation, and atmospheric water vapor. It has important implications for planning wind energy resources, predicting extreme weather events such as tropical cyclones, extra-tropical cyclones, and atmospheric rivers. FourCastNet matches the forecasting accuracy of the ECMWF Integrated Forecasting System (IFS), a state-of-the-art Numerical Weather Prediction (NWP) model, at short lead times for large-scale variables, while outperforming IFS for small-scale variables, including precipitation. FourCastNet generates a week-long forecast in less than 2 seconds, orders of magnitude faster than IFS. The speed of FourCastNet enables the creation of rapid and inexpensive large-ensemble numerical weather forecasts. In addition, conventional

TECHNICAL REPORT

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

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

Abstract—In this paper, we present Pangu-Weather, a deep learning based system for fast and accurate global weather forecast. For this purpose, we establish a data-driven environment by downloading 13 years of hourly global weather data from the 5th generation of ECMWF reanalysis (ERA5) data and train a few deep neural networks with about 256 million parameters in total. The spatial resolution of forecast is 0.25° × 0.25°, comparable to the ECMWF Integrated Forecast Systems (IFS). More importantly, for the first time, an AI-based method outperforms state-of-the-art numerical weather prediction (NWP) methods in terms of accuracy (latitude-weighted RMSE and ACC) of all factors (e.g., geopotential, specific humidity, wind speed, temperature, etc.) and in all time ranges (from one hour to one week). There are two key strategies to improve the prediction accuracy: (i) designing a 3D Earth Specific Transformer (DEST) architecture that formulates the height (pressure level) information into cubic data, and (ii) applying a hierarchical temporal aggregation algorithm to alleviate cumulative forecast errors. In deterministic forecast, Pangu-Weather shows great advantages for short to medium-range forecast (i.e., forecast time ranges from one hour to one week). Pangu-Weather supports a wide range of downstream forecast scenarios, including extreme weather forecast (e.g., tropical cyclone tracking) and large-member ensemble forecast in real-time. Pangu-Weather not only ends the debate on whether AI-based methods can surpass conventional NWP methods, but also reveals novel directions for improving deep learning weather forecast systems.

Index Terms—Numerical Weather Prediction, Deep Learning, Medium-range Weather Forecast.

1 INTRODUCTION

Weather forecast is one of the most important scenarios of scientific computing. It offers the ability of predicting future weather changes, especially the occurrence of extreme weather events (e.g., floods, droughts, hurricanes, etc.), which has large values to the society (e.g., daily activities, agriculture, energy production, transportation, industry, etc.). In the past decade, with the bloom of high-performance computational device, the community has witnessed a rapid development in the research field of numerical weather prediction (NWP) [1]. Conventional NWP methods mostly follow a simulation-based paradigm which formulates the physical rules of atmospheric states into partial differential equations (PDEs) and solves them using numerical simulations [2], [3], [4]. Due to the high complexity of solving PDEs, these NWP methods are often very slow, e.g., with a spatial resolution of 0.25° × 0.25°, a single simulation procedure for 10-day forecast can take hours of computation using hundreds of nodes in a supercomputer [5]. This largely reduces the timeliness in daily weather forecast and the number of ensemble members that can be used for probabilistic weather forecast. In addition, conventional

Global medium-range weather forecasting is critical to decision-making across many social and economic domains. Traditional numerical weather prediction uses increased compute resources to improve forecast accuracy, but cannot directly use historical weather data to improve the underlying model. We introduce a machine learning-based method called "GraphCast", which can be trained directly from reanalysis data. It predicts hundreds of weather variables, over 10 days at 0.25° resolution globally, in under one minute. We show that GraphCast significantly outperforms the most accurate operational deterministic systems on 90% of 1380 verification targets, and its forecasts support better severe event prediction, including tropical cyclones, atmospheric rivers, and extreme temperatures. GraphCast is a key advance in accurate and efficient weather forecasting, and helps realize the promise of machine learning for modeling complex dynamical systems.

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Keywords: Weather forecasting, ECMWF, ERA5, HRES, learning simulation, graph neural networks

Introduction

It is 05:45 UTC in mid-October, 2022, in Bologna, Italy, and the European Centre for Medium-Range Weather Forecasts (ECMWF)'s new High-Performance Computing Facility has just started operation. For the past several hours the Integrated Forecasting System (IFS) has been running sophisticated calculations to forecast Earth's weather over the next days and weeks, and its first predictions have just begun to be disseminated to users. This process repeats every six hours, every day, to supply the world with the most accurate weather forecasts available.

The IFS, and modern weather forecasting more generally, are triumphs of science and engineering. The dynamics of weather systems are among the most complex physical phenomena on Earth, and each day, countless decisions made by individuals, industries, and policymakers depend on accurate weather forecasts, from deciding whether to wear a jacket or to flee a dangerous storm. The dominant approach for weather forecasting today is "numerical weather prediction" (NWP), which involves solving the governing equations of weather using supercomputers. The success of NWP lies in the rigorous and ongoing research practices that provide increasingly detailed descriptions of weather phenomena, and how well NWP scales to greater accuracy with greater computational resources [3, 2]. As a result, the accuracy of weather forecasts have increased year after year, to the point where the surface temperature, or the path of a hurricane, can be predicted many days ahead—a possibility that was unthinkable even a few decades ago.

arXiv:2202.07575v1 [physics.ao-ph] 15 Feb 2022

arXiv:2202.11214v1 [physics.ao-ph] 22 Feb 2022

arXiv:2211.02556v1 [physics.ao-ph] 3 Nov 2022

arXiv:2212.12794v2 [cs.LG] 4 Aug 2023

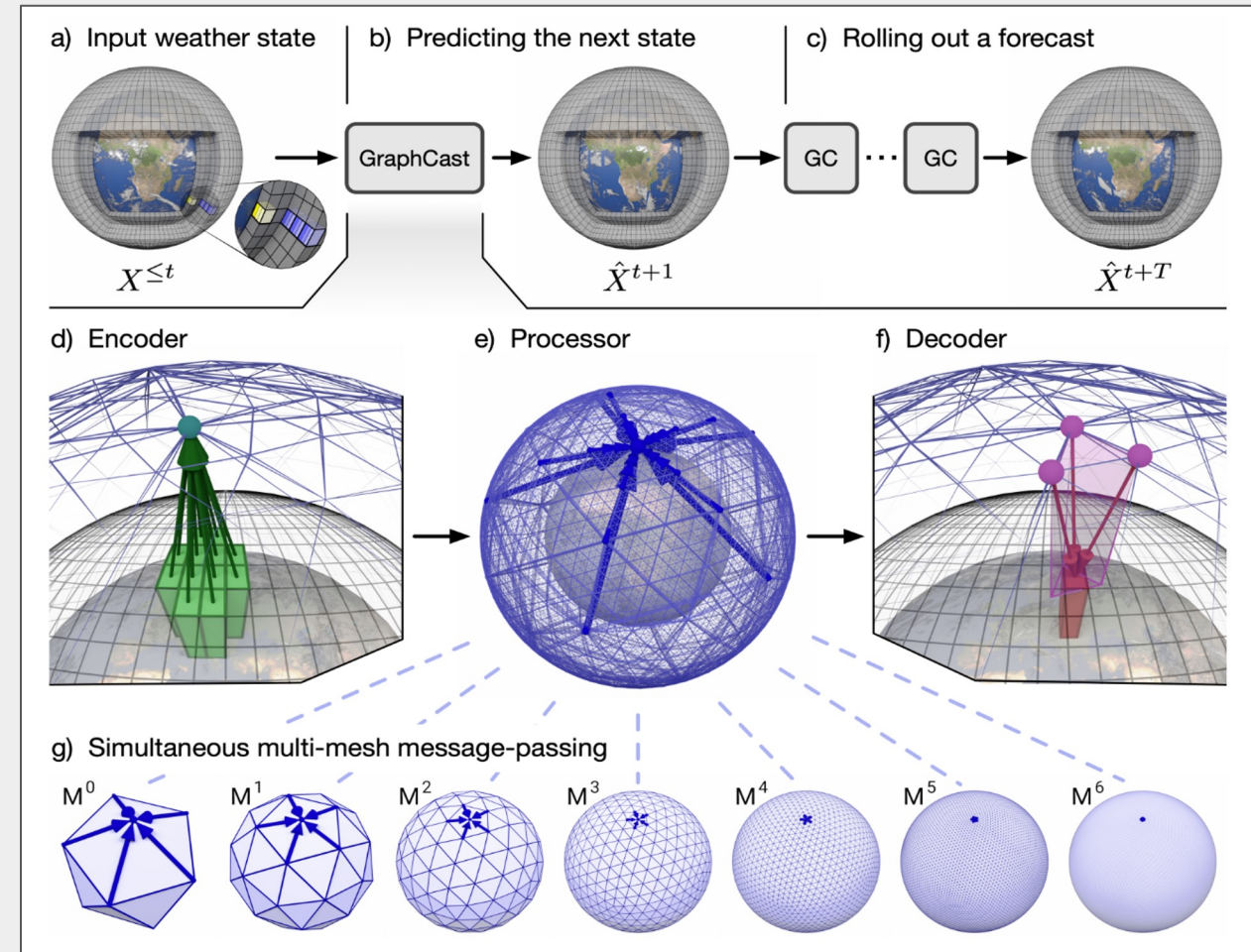
How it works

Models: Deep Neural Networks, e.g.:

- Fourier Neural Operators
- Graph Neural Networks
- Collection of models for different time scales

Training:

- Supervised learning
- Optimized for average performance
- Deterministic forecasts (not probabilistic)



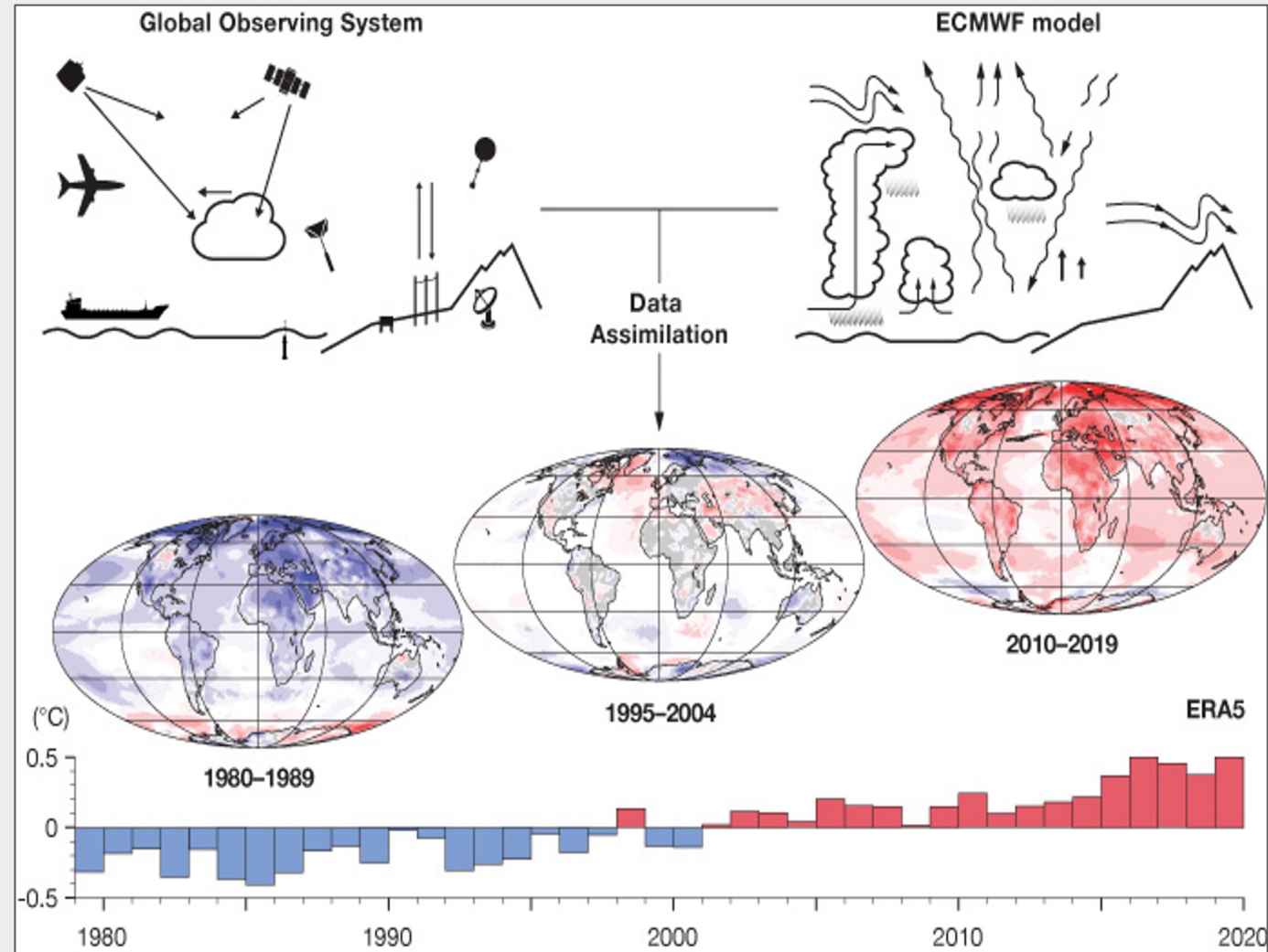
GraphCast architecture

[doi:10.48550/arXiv.2212.12794](https://doi.org/10.48550/arXiv.2212.12794)

How it works

Training data: [ERA5 reanalysis dataset](#)

- Reanalysis: incorporating observations into a physically consistent system to create a best guess of the true state of the system



[doi:10.1002/qj.3803](https://doi.org/10.1002/qj.3803)

<https://www.ecmwf.int/en/about/media-centre/focus/2023/fact-sheet-reanalysis>

How it works

Model	Training	Inference
Pangu-Weather Huawei	16 days on 192 V100 GPUs	24 hours forecast 1xV100 1.4 seconds on
GraphCast Google DeepMind	21 days on 32 Cloud TPU V4 devices (~128 GPUs)	10 days forecast 1 Cloud TPU V4 < 60 seconds
NWP (ECMWF HRES) *Higher resolution	-	10 days forecast 1/3/6 hours 11 664 cores HPC cluster

ML weather models: Remaining challenges

Extreme event detection and forecasting

- ML “foundation models” were trained to predict averages
- Reanalysis data doesn't capture some extreme events

Semi/Unsupervised learning

- Reduce reliance on Reanalysis data

Probabilistic forecasts

Will this scale from weather to longer (climate) time-scales?

Progress and remaining challenges

Addressing data limitations

- Climate models' time/space scales are too coarse for many adaptation/mitigation tasks
- Class imbalance: e.g., extreme events are rare by definition!
- Limited *labeled* data
- Unsupervised learning can help for all of the above!
- Data is limited along the time dimension
 - Can we substitute data diversity and granularity over space?

Non-stationarity

- Climate *change* means we cannot assume i.i.d. data!
- ML models need to adapt over time, and space

Interpretability

- Evaluation of generative models is an active research area of core ML

Long-term goals

Cascading Hazards

- Goal: move beyond individual weather extremes, to how they couple
- With massive wildfires everywhere, there is extreme urgency!

Climate Justice

- Our research should always help increase climate equity
- Ultimately, we should strive for approaches to help UNDO the legacy of climate IN-justice



Climate and Machine Learning Boulder (CLIMB)



Thank you!

And many thanks to:

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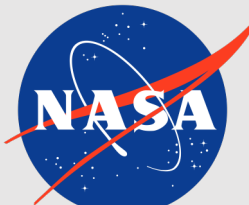
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Gavin A. Schmidt, *NASA Senior Advisor on Climate*

Saumya Sinha, *National Renewable Energy Lab*

Cheng Tang, *Amazon*





AI Research for Climate Change and Environmental Sustainability (ARCHES)

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