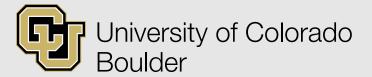


Al Research for Climate Change and Environmental Sustainability

Claire Monteleoni INRIA Paris









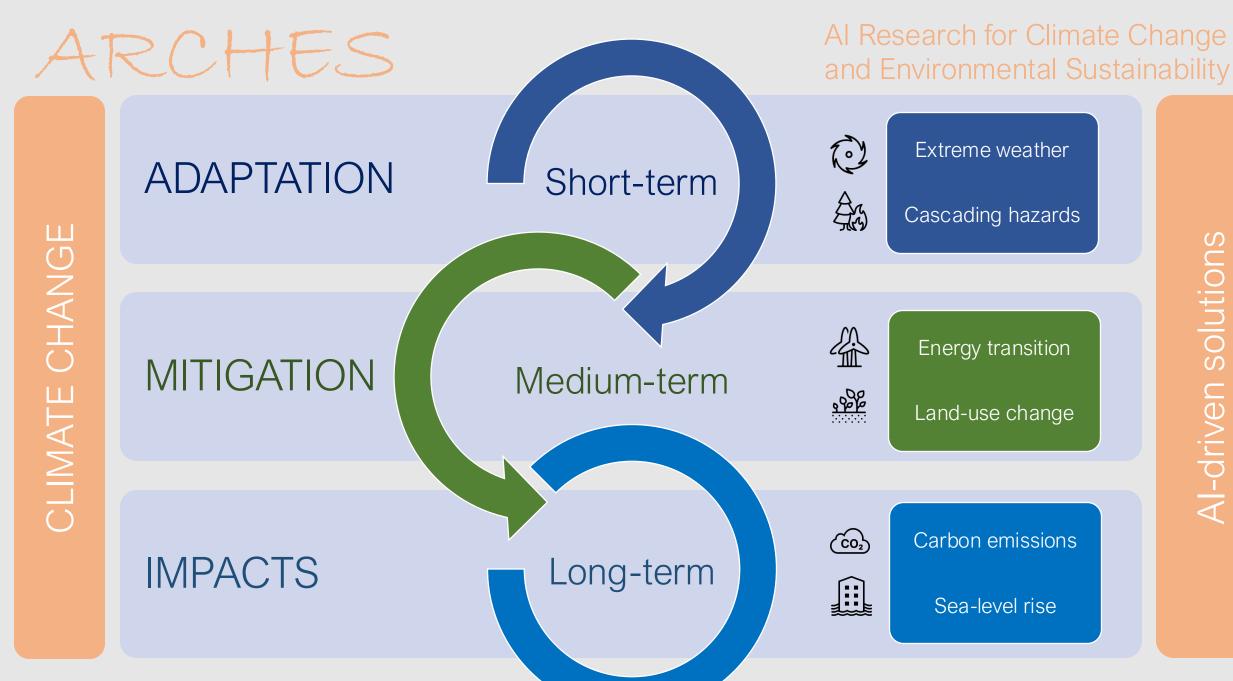


Climate Informatics: using Machine Learning to address Climate Change



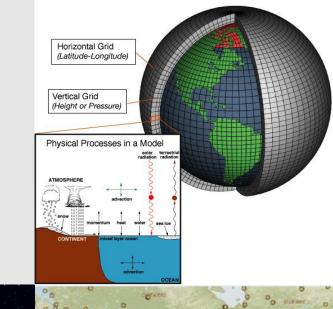
2008	Started research on Climate Informatics, with Gavin Schmidt, NASA
2010	"Tracking Climate Models" [Monteleoni et al., NASA CIDU, Best Application Paper Award]
2011	Launched International Workshop on Climate Informatics, New York Academy of Sciences
2012	Climate Informatics Workshop held at NCAR, 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
2024	13 th Conference on Climate Informatics, Turing Institute, London

2025 14th Conference on Climate Informatics, April 28-30th, Rio de Janeiro, Brazil



Approach: Exploit all available data

- ☐ Simulated data generated by physics-based models
 - ☐ Numerical Weather Prediction (NWP) models
 - ☐ General Circulation Models (GCM)
 - ☐ Regional Climate Models (RCM)
- Reanalysis data
 - ☐ Gridded data products from <u>data assimilation</u>:
 - applies physical laws to observations
- Observation data
 - ☐ Satellite remote sensing data
 - ☐ In-situ data

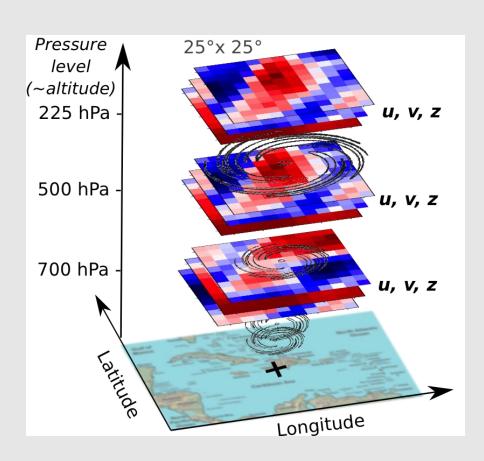


Al Methods

- □ Semi-supervised, unsupervised, self-supervised learning
 □ New methods for downscaling (super-resolution), interpolation of geospatial data
 - ☐ New pretext tasks for self-supervised learning, e.g., STINT [Harilal et al., 2024]
 - ☐ Regularization via multi-tasking over variables, lead-times
- Generative Al
 - ☐ VAE, Normalizing Flows
 - ☐ Diffusion and flow-based training
 - ☐ Develop new generative downscaling methods, e.g., [Groenke et al., 2020]
- Learning under non-stationarity
 - ☐ Learn level of non-stationarity over time and space

ADAPTATION

Al for Extreme Weather and Cascading Hazards



Hurricane track prediction

Forecasting Indian Summer Monsoon precipitation extremes

Avalanche detection

[Giffard-Roisin et al., Frontiers 2020]

Generative AI for weather forecasting



MITIGATION

Reducing carbon emissions

Accelerate green energy transition

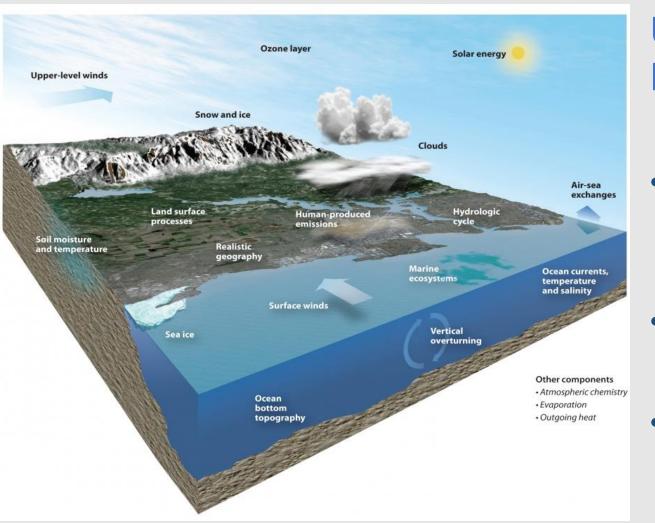
- Al-driven forecasting of solar, wind
- Al to downscale solar and wind data

Reduce compute for weather and climate modeling

 Once trained, AI is significantly faster at prediction than physical models

IMPACTS

Al for Understanding and Predicting Climate Change



Use AI to learn relations between IPCC simulations and observations

 Robustify climate model ensemble forecasts

Projecting long-term sea-level rise

Projecting long-term carbon emissions

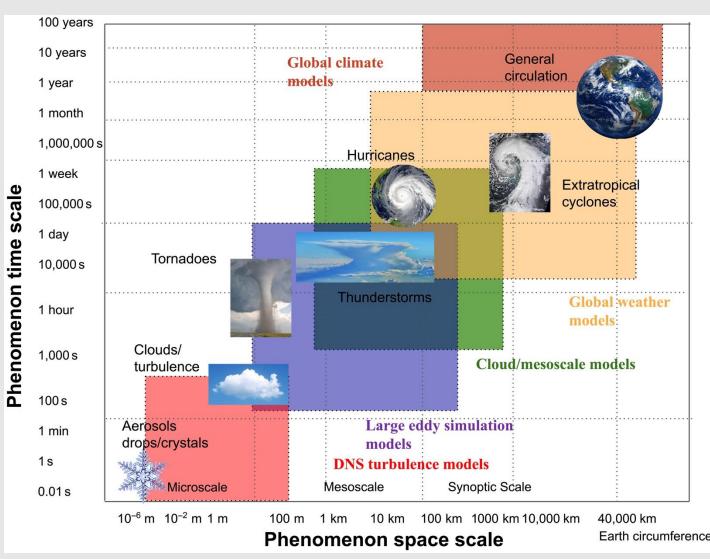
UCAR Science Education

Al for downscaling spatiotemporal data

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

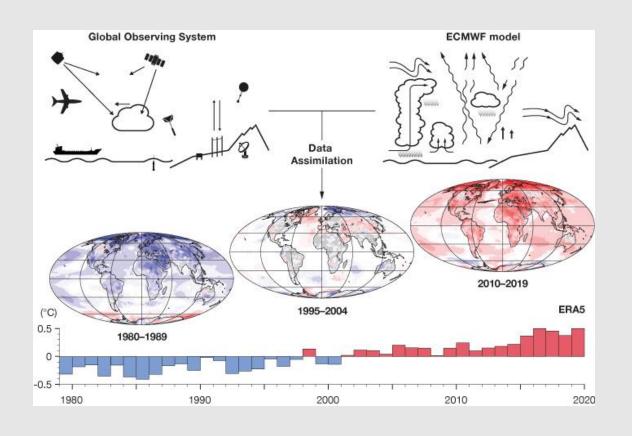
- Climate change adaptation
- Climate change mitigation
- Projecting long-term impacts

Approach: Use ML to <u>downscale</u> climate model data to relevant scales



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

Revolution in Al for weather forecasting



Since 2022, a variety of AI models have shown weather forecasting performance comparable or **BETTER** than numerical weather prediction (NWP).

These deep learning (DL) models are trained on <u>reanalysis</u> data (ERA5) to predict the next weather state given the current state

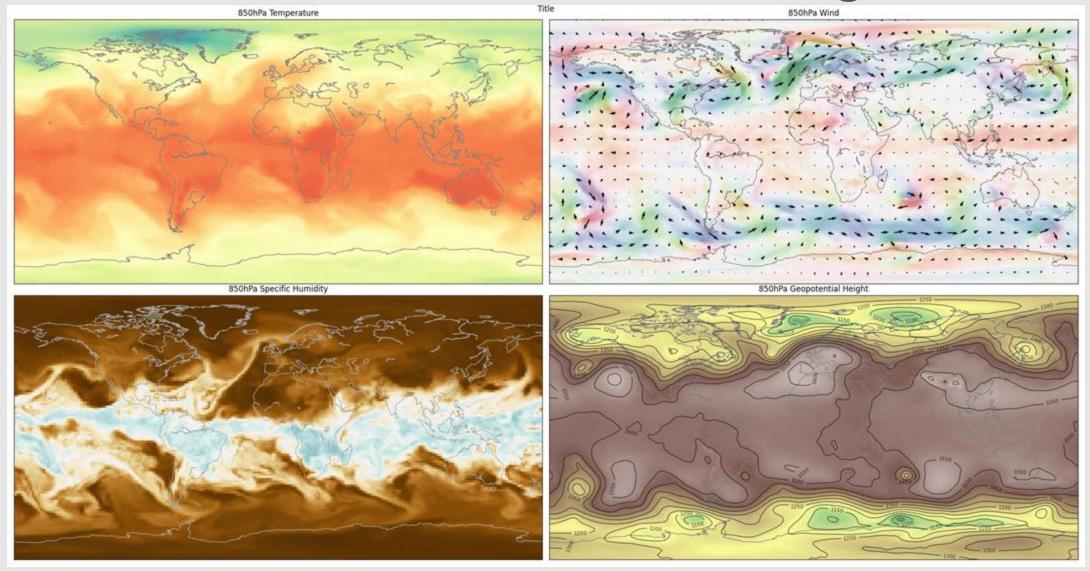
Model predictions are then « rolled-out » to forecast 7-10 days in the future

What is reanalysis data?

ArchesWeatherGen Geopotential Temperature Humidity Wind Speed 850hPa temperature CRPS [K] 850hPa wind speed CRPS [m/s] 500hPa geopotential CRPS [kg2/m2] 700hPa specific humidity CRPS [g/kg] IFS ENS 0.76 1.32 1.54 0.22 0.39 0.50 0.69 0.75 0.97 1.35 1.94 2.10 262 323 0.32 0.53 ArchesWeatherGen GenCast (oper.) 21 113 261 319 0.45 0.69 1.28 1.52 0.21 0.35 0.47 0.66 0.73 0.53 0.90 1.28 1.91 2.07 over ENS (%) average NeuralGCM Ens NeuralGCM ENS 253 318 0.71 1.29 1.54 0.37 0.48 0.67 0.75 0.95 1.30 1.91 2.10 1.28 1.53 GenCast 25 0.67 0.75 1.27 1.90 2.08 fCRPS skill score 3-10 days ArchesWeatherGer 55 110/ 0.47 0.67 0.93 1.29 1.90 DDPM(ArchesWeather backbone) Probabilistic Climatology **IFS ENS** Lead time [days] Lead time [days] Lead time [days] Lead time [days] State-of-the-art 10^{2} 10^{3} Training Budget (V100-days) Better ← % difference in RMSE vs IFS HRES → Worse performance, using Surface Pressure 10m Wind Speed Precipitation ArchesWeatherGen MUCH less compute! CRPS [m/s] NeuralGCM Ens 118 0.56 0.78 1.12 1.21 0.64 0.97 1.24 1.65 1.77 DDPM(ArchesWeather backbone) 115 246 0.51 0.74 1.10 1.19 1.59 1.73 ML / hybrid mod **IFS ENS** 1.12 1.57 1.72 239 0.72 1.08 1.19 ArchesWeather-Mx4 ArchesWeatherCo 0.54 0.75 1.10 Probabilistic Climatolog 10 10 10 5 10 Lead time [days] Lead time [days] Lead time [days] Lead time [days] GraphCast 10^{2} 10^{3} 10^{4} Training Budget (V100-days)

Better ← % difference in RMSE/SEEPS vs IFS HRES → Worse

Generative AI for weather forecasting



[Arches Weather Gen, Couairon, Singh, Charantonis, Lessig, Monteleoni, 2024]

Al for Climate Data Equity

- Train models in high-data regions and apply them in low-data regions
 - Train and validate them in high-data regions
 - Fine-tune them using the limited data in the low-data regions and use them to generate more data.
- Contribution to climate data equity
 - Local scales (e.g. legacy of environmental injustice in USA)
 - 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

"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."

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

Are Black Americans Underserved by the NWS Radar Network?

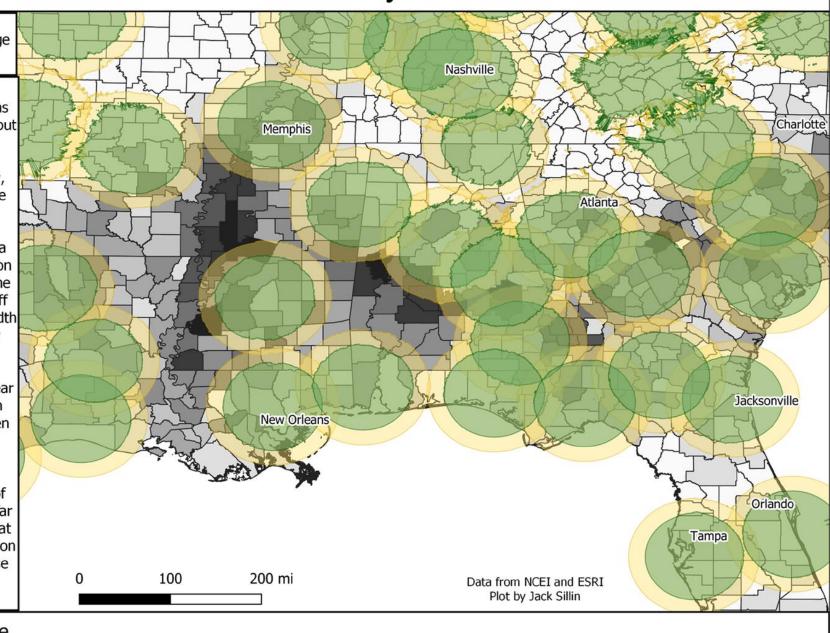
Excellent Radar Coverage
Good Radar Coverage

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.



Black Population Share

0-10%

10-20%

20-30%

30-40

40-5

50-6

60-7

70-8

8

80-90%

90-100

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:

Arindam Banerjee, *University of Illinois Urbana-Champaign* Nicolò Cesa-Bianchi, *Università degli Studi di Milano* Tommaso Cesari, *Toulouse School of Economics* Guillaume Charpiat, *INRIA Saclay*

Cécile Coléou, Météo-France & CNRS

Michael Dechartre, Irstea, Université Grenoble Alpes

Nicolas Eckert, Irstea, Université Grenoble Alpes

Brandon Finley, *University of Lausanne*

Sophie Giffard-Roisin, IRD Grenoble

Brian Groenke, Alfred Wegener Institute, Potsdam

Nidhin Harilal, University of Colorado Boulder

Tommi Jaakkola, MIT

Anna Karas, Météo-France & CNRS

Fatima Karbou, Météo-France & CNRS

Balázs Kégl, Huawei Research & CNRS

David Landry, INRIA Paris

Luke Madaus, Jupiter Intelligence

Scott McQuade, Amazon

Ravi S. Nanjundiah, Indian Institute of Tropical Meteorology

Moumita Saha, Philips Research India

Gavin A. Schmidt, NASA Senior Advisor on Climate

Saumya Sinha, National Renewable Energy Lab

Cheng Tang, Amazon





Inria Al Research for Climate Change and Environmental Sustainability (ARCHES)





An interdisciplinary, open access journal dedicated to the potential of artificial intelligence and data science to enhance our understanding of the environment, and to address climate change.

Data and methodological scope: Data Science broadly defined, including:

Machine Learning; Artificial Intelligence; Statistics; Data Mining; Computer Vision; Econometrics

Environmental scope, includes:

Water cycle, atmospheric science (including air quality, climatology, meteorology, atmospheric chemistry & physics, paleoclimatology)

Climate change (including carbon cycle, transportation, energy, and policy)

Sustainability and renewable energy (the interaction between human processes and ecosystems, including resource management, transportation, land use, agriculture and food)

Biosphere (including ecology, hydrology, oceanography, glaciology, soil science)

Societal impacts (including forecasting, mitigation, and adaptation, for environmental extremes and hazards) Environmental policy and economics

www.cambridge.org/eds







Environmental Data Science Innovation & Inclusion Lab

A national accelerator linking data, discovery, & decisions



NSF's newest data synthesis center, hosted by the University of Colorado Boulder & CIRES, with key partners CyVerse & the University of Oslo





