Confronting Climate Change with Generative and Self-Supervised Machine Learning

Claire Monteleoni

INRIA Paris

University of Colorado Boulder

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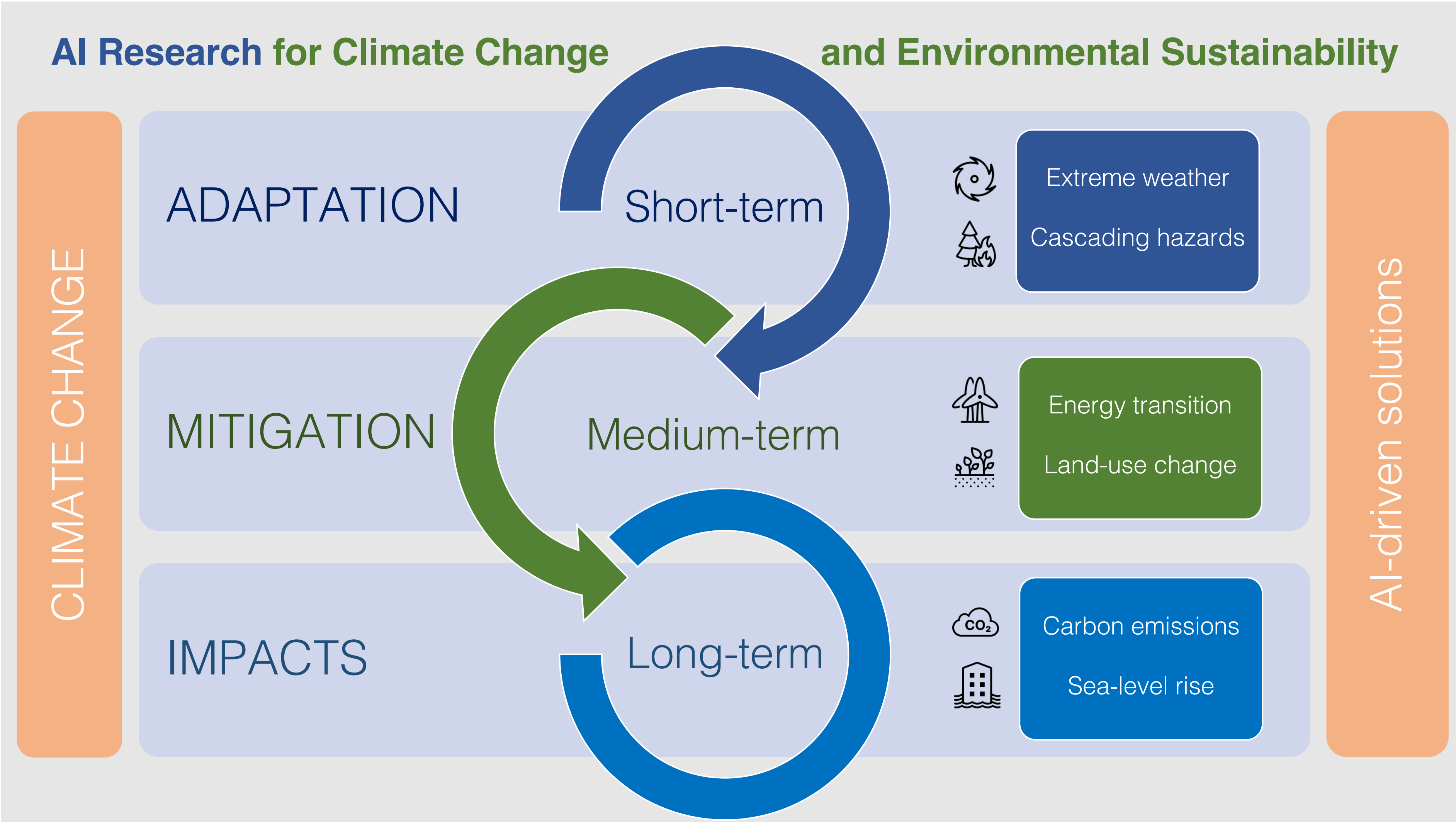
"The AI opportunity for the Earth is significant. Today's AI explosion will see us add AI to more and more things every year.... As we think about the gains, efficiencies and new solutions this creates for nations, business and for everyday life, we must also think about how to maximize the gains for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

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

Climate Informatics: 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 13th Conference on Climate Informatics, Turing Institute, London

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


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
CO_2
Carbon emissions
Sea-level rise
AI-driven solutions

Outline

What is self-supervised learning?

A pretext task for temporal interpolation of geospatial data

What is generative deep learning?

Normalizing flows for downscaling geospatial data

Implications for Climate Data Equity

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Unsupervised Deep Learning

- Supervised DL. Prediction loss is a function of the label, y, and the network's output on input x.

Network output

$$f_W(x) = \hat{y}$$

Loss function

$$\mathcal{L}(\hat{y}, y)$$

- Unsupervised DL. Prediction loss is only a function of x, and the network's output on input x. There is no label, y.

Network output

$$f_W(x) = \hat{x}$$

Loss function

$$\mathcal{L}(\hat{x}, x)$$

Self-Supervised Approach to Unsupervised learning

Self-supervised learning
A state-of-the-art approach to (deep) unsupervised learning

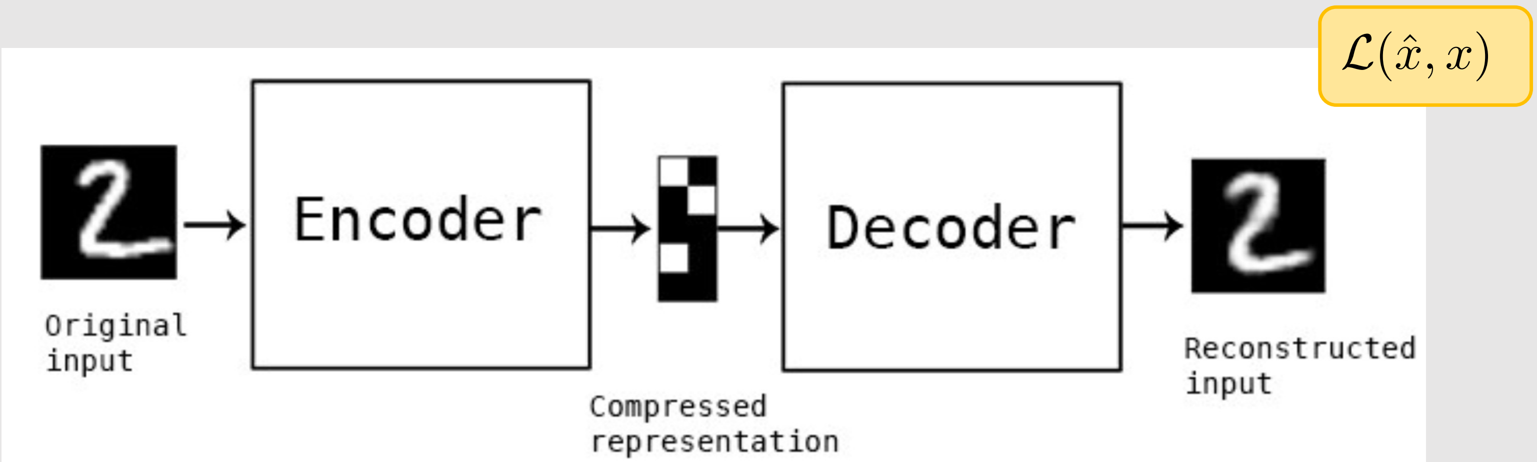
Design a pretext task:

- Design a supervised learning task using only the available data.
- Train a model on this task such that,
- the learned features (or the learned posterior over a feature space) will be useful for another (down-stream) task.

Pretext Task: Example

Classic example of a pretext task: Autoencoder

- Train a neural network in an unsupervised way
  - Use the unlabeled data both as input, and to evaluate the output
- After training, the bottleneck layer will be a compact representation of the input distribution



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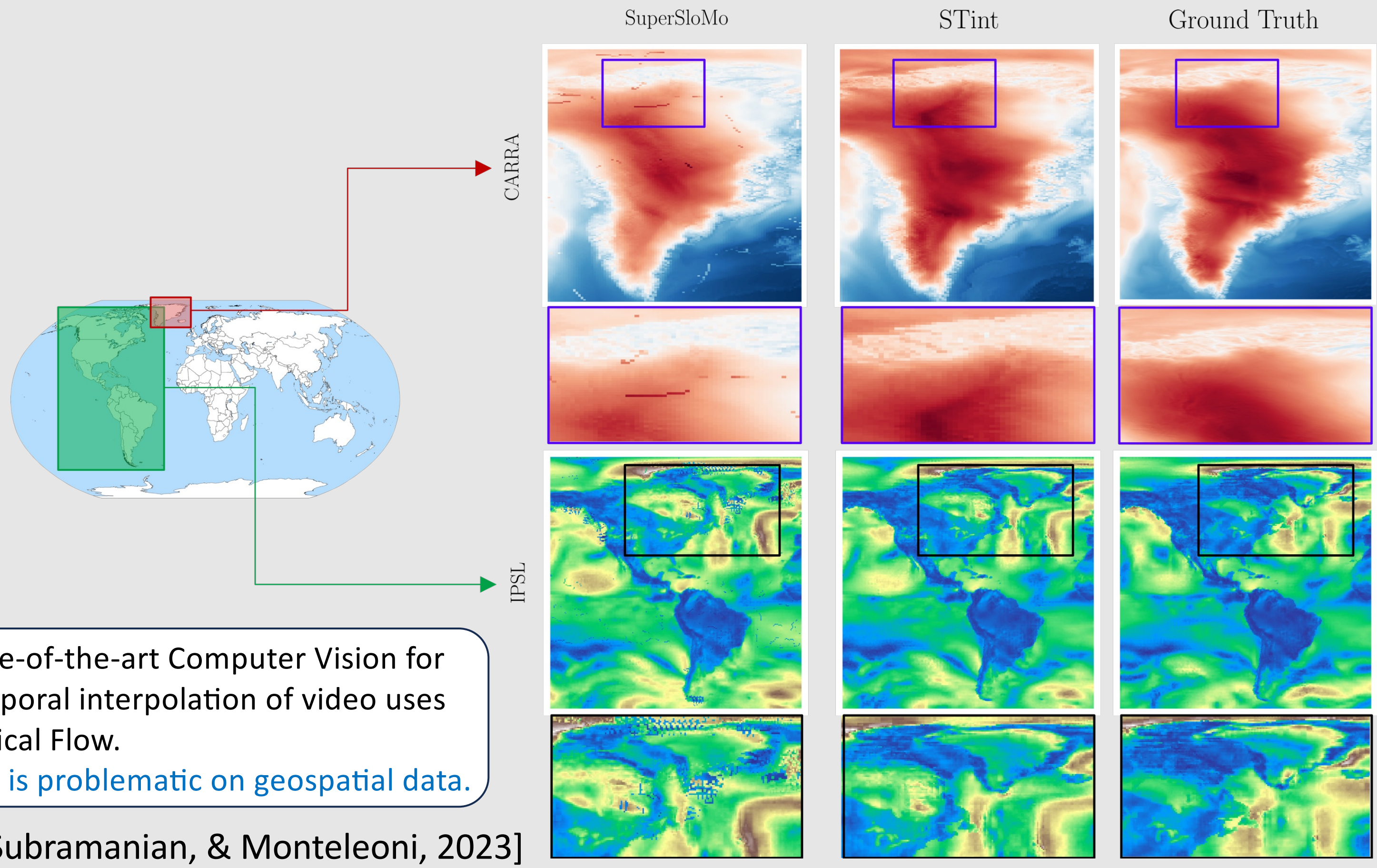
The problem

- 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



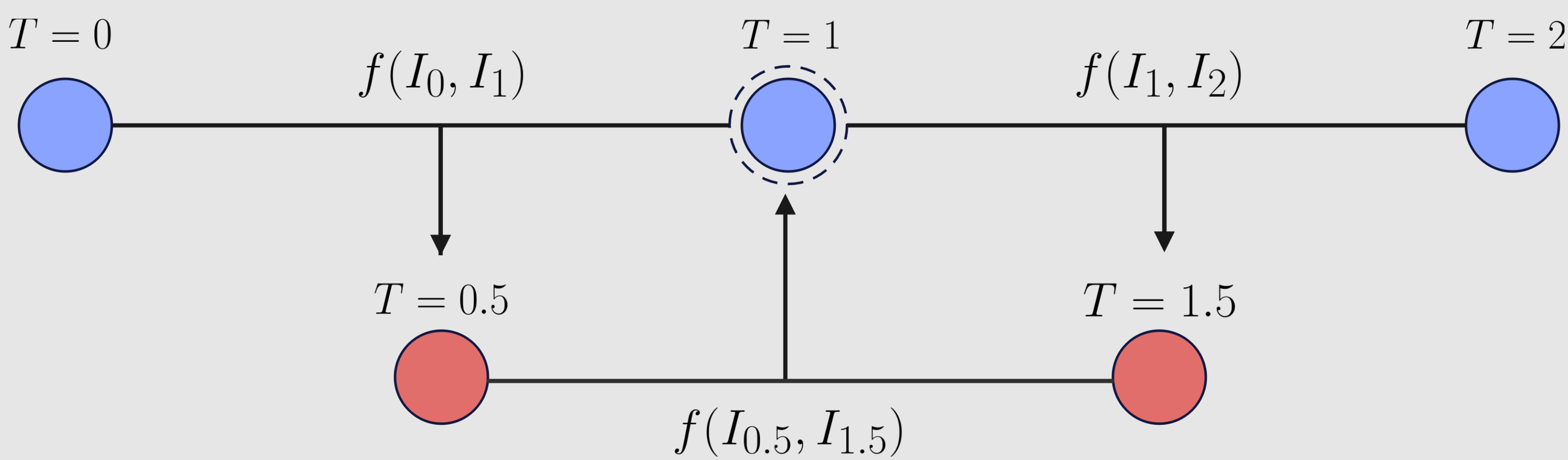
State-of-the-art Computer Vision for temporal interpolation of video uses Optical Flow.
This is problematic on geospatial data.

[Harilal, Hodge, Subramanian, & Monteleoni, 2023]

A pretext task for temporal downscaling

STINT: Self-supervised Temporal Interpolation for Geospatial Data

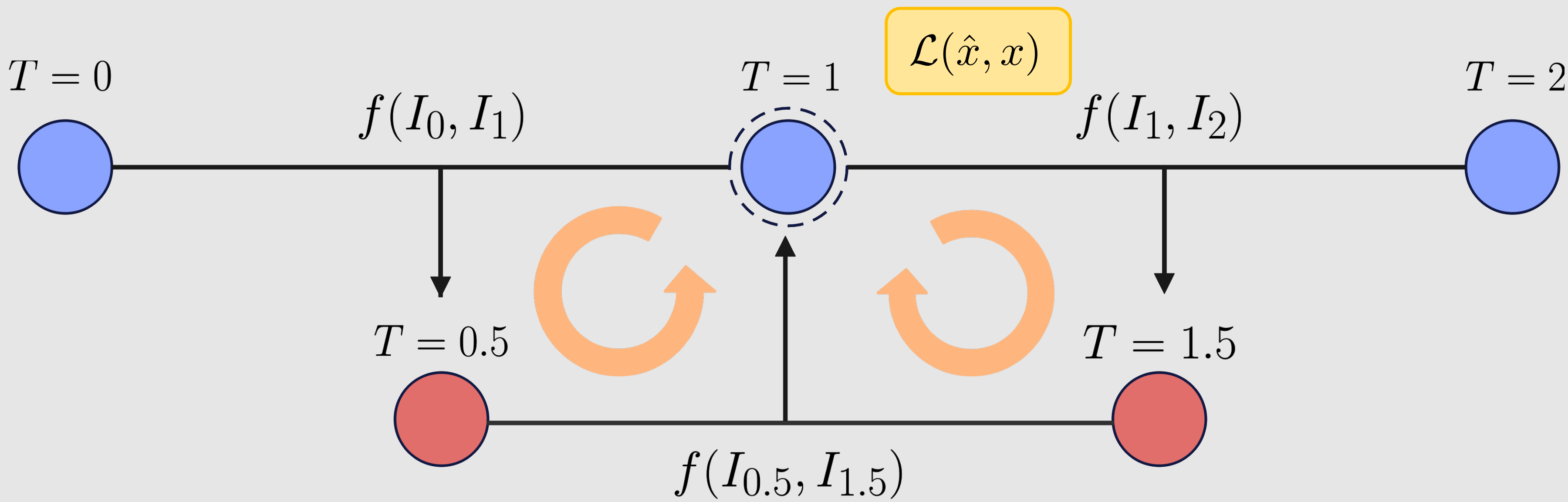
[Harilal, Hodge, Subramanian, & Monteleoni, 2023]



A pretext task for temporal interpolation

STINT: Self-supervised Temporal Interpolation for Geospatial Data

[Harilal, Hodge, Subramanian, & Monteleoni, 2023]



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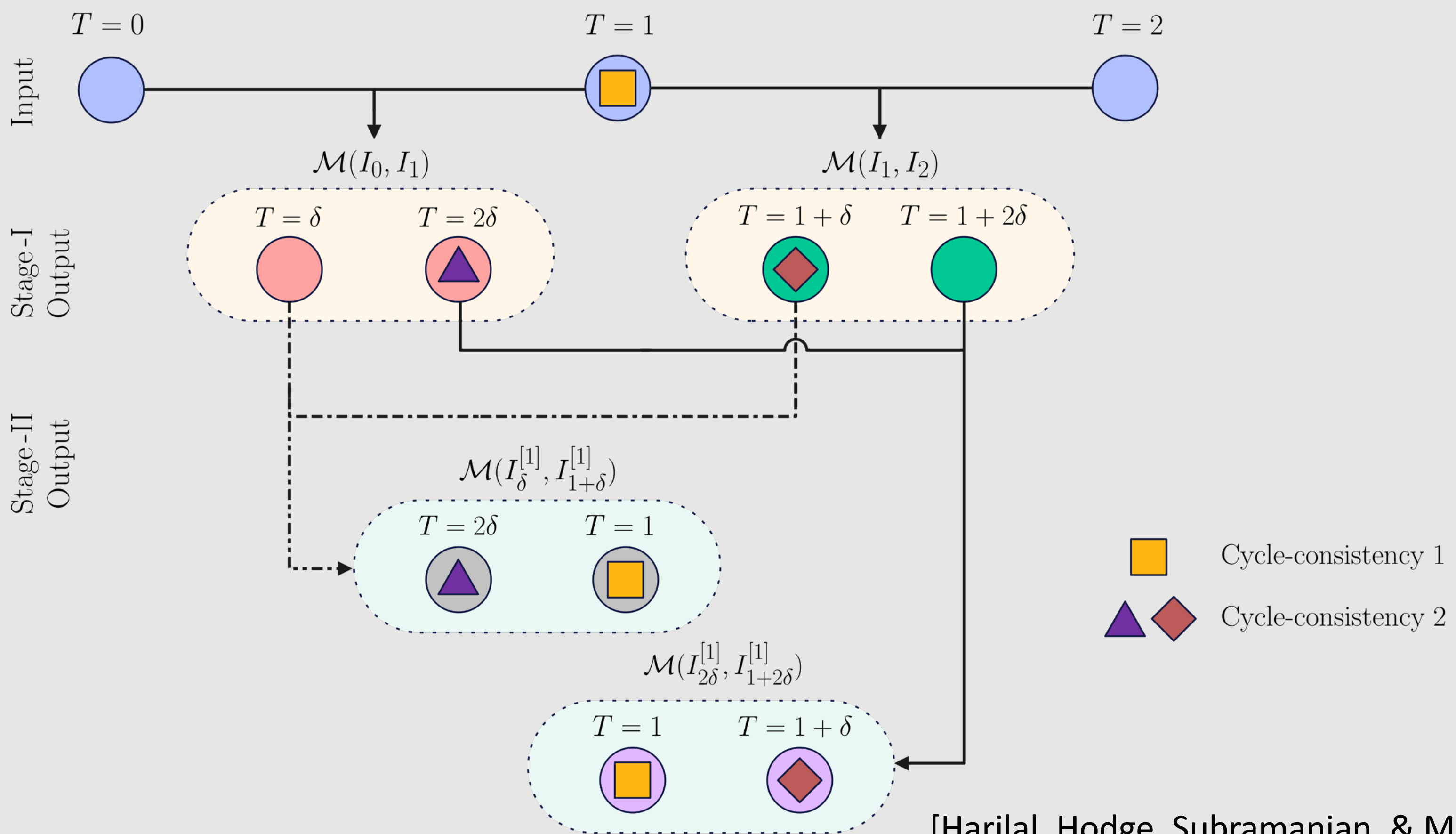
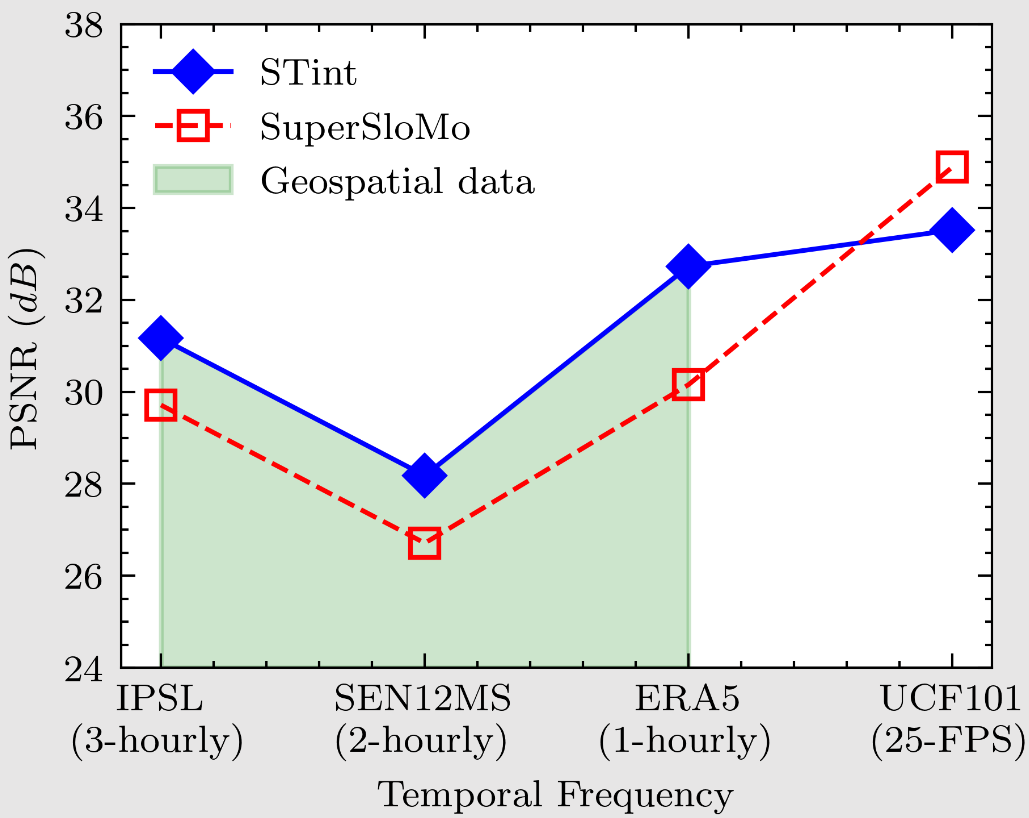


[Harilal, Hodge, Subramanian, & Monteleoni, 2023]

STINT: Self-supervised Temporal Interpolation



	$\frac{MSE}{Capacity}$ (↓)	PSNR (↑)	SSIM (↑)
ERA5 Solar			
Baseline	0.3086	25.238	0.623
SuperSloMo	0.0907	30.157	0.733
Proposed	**0.0561**	**32.731**	**0.792**
IPSL Wind			
Baseline	0.6206	24.097	0.619
SuperSloMo	0.4150	29.713	0.681
Proposed	**0.2904**	**31.167**	**0.713**
CARRA Temperature			
Baseline	0.5319	27.832	0.667
SuperSloMo	0.1604	30.276	0.724
Proposed	**0.0975**	**31.908**	**0.775**

[Harilal, Hodge, Subramanian, & Monteleoni, 2023]

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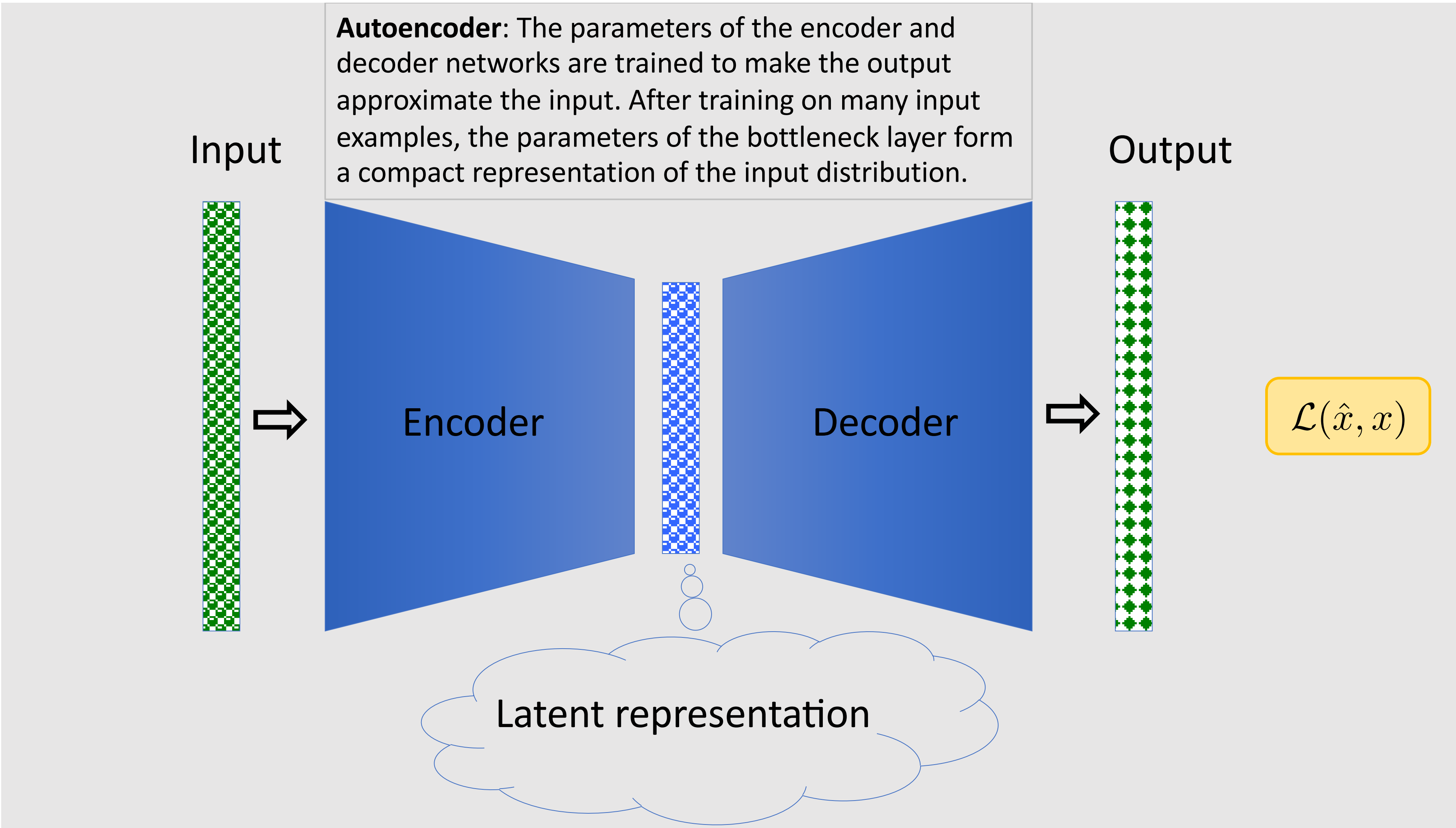
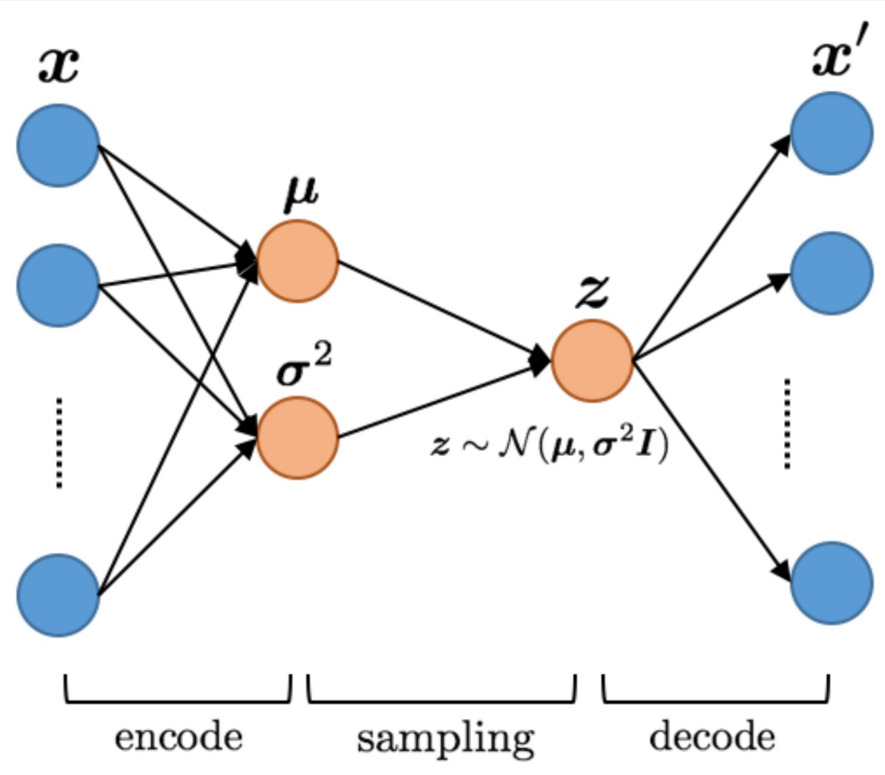
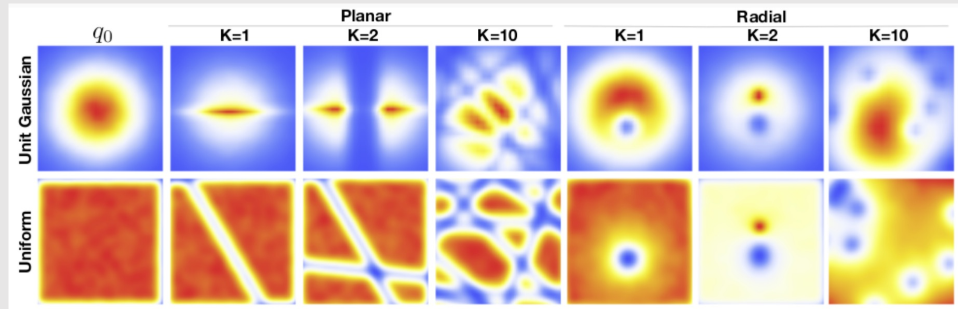

Autoencoder: The parameters of the encoder and decoder networks are trained to make the output approximate the input. After training on many input examples, the parameters of the bottleneck layer form a compact representation of the input distribution.
Input
Output
Encoder
Decoder
$\mathcal{L}(\hat{x}, x)$
Latent representation

Variational Autoencoder (VAE)

Learn a distribution over latent representations, instead of a single encoding



Normalizing Flows

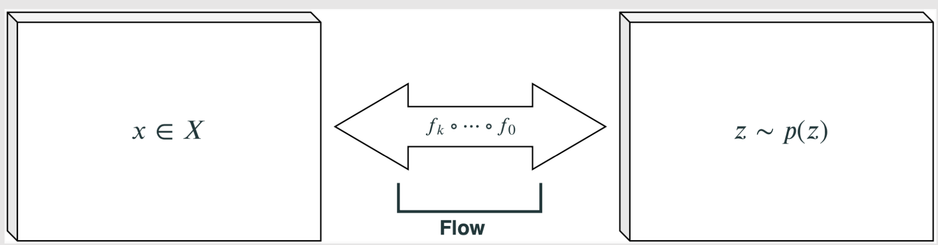


[Rezende & Mohamed, ICML 2015]

Can be viewed as extension of VAE beyond Gaussian assumption on latent space

Learn a series of invertible transformations, $\{f_i\}$, from a simple prior on latent space, Z, to allow for more informative distributions on the latent space:

$$z_k = f_k \circ f_{k-1} \circ \cdots \circ f_1(z_0)$$



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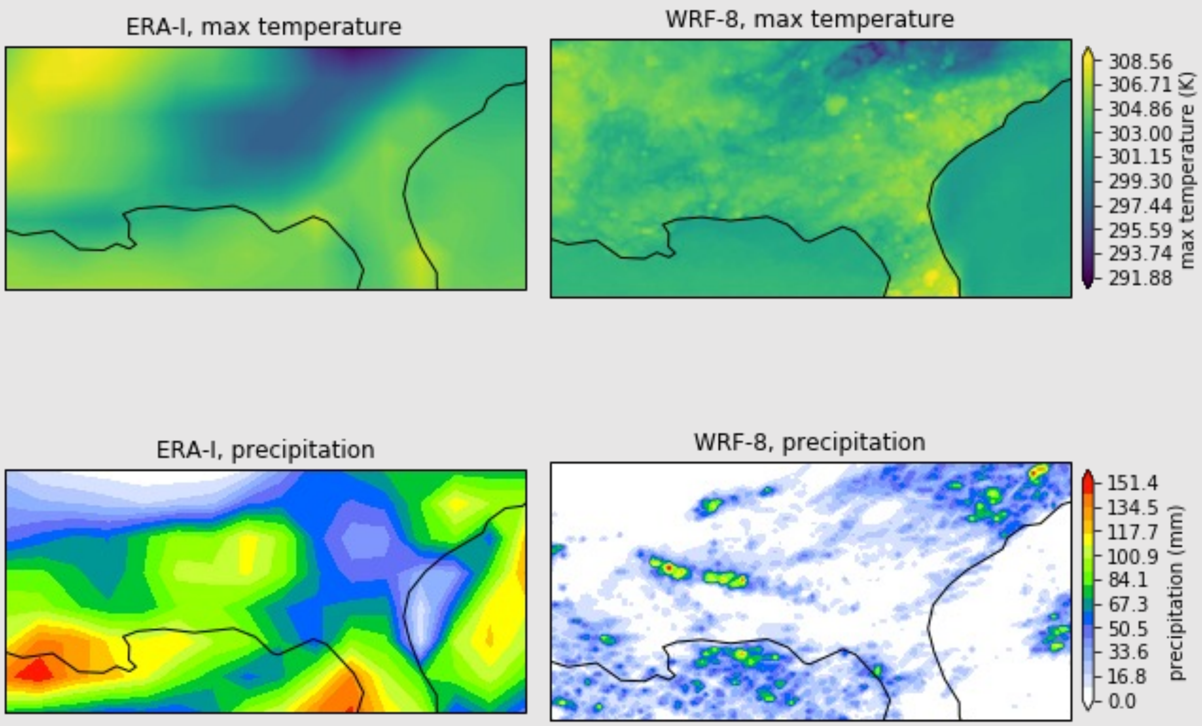
Normalizing Flows: Application to Spatial Downscaling

[Groenke, Madaus, & Monteleoni, Climate Informatics 2020]

ERA: reanalysis data, 1° resolution; WRF: numerical weather model prediction, $\frac{1}{8}$ ° resolution



Downscaling as Domain Alignment

- Domain alignment task: given random variables X, Y, learn a mapping f: X → Y such that, for any $x_i \in X$ and $y_i \in Y$,

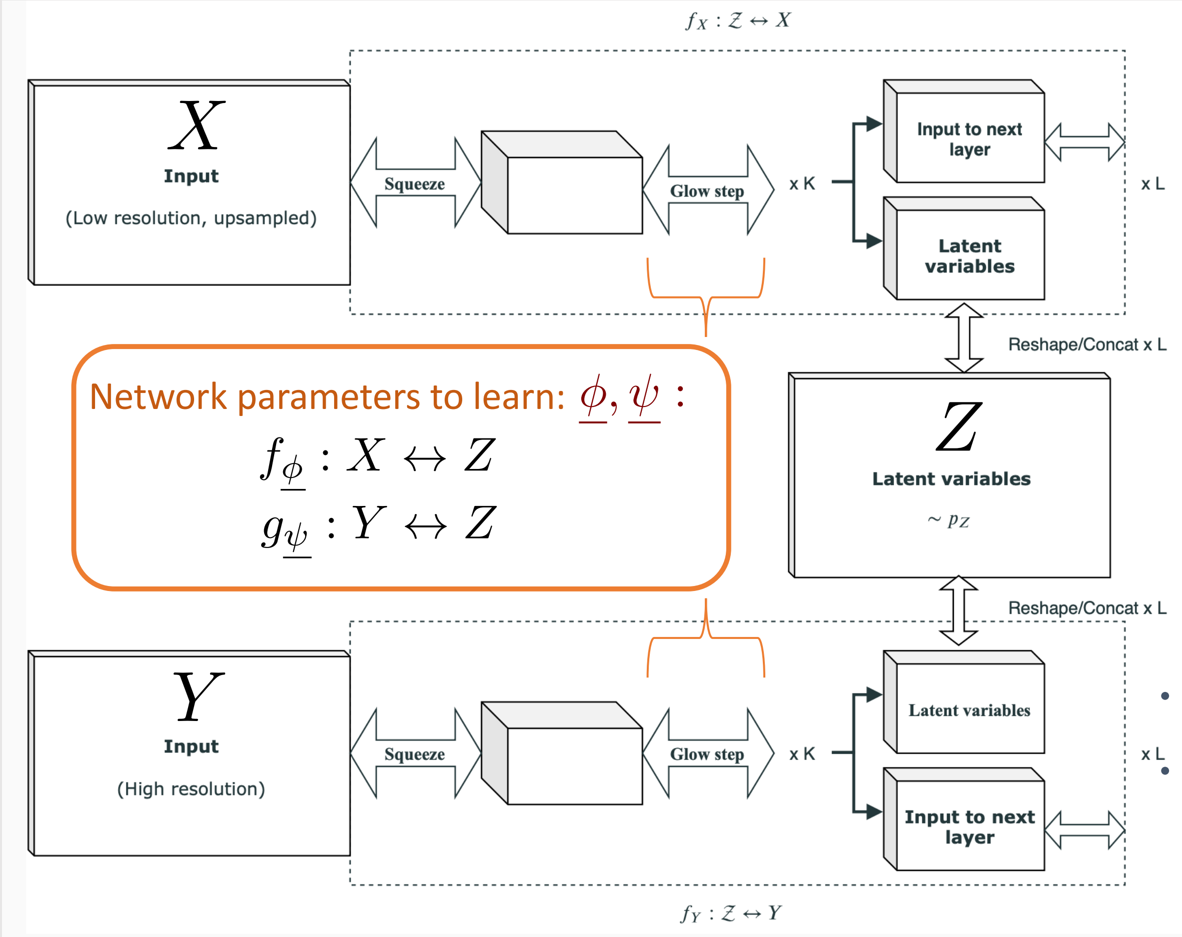
$$f(x_i) \sim P_Y \qquad\qquad f^{-1}(y_i) \sim P_X$$

- Downscaling as domain alignment
  - Given i.i.d. samples at low resolution (X) and high-resolution (Y)
  - Learn the joint PDF over X and Y by assuming conditional independence over a shared latent space Z,

$$P_{XY}(x,y) = \int_{z\in Z} P_{XYZ}(x,y,z)dz \;= \int_{z\in Z} P(x|z)P(y|z)P_Z(z)dz$$

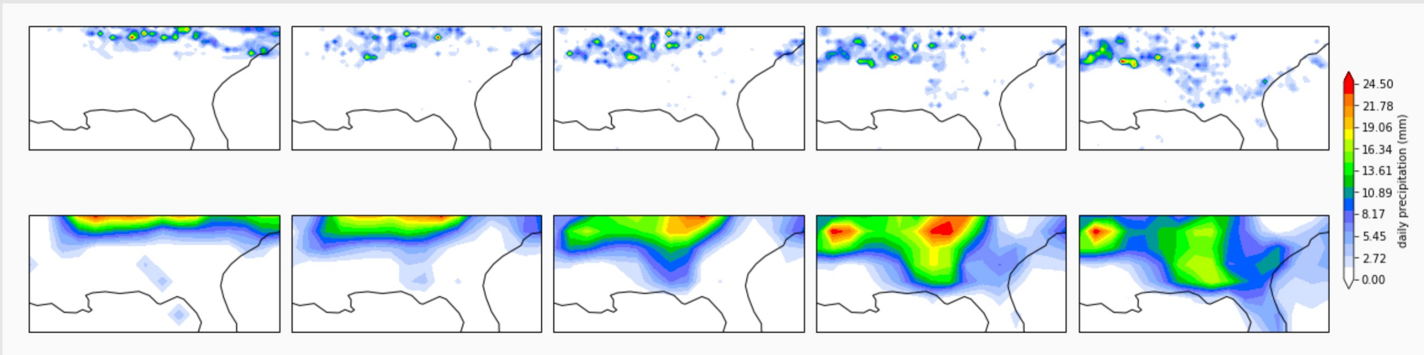
  - Model $P(x|z), P(y|z)$ using AlignFlow [Grover et al. 2020]
    - Starting with a simple prior on P_Z, learn normalizing flows
    - No pairing between x and y examples needed!

ClimAlign architecture



- Architecture follows AlignFlow [Grover et al., 2020]
- Normalizing flow: Glow [Kingma & Dhariwal, 2018]

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

[Groenke, Madeus, & Monteleoni, Climate Informatics 2020]

Summary & Outlook

A pretext task for temporal downscaling of geospatial data

- Works best when input data is spatially aligned

Normalizing flows for spatial downscaling of geospatial data

- Does not require temporal alignment of the coarse and fine scale data
- Works best when data is spatially aligned

Is there one pretext task for downscaling in both space and time?

- Does it provide features that are useful for other downstream tasks?

Other generative DL projects

- Landry, D., Charantonis, A., & Monteleoni, C. (2024). Leveraging deterministic weather forecasts for in-situ probabilistic temperature predictions via deep learning. Monthly Weather Review.
- Generative downscaling for solar and wind energy planning
- Ensemble generation via climate model emulation with diffusion training

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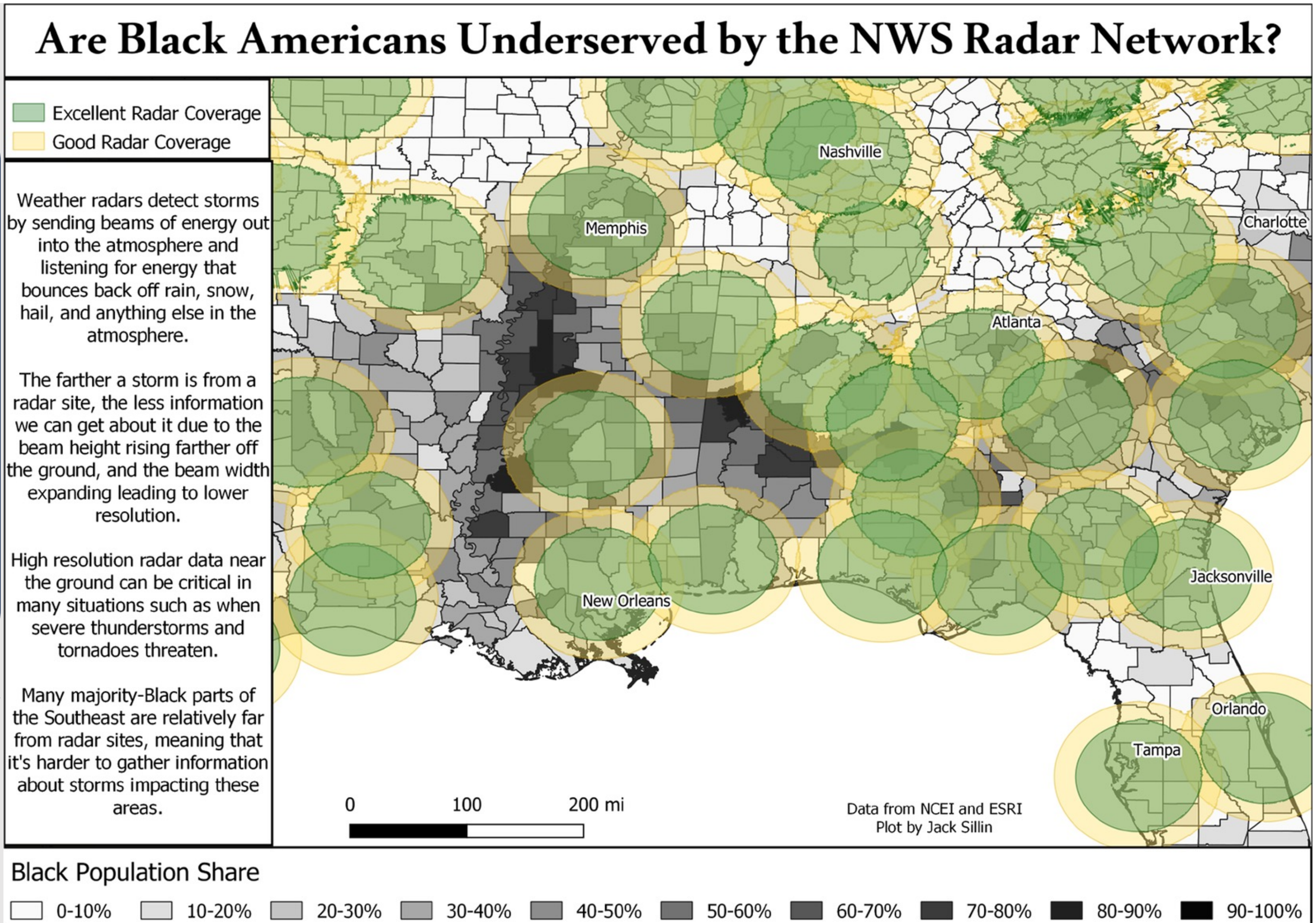
"Many majority-Black parts of the Southeast [USA] are relatively far from radar sites, meaning that it's harder to gather information about storms impacting these areas."



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)
  - 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*

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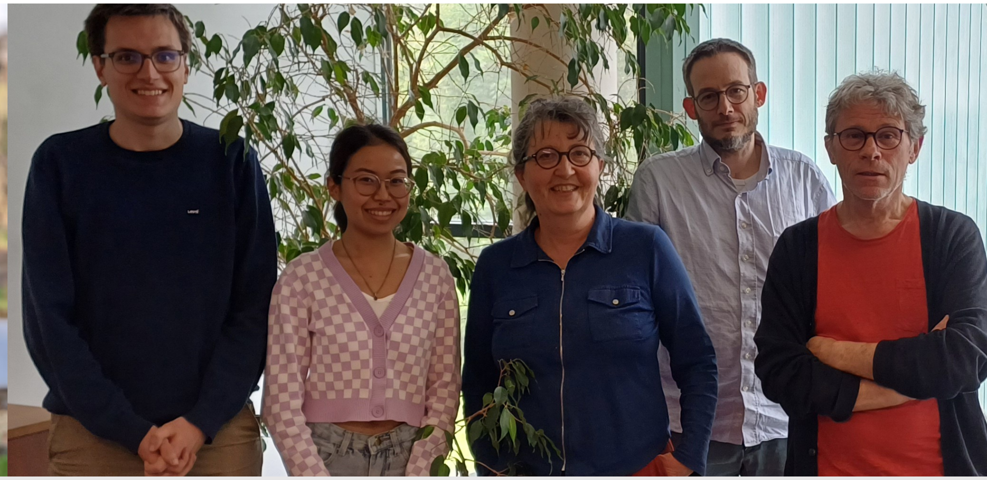


AI Research for Climate Change and Environmental Sustainability (ARCHES)

Environmental Data Science Innovation & Inclusion Lab

A national accelerator linking data, discovery, & decisions

ESIIL

NSF's newest data synthesis center,
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