AI Research
for Climate Change and Environmental Sustainability

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Inria

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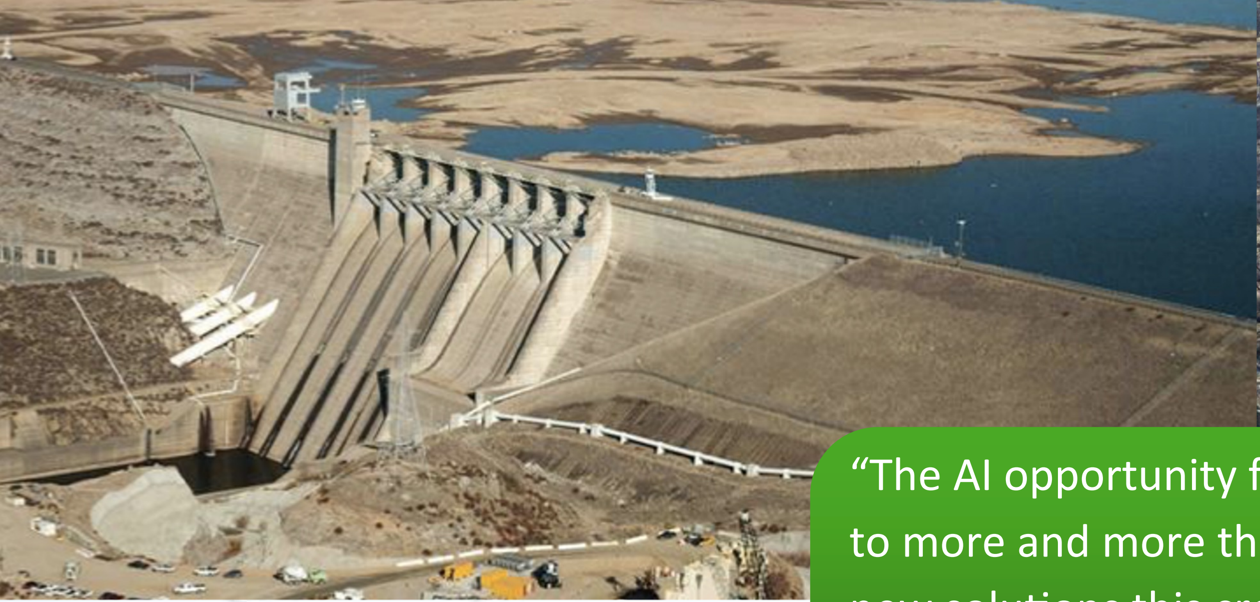
December 2021: Boulder County, Colorado

- 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



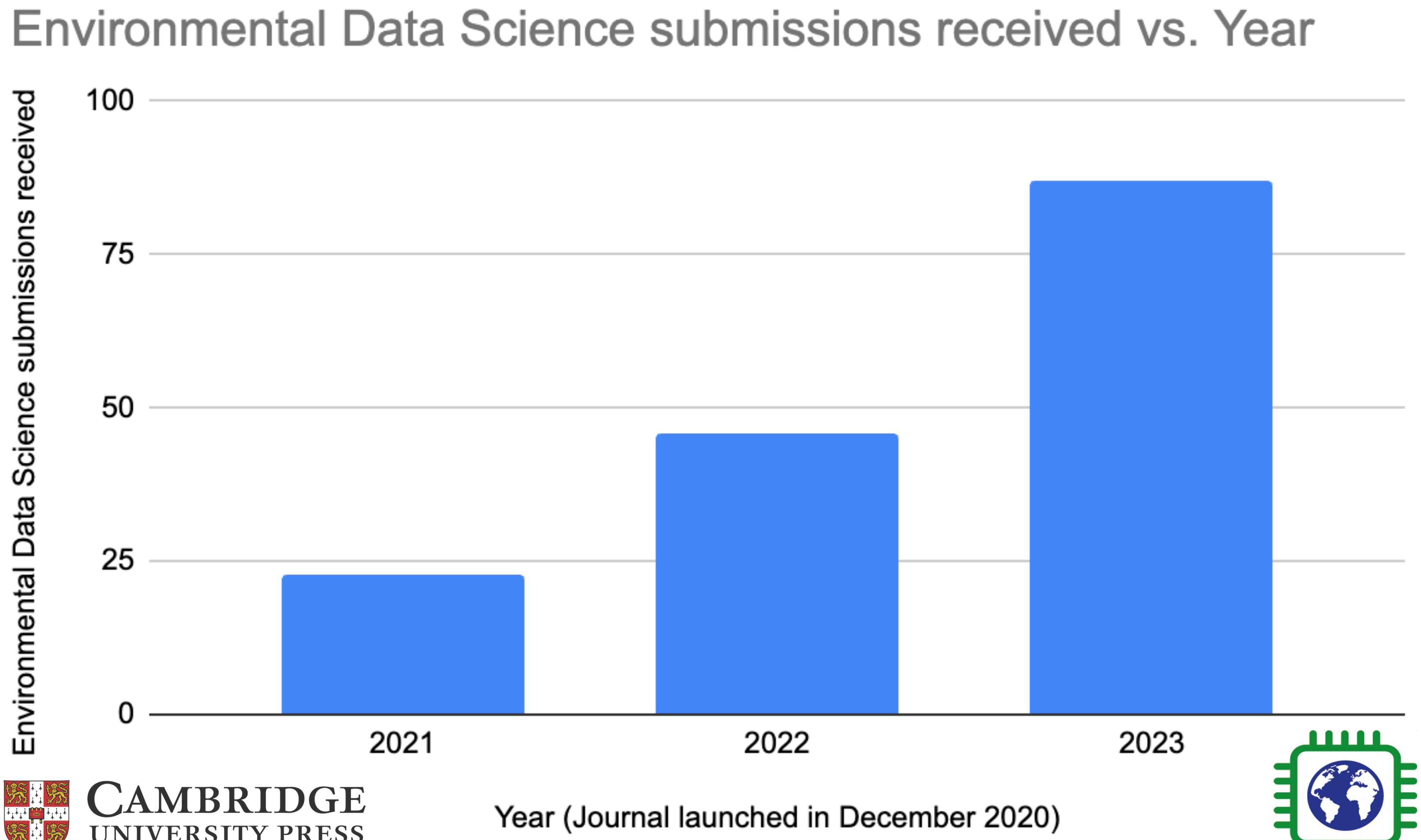
"The AI opportunity for the Earth is significant. Today's AI explosion will see us add AI to more and more things every year.... As we think about the gains, efficiencies and new solutions this creates for nations, business and for everyday life, we must also think about how to maximize the gains for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

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

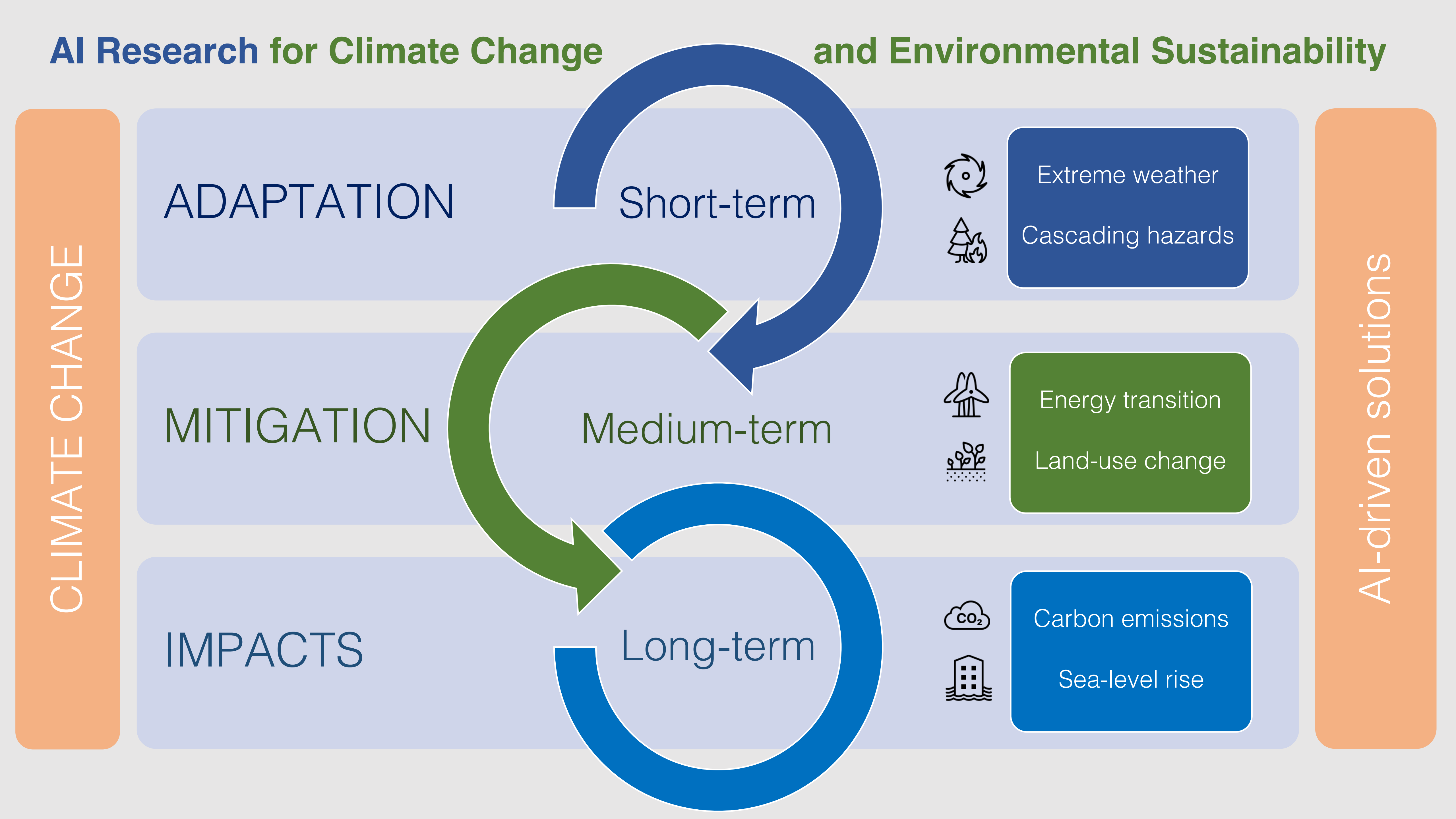
Climate Informatics is based on the vision that Machine learning can shed light on climate change

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, Cambridge, UK
2024 13th Conference on Climate Informatics, Turing Institute, London

Exponential growth in Environmental Data Science

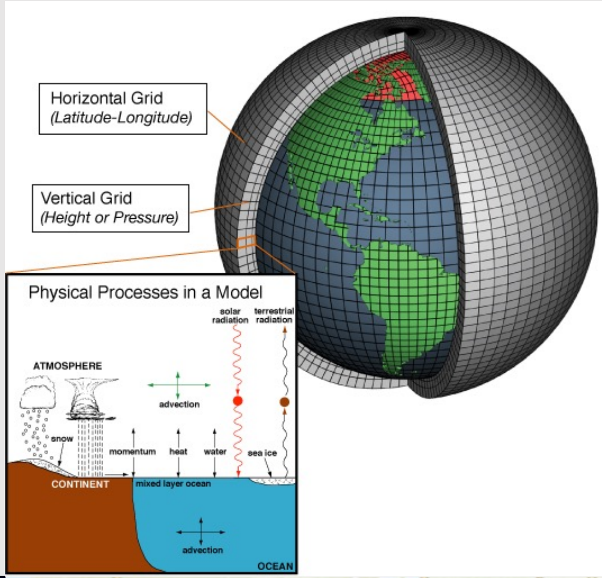


CAMBRIDGE
UNIVERSITY PRESS


AI Research for Climate Change and Environmental Sustainability
CLIMATE CHANGE
ADAPTATION
Short-term
Extreme weather
Cascading hazards
MITIGATION
Medium-term
Energy transition
Land-use change
IMPACTS
Long-term
Carbon emissions
Sea-level rise
CO_2
AI-driven solutions

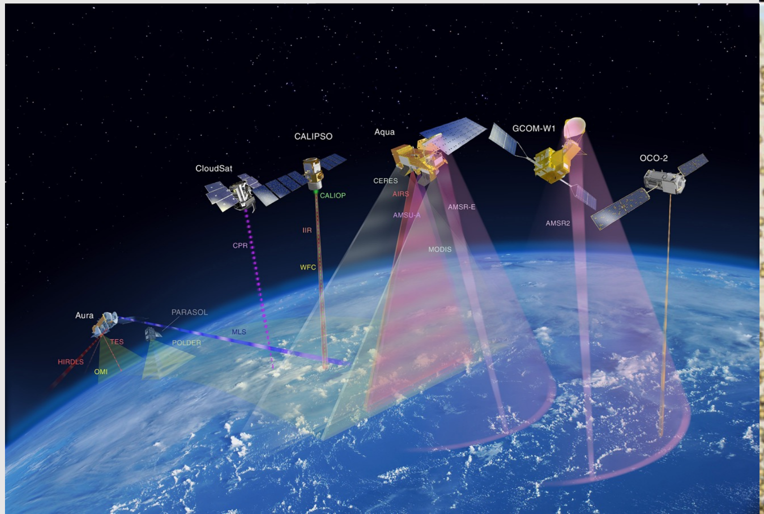
Approach: Exploit all available data

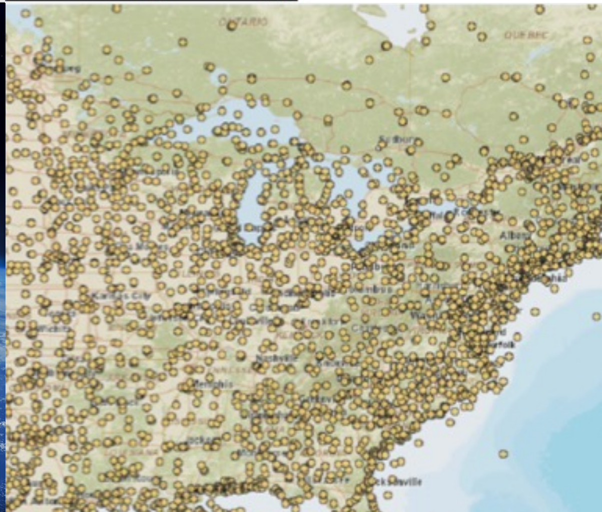
- Simulated data generated by physics-based models
  - Numerical Weather Prediction (NWP) models
  - General Circulation Models (GCM)
  - Regional Climate Models (RCM)



- Reanalysis data
  - Gridded data products from data assimilation: applies physical laws to observations

- Observation data
  - Satellite remote sensing data
  - In-situ data



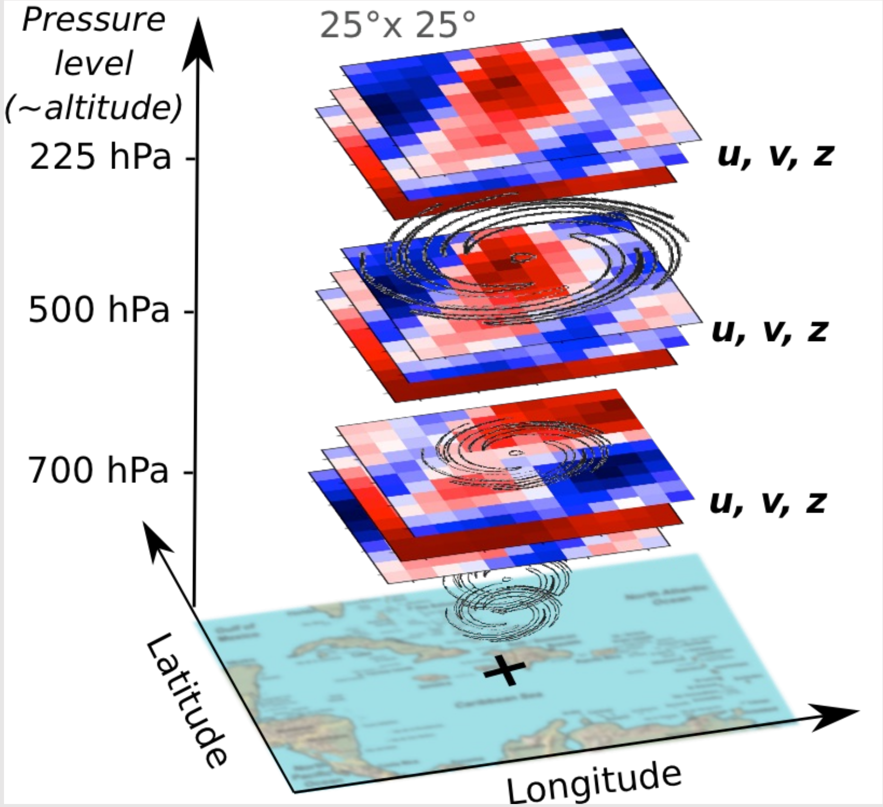


AI Methods

- 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 AI
  - VAE, Normalizing Flows
  - Diffusion models
  - 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

AI for Extreme Weather and Cascading Hazards



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

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] with India Meteorological Department (IMD)

Avalanche detection using CNN; VAE

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

ADAPTATION

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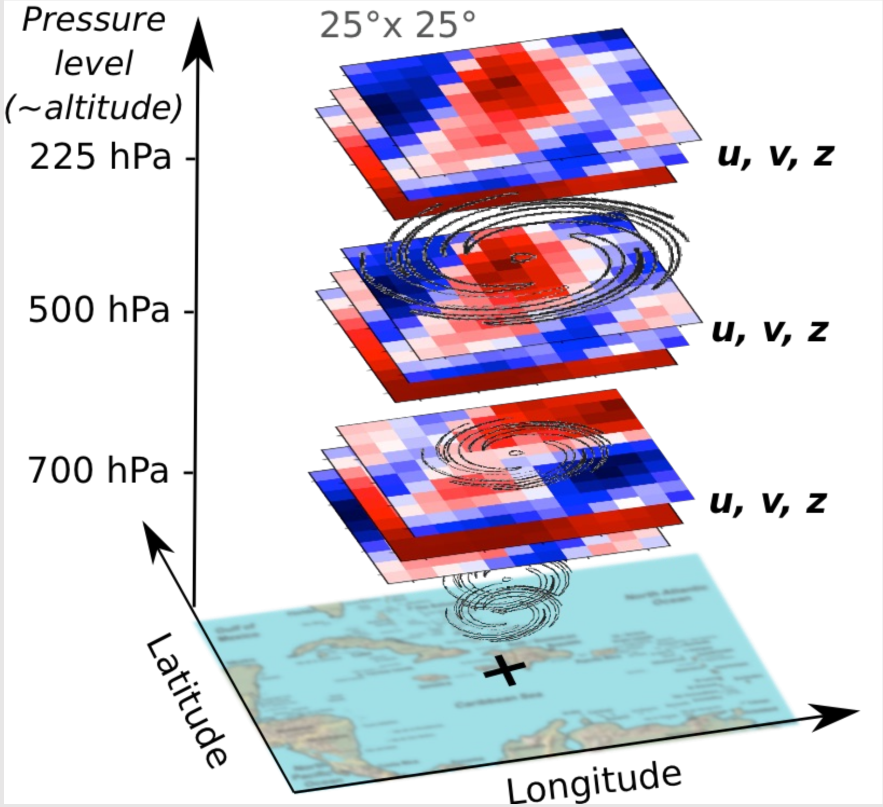


Hurricane track prediction via fused CNNs
[Giffard-Roisin et al., Frontiers 2020]

- Generative AI for weather forecasting
  - Build on the 2023 "AI revolution" in weather
  - Extend the benefits of diffusion models

  [Landry, Charantonis & Monteleoni, Month. Weather Rev. 2024]
- Precipitation
  - Key factor in many extreme events (flood/wildfire)
  - Difficult to measure, especially over water/ice
  - Discrete in time and space
- Extreme events
  - Such "outlier" events/hazards have outsized societal impacts
  - Rare → class-imbalance in historical data
  - Reanalysis data doesn't capture all the extreme events
  - The AI models are trained to predict averages, not extremes

MITIGATION

Reducing carbon emissions

Accelerate green energy transition

- AI-driven forecasting of solar, wind

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

- AI to downscale climate model outputs
  - [Harilal et al., NeurIPS workshop 2022] with NREL & IIT Roorkee
  - EDF projects: future wind & PV farms

AI-modeling effects of land(-use)-change on CO_2 emissions

- Currently large uncertainties in impacts
- Generate new scenarios with AI

Reduce compute needed for weather and climate modeling

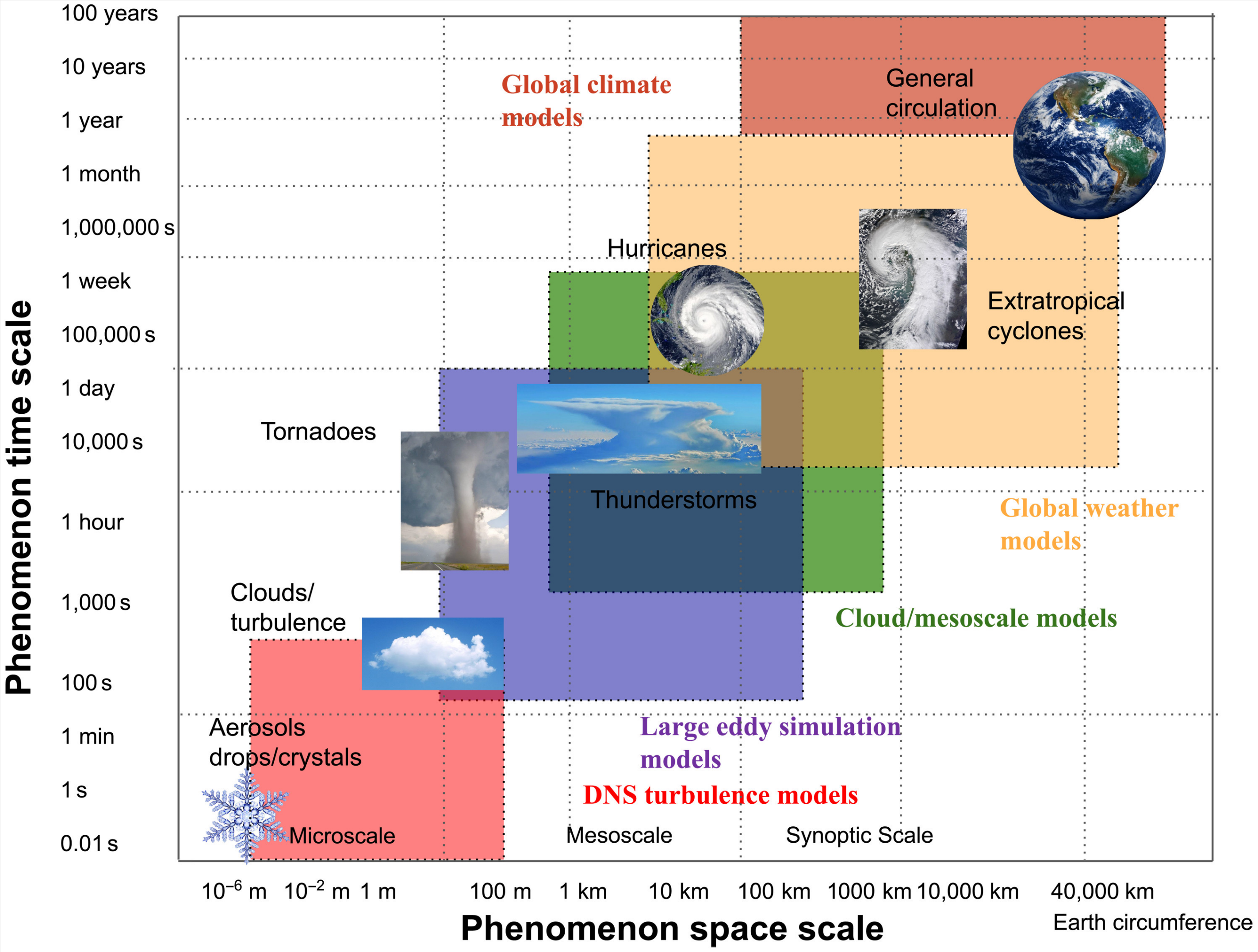
- Once trained, AI is significantly faster at prediction than physical models

Downscaling climate model simulations

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

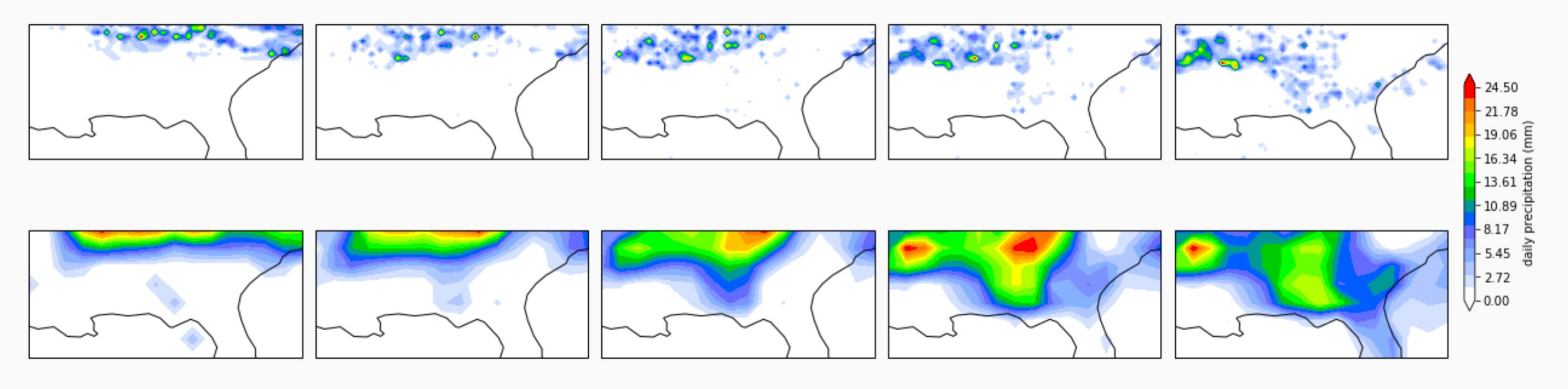
Approach: Use generative AI to downscale climate model data to relevant scales



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

ClimAlign: Unsupervised, generative downscaling

[Groenke, Madaus & Monteleoni, Climate Informatics 2020]



General downscaling technique via domain alignment with normalizing flows

[AlignFlow: Grover et al., AAAI 2020][Glow: Kingma & Dhariwal, NeurIPS 2018]

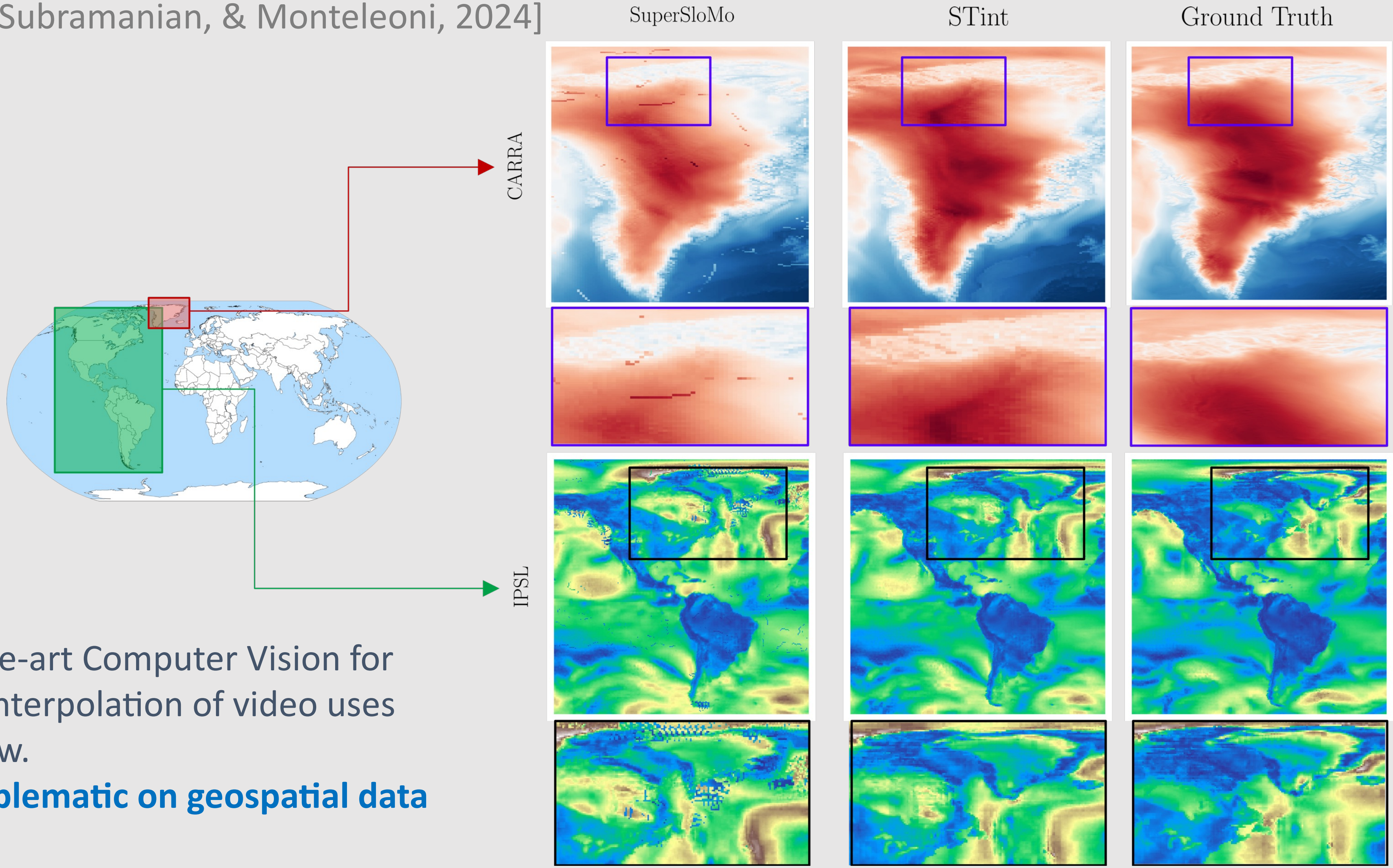
- **Unsupervised**: do not need paired maps at low and high resolution
- **Generative**: can sample from posterior over latent representation OR sample conditioned on a low (or high!) resolution map
- **Intepretable**, e.g., via interpolation

Why can't we just use existing AI algorithms?

- Climate change applications involve geospatial data evolving with time
  - Observation data that has been gridded over the globe using data assimilation
  - Simulations output by physics-driven models (NWP, GCM, RCM)
- These are tensors of real-values over latitude, longitude, time,
  and possibly over multiple climatological variables
- Computer Vision algorithms for "spatiotemporal data," rely on properties of video data that do not generalize well to geospatial data
  - e.g., depth, edges, and "objects"
  - vs. ephemeral patterns in fluids

STINT: Self-supervised Temporal Interpolation

[Harilal, Hodge, Subramanian, & Monteleoni, 2024]

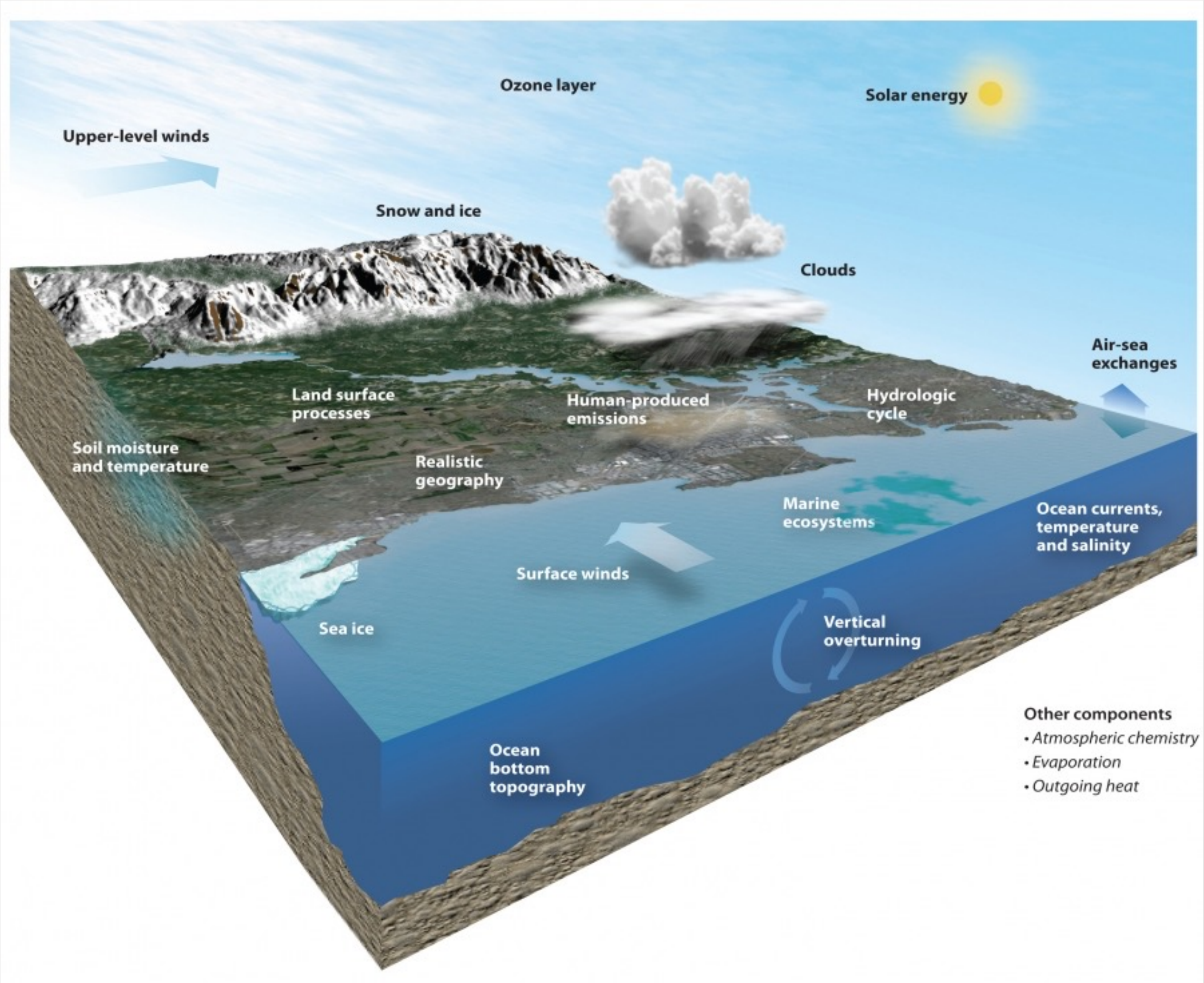


State-of-the-art Computer Vision for temporal interpolation of video uses Optical Flow.

This is problematic on geospatial data

IMPACTS

AI for Understanding and Predicting Climate Change



UCAR Science Education

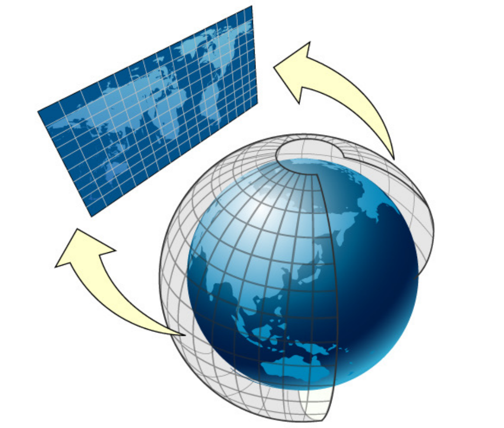
- Robustify climate model ensemble forecasts
  - Online learning for non-stationary spatiotemporal data [Multiple papers e.g., AAAI 2012, ALT 2020]
  - Generative AI for ensemble generation
- Projecting long-term sea-level rise
  - NASA: AI-fusion of climate model ensembles to predict future satellite altimetry [AGU 2022, ICLR 2023 workshop] – with NCAR, CU Boulder
- Projecting long-term carbon emissions
  - Extend ML models for carbon-flux to long-term

Our 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

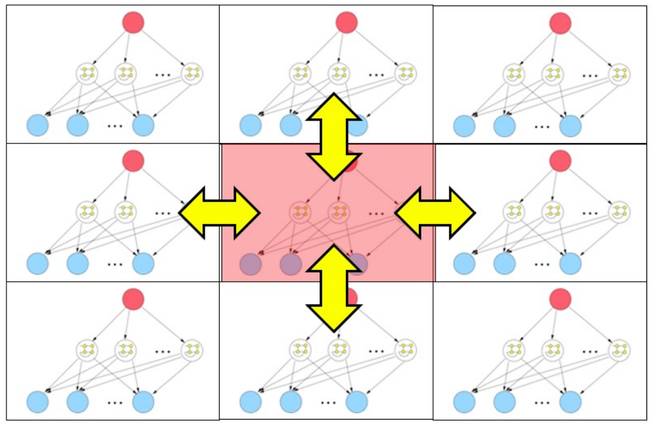
→ Position-Paper: Innovation in Application-Driven Machine Learning
[Rolnick et al., ICML 2024]

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

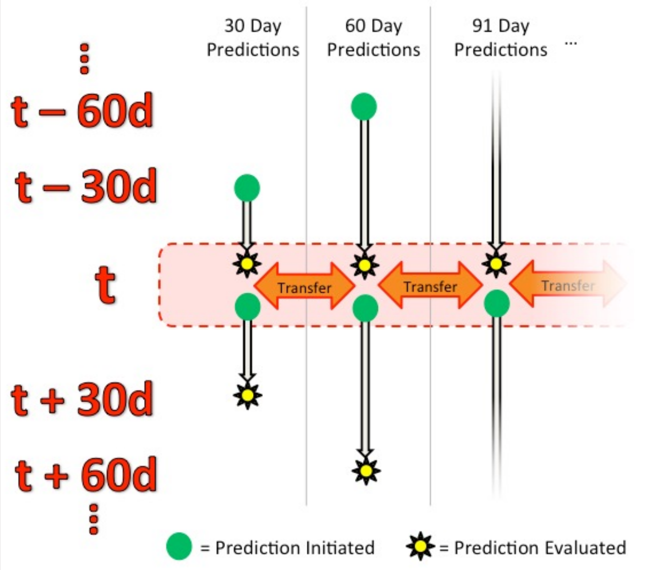


Distributed online learning: new ML framework

New “regret” theoretical analysis [Cesa-Bianchi, Cesari, & **M**, ALT 2020]

Prediction at multiple timescales simultaneously

Applications to both climate science, and financial volatility [McQuade & **M**, CI 2015; SIGMOD DSMM 2016]



Long-term goals

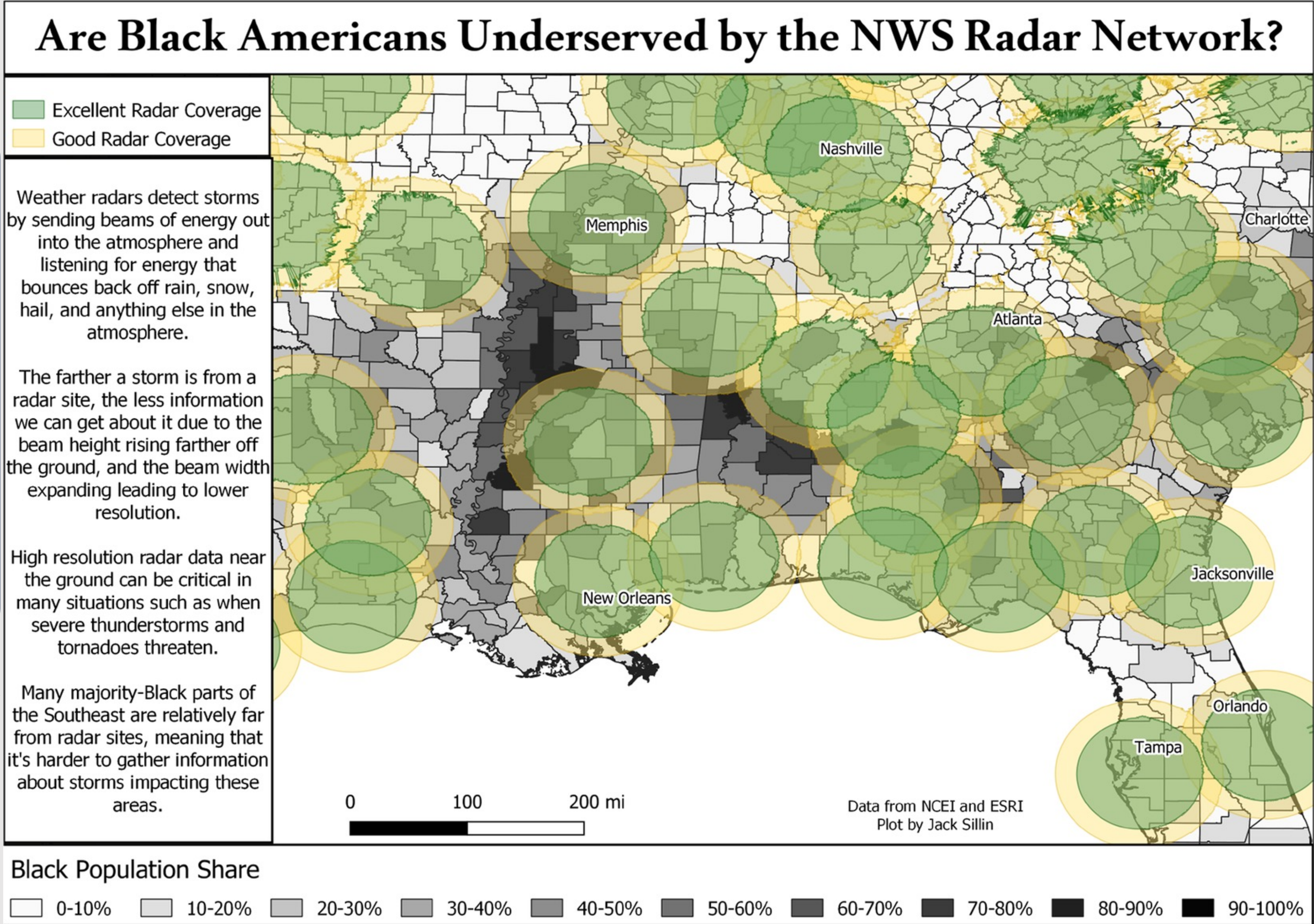
Cascading Hazards

- 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

“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]

AI for Climate Data Equity

- Train models in high-data regions and apply them in low-data regions
  - Can evaluate them against supervised learning models in high-data regions
  - Can fine-tune them using the limited data in the low-data regions

- Contribution to climate data equity
  - Local scales (e.g. legacy of environmental injustice in USA)
    - Learn “virtual sensors”
  - 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

Climate and Machine Learning Boulder (CLIMB)

Boulder

NSF

Climate Change AI

futurearth
Research. Innovation. Sustainability.

Thank you!

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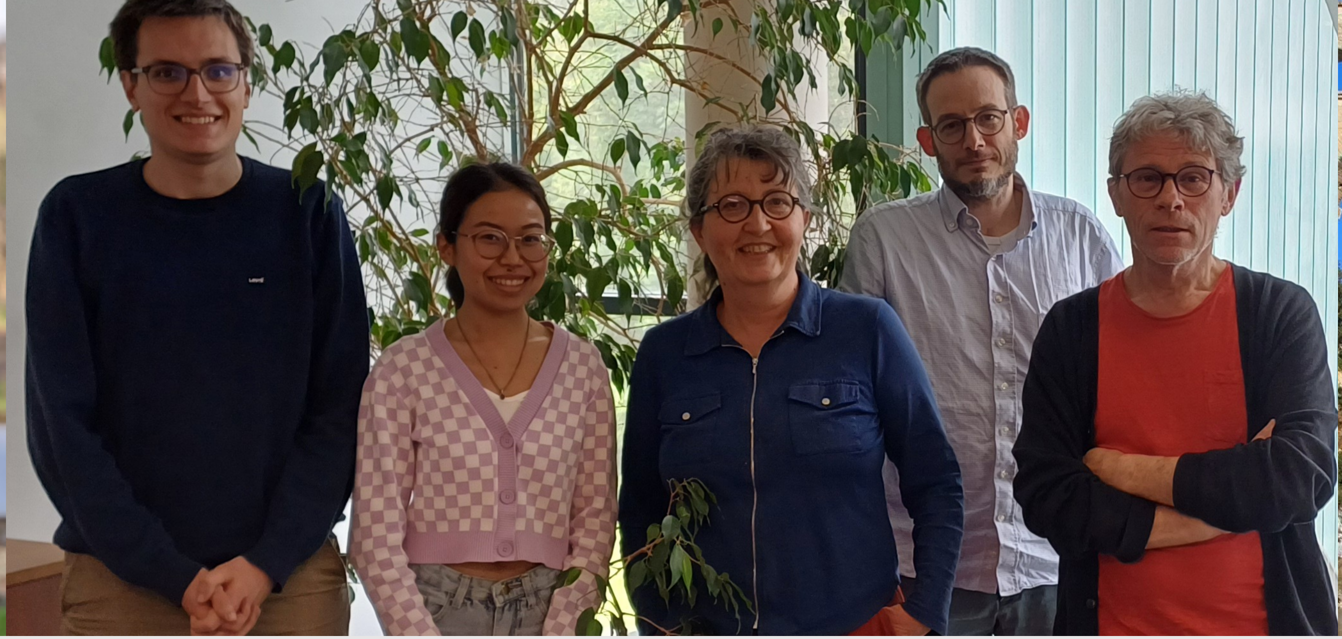
Saumya Sinha, *National Renewable Energy Lab*
Cheng Tang, *Amazon*

METEO FRANCE

NASA



ARCHES: AI Research for Climate Change and Environmental Sustainability

Environmental Data **S**cience **I**nnovation & **I**nclusion **L**ab

A national accelerator linking data, discovery, & decisions

ESIIL

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

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