Super-resolution and downscaling

12.S992 AI for Climate Action

Spring 2026

Speaker: Abigail Bodner

Super-resolution

A discretized model world

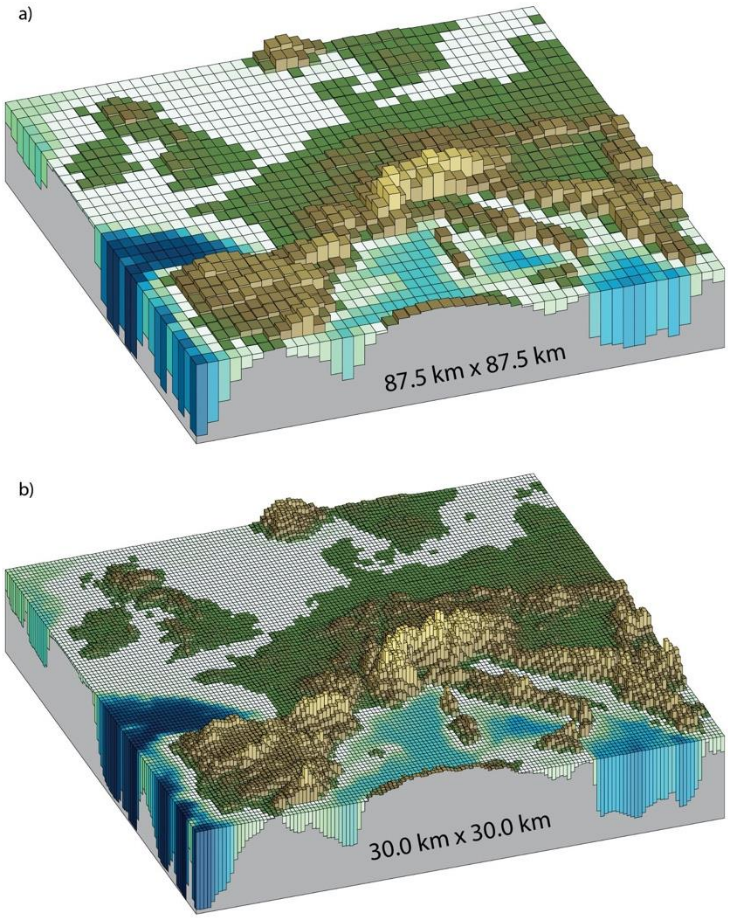

Figure 1.14 | Horizontal resolutions considered in today's higher resolution models and in the very high resolution models now being tested: (a) Illustration of the European topography at a resolution of 87.5 × 87.5 km; (b) same as (a) but for a resolution of 30.0 × 30.0 km.

Cubasch, U., D. Wuebbles, D. Chen, M.C. Facchini, D. Frame, N. Mahowald, and J.-G. Winther, 2013: Introduction. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

What's smaller than 100km?

https://en.wikipedia.org/wiki/Geography_of_the_United_Kingdom

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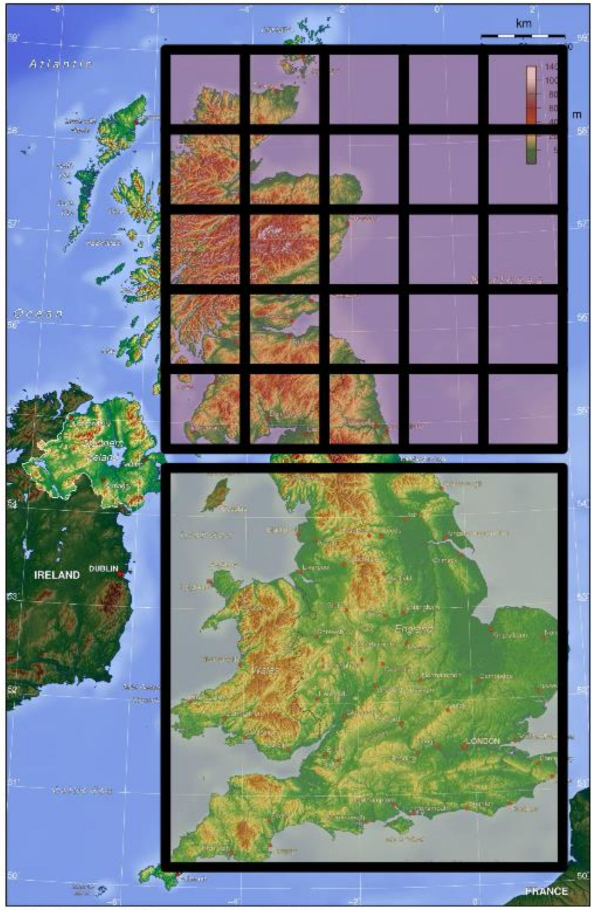

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New Models
(~100km)

Old Models
(~500km)

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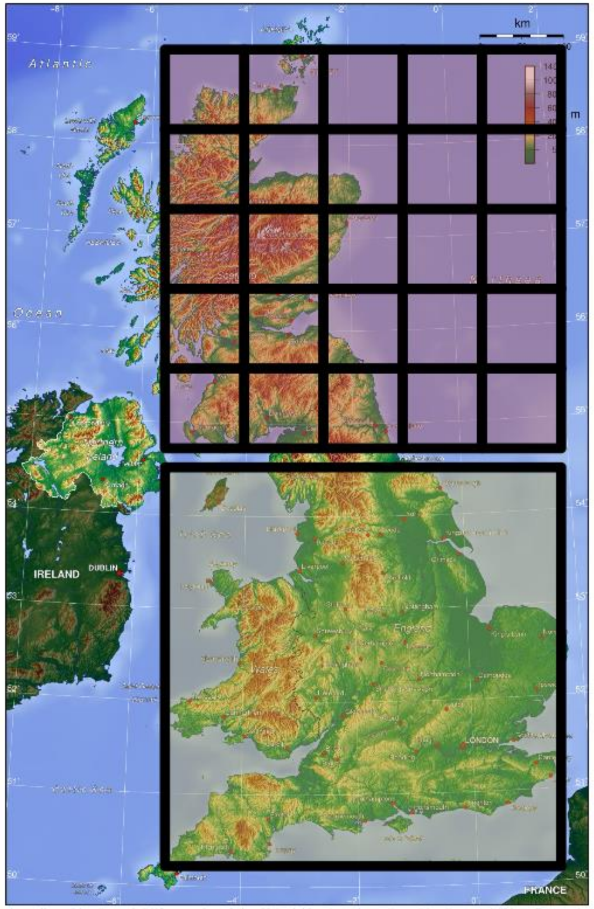

New Models
(~100km)

Old Models
(~500km)

Clouds (atmosphere) & surface conditions (land)

https://en.wikipedia.org/wiki/Geography_of_the_United_Kingdom ; https://en.wikipedia.org/wiki/New_Forest ; https://en.wikipedia.org/wiki/Iceberg ; https://en.wikipedia.org/wiki/Phytoplankton

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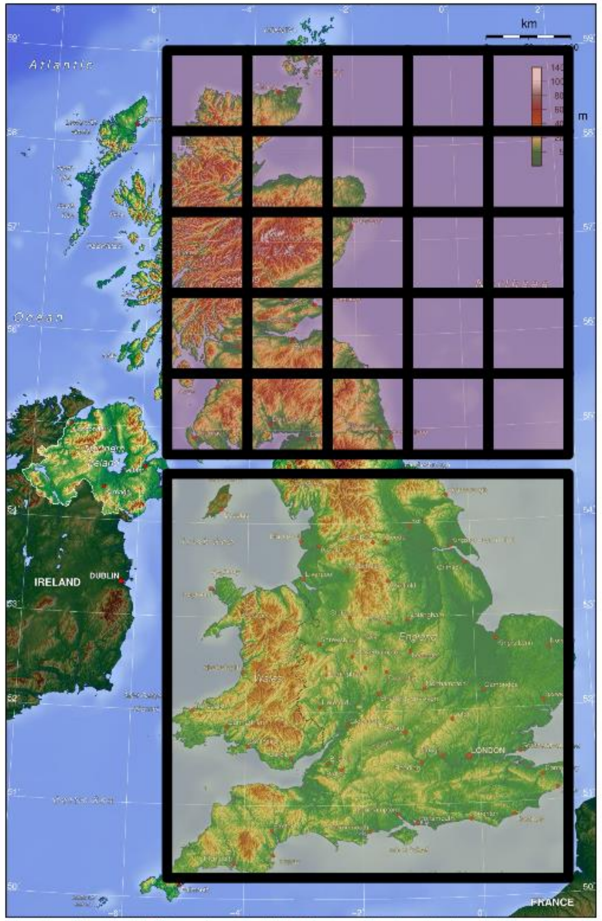

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Icebergs (cryosphere)

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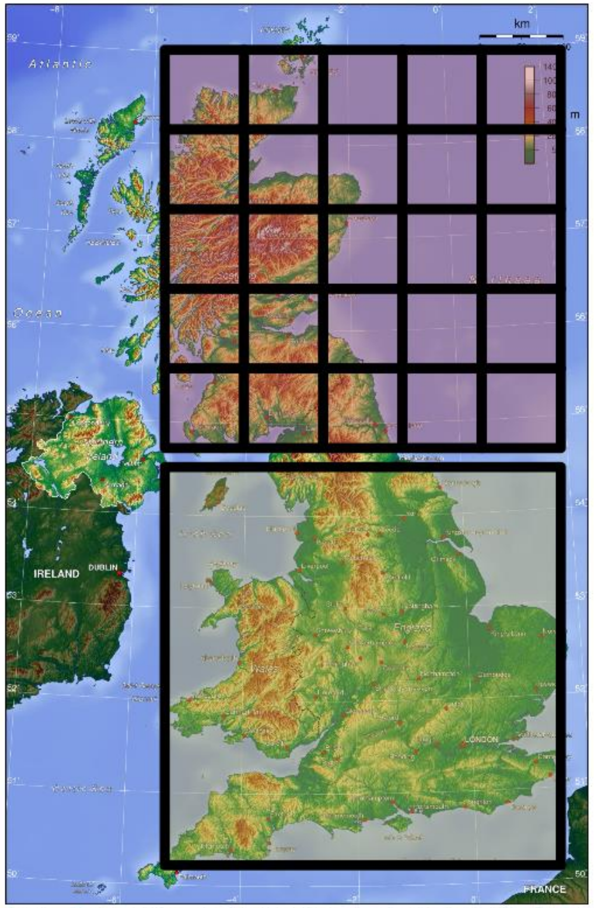

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Eddies (ocean) & phytoplankton (biology)

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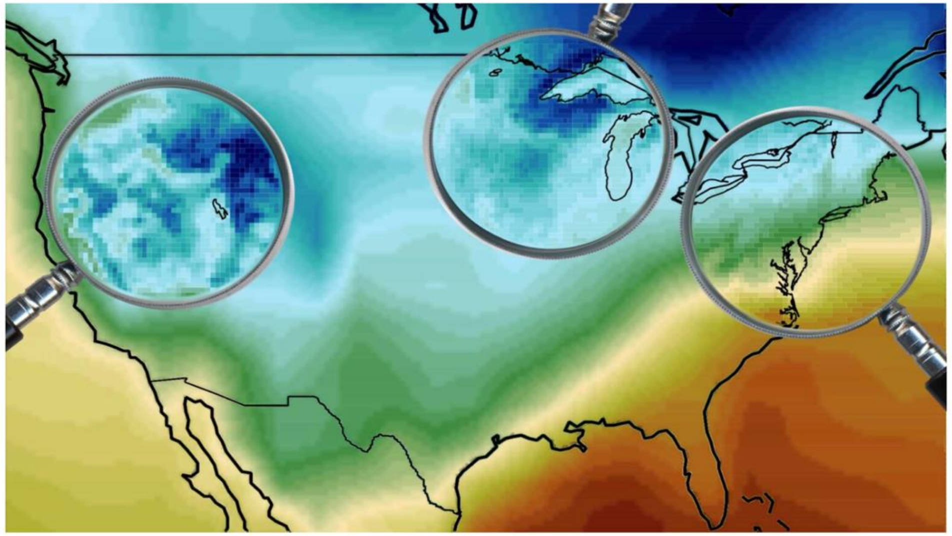
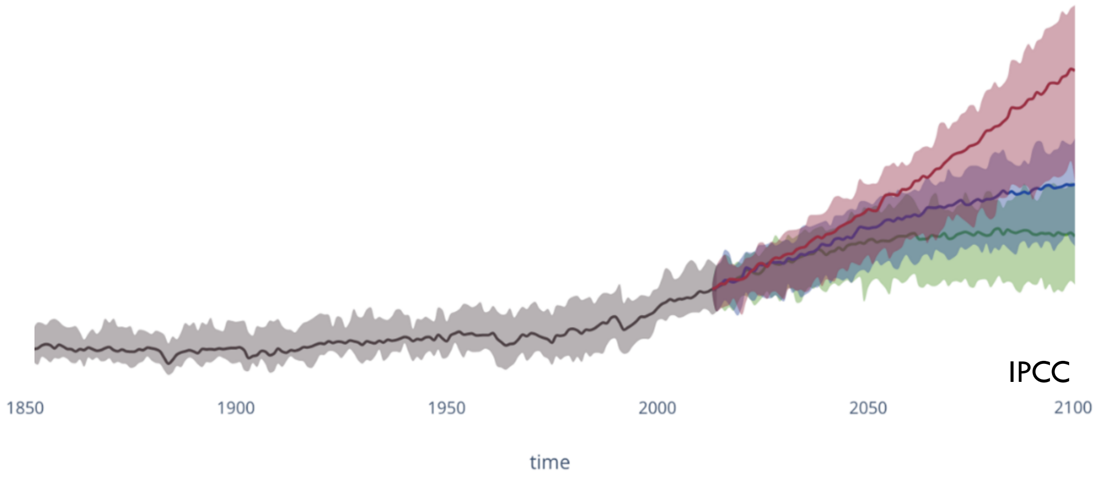
Also known as “upsampling” or ”downscaling”

The process of going from a low-resolution (LR) field to a fine-resolution (FR) equivalent

GFDL





Dynamical vs statistical downscaling

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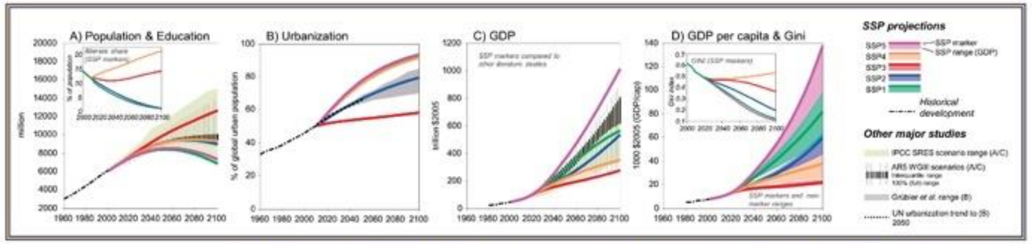

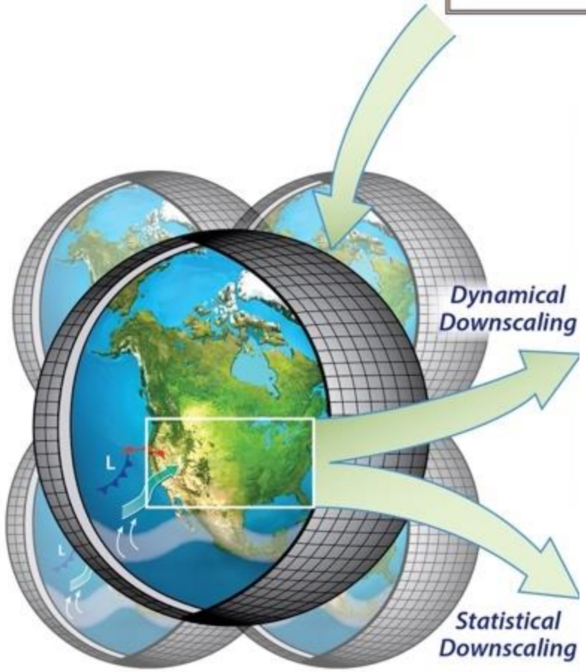

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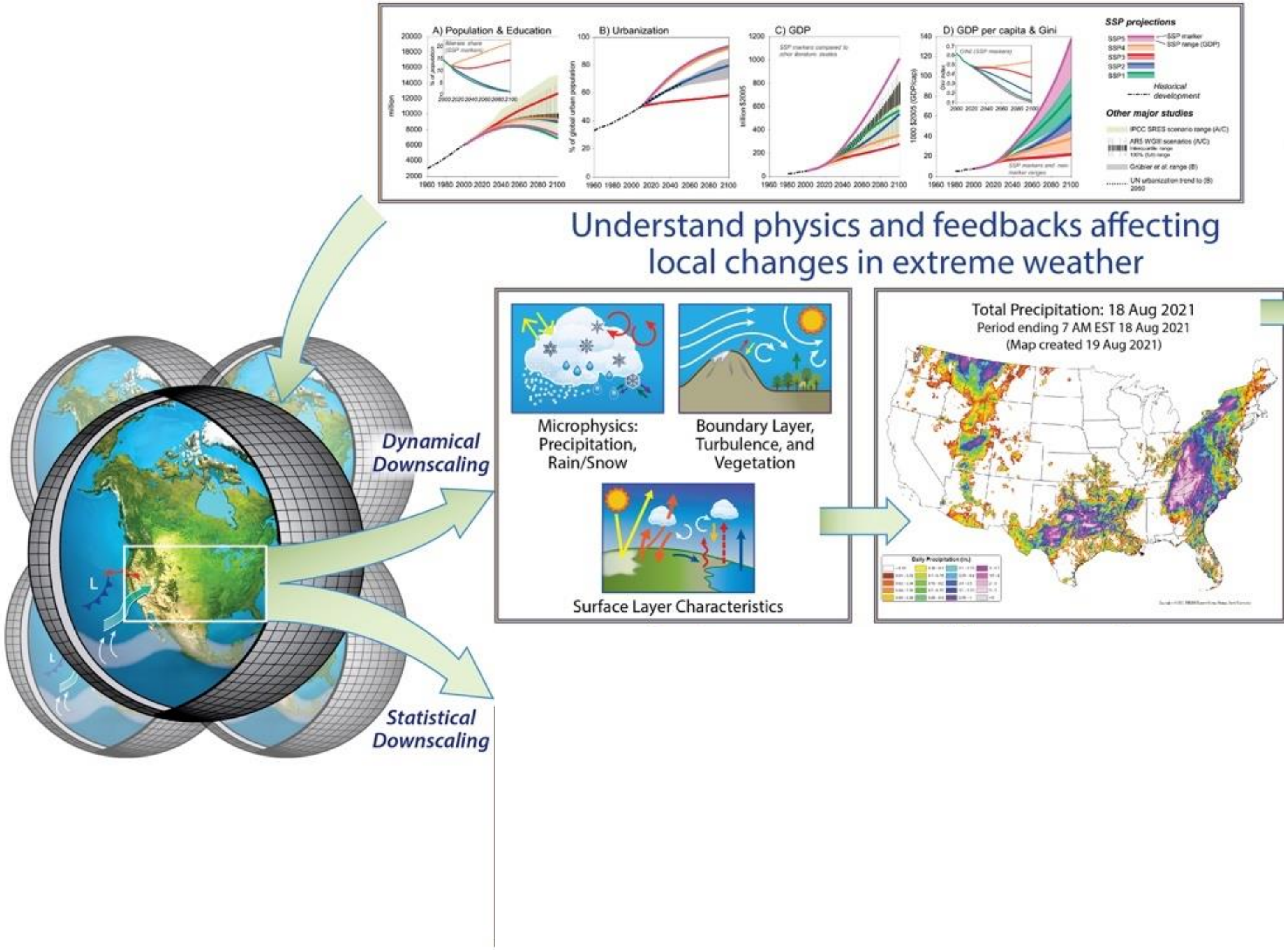
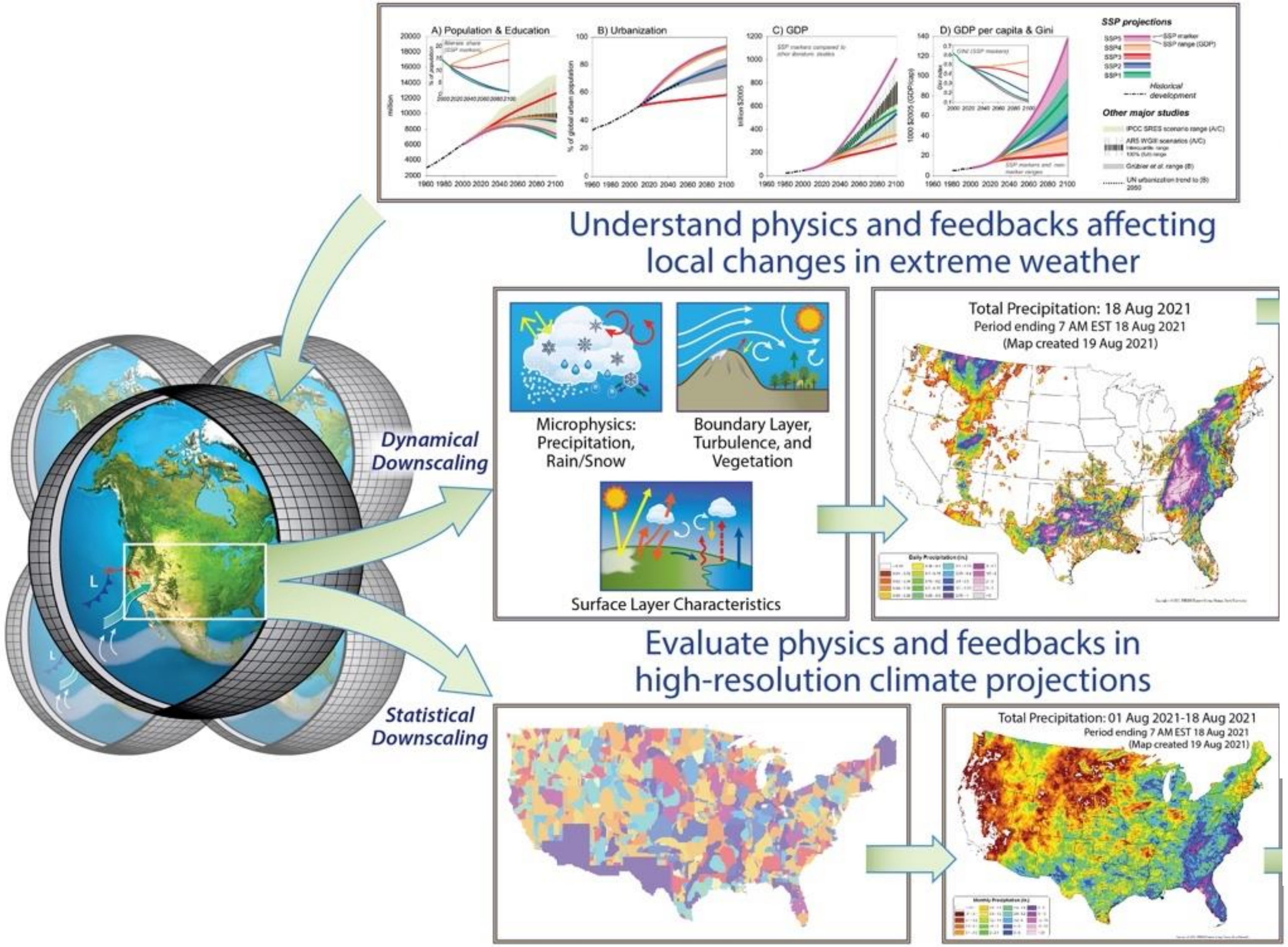


BERKELEY LAB DOWNSCALING
Earth & Environmental Sciences Area

EESA21-045

Dynamical vs statistical downscaling



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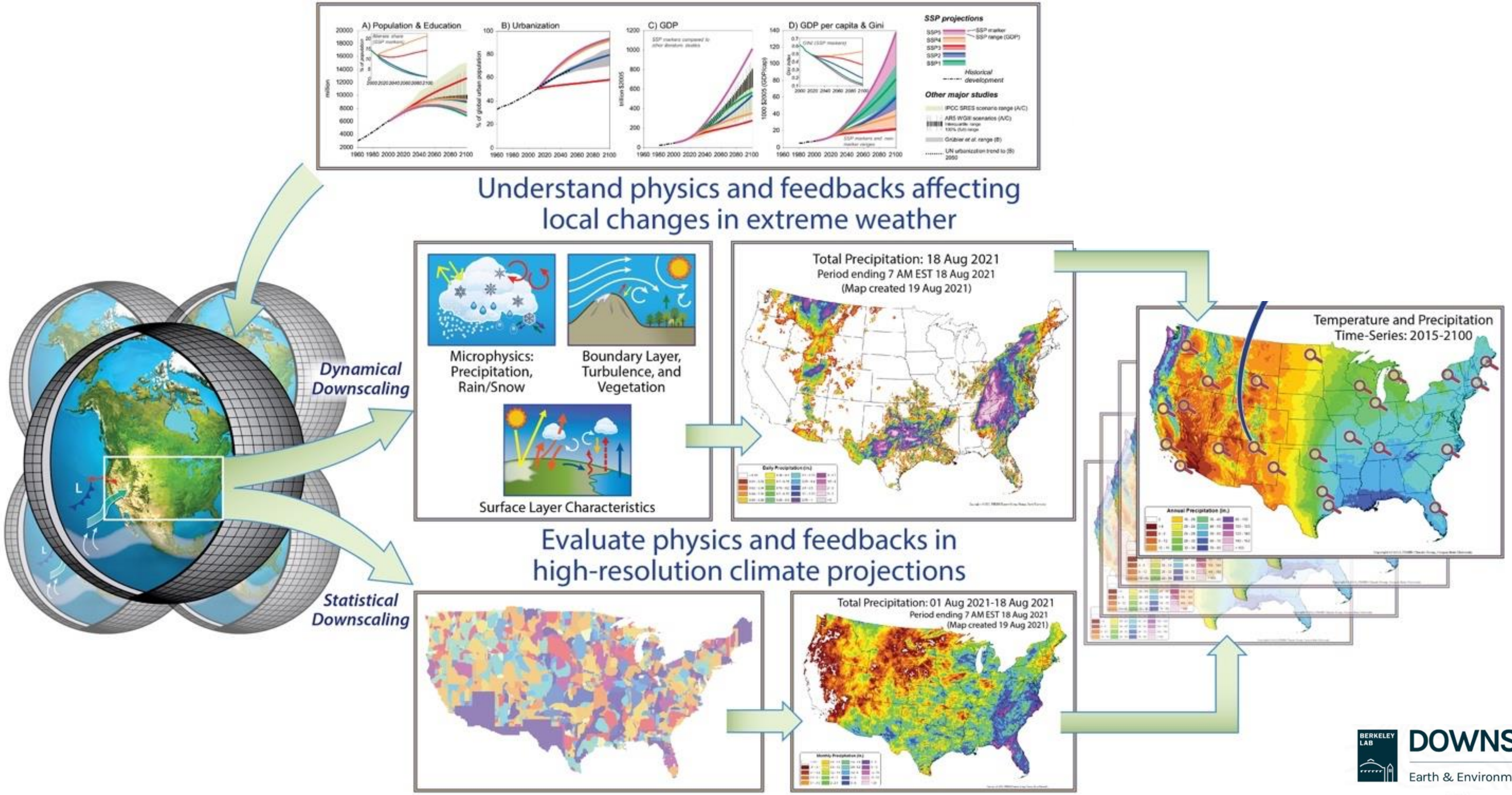

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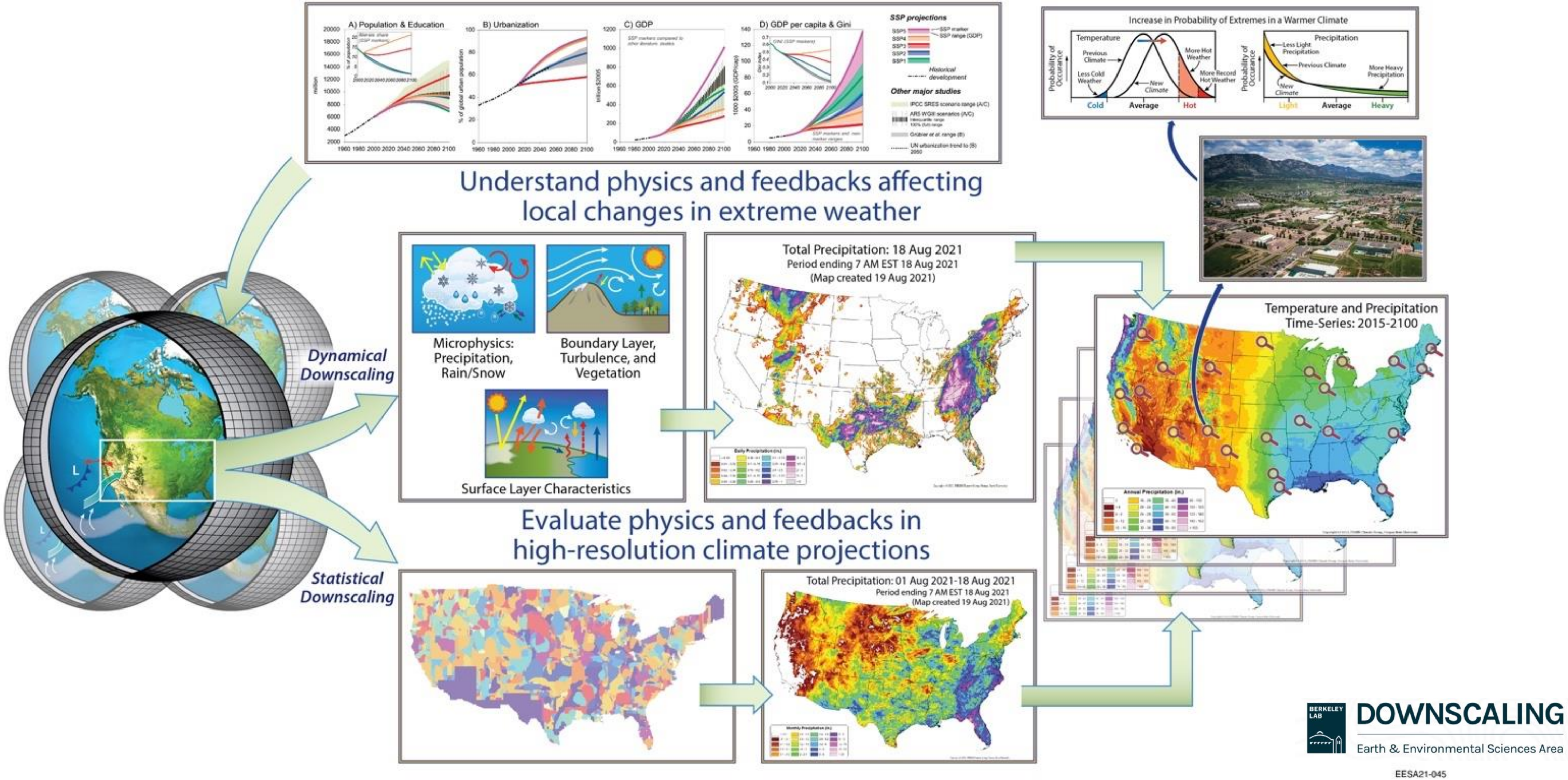

2010

Model: Classical & hybrid models

SVMs and Random Forests establish robust non-linear mappings, outperforming linear baselines.

Problem formulation: Statistical regression problem

Can we find a function f that maps predictors to a local variable?
f(GCM_predictors) → Local_Value.

Trust deficit & its solution: High interpretability

“Glass box” models are relatively transparent.
Feature importance can be inspected, fostering trust.

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Problem fo

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2016

Model: The deep learning shift

CNNs and U-Nets leverage spatial biases to capture complex patterns and fine details.

Problem formulation: Image-to-image problem

Can we treat a coarse climate field as a low-res image to generate a high-res version? f(Coarse_Grid) → Fine_Grid

Trust deficit & its solution: The “black box” emerges

Deep architectures become opaque, making it hard to understand their reasoning and creating a “trust deficit”.

Najafi et al (2026)

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Problem form

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Trust deficit

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2021

Model: Generative & transformer frontiers

GANs, Diffusion, and Transformers achieve SOTA realism, UQ, and generalization.

Problem formulation: Physics-constrained uncertainty

Can we generate a physically consistent *ensemble* of possibilities with reliable uncertainty?
f(Coarse_Grid) → Ensemble of {Fine_Grid|Physical_Laws}.

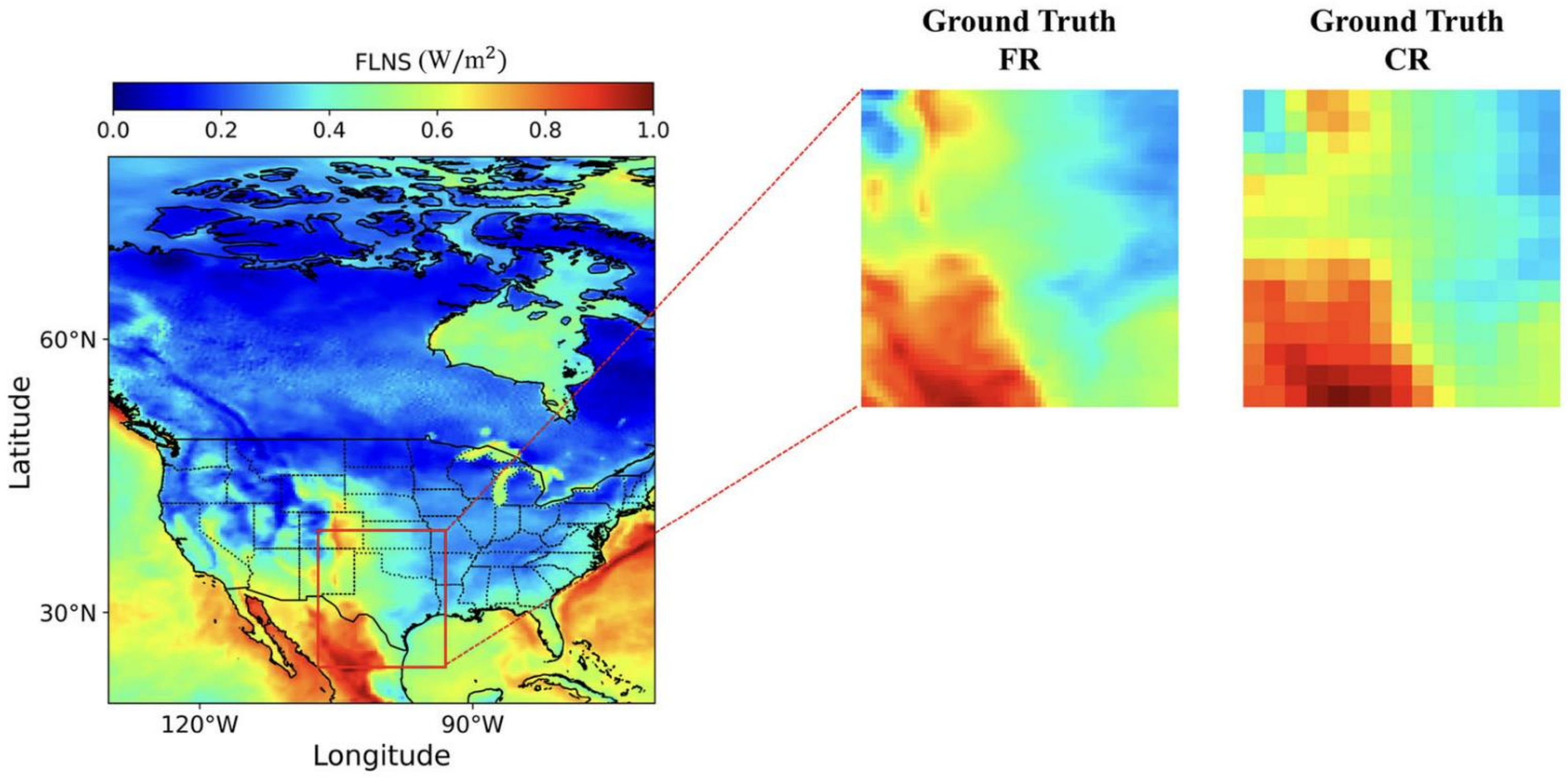
Trust deficit & its solution: Rebuilding trust

In response to opacity, XAI and PIML are developed to unmask the black box and enforce physical consistency.

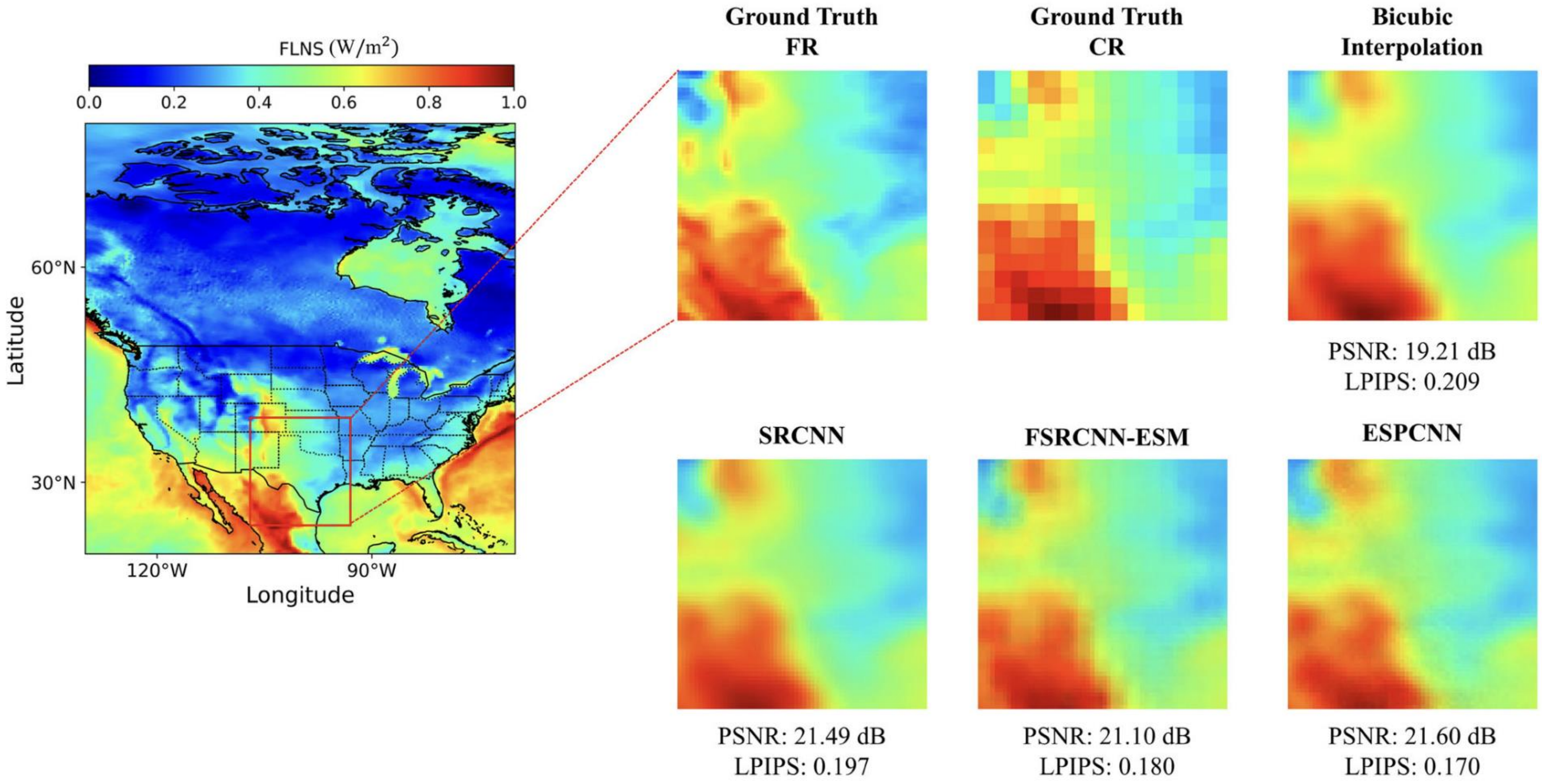
Najafi et al (2026)

Super-resolution

Super-resolution



Pawar et al (2024)



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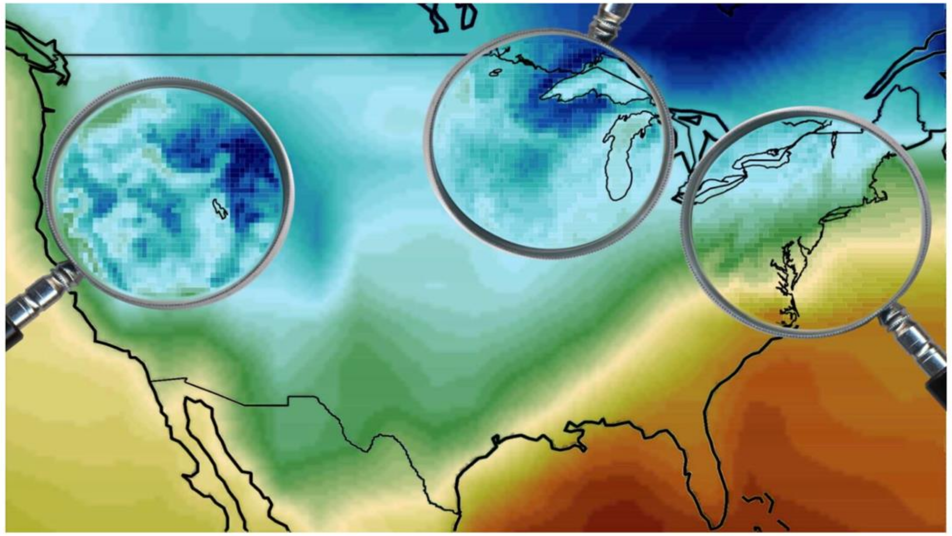
Challenges

GFDL



Super-resolution

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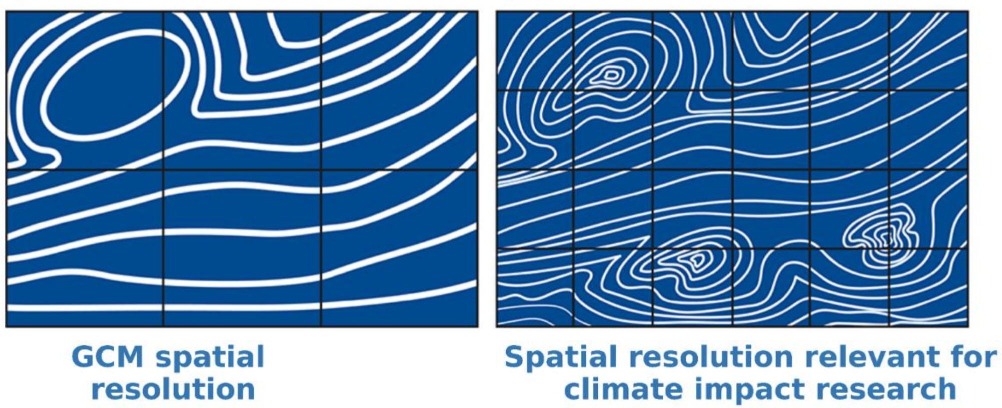
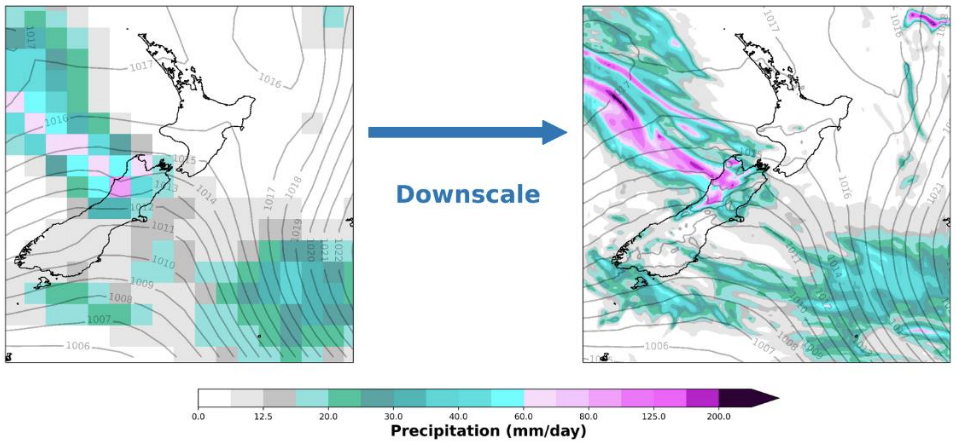
The process of going from a low-resolution (LR) field to a fine-resolution (FR) equivalent

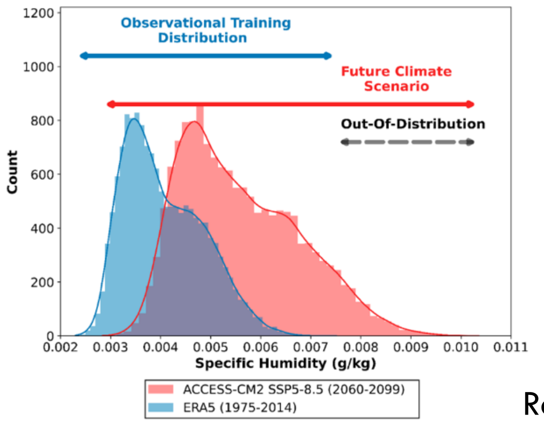
Challenges

- No feedback of FR back onto low resolution evolution (recall parameterizations)
- Requires that predicted FR remains physically consistent
- Desired that captures extremes in FR
- Preforms well out of distribution

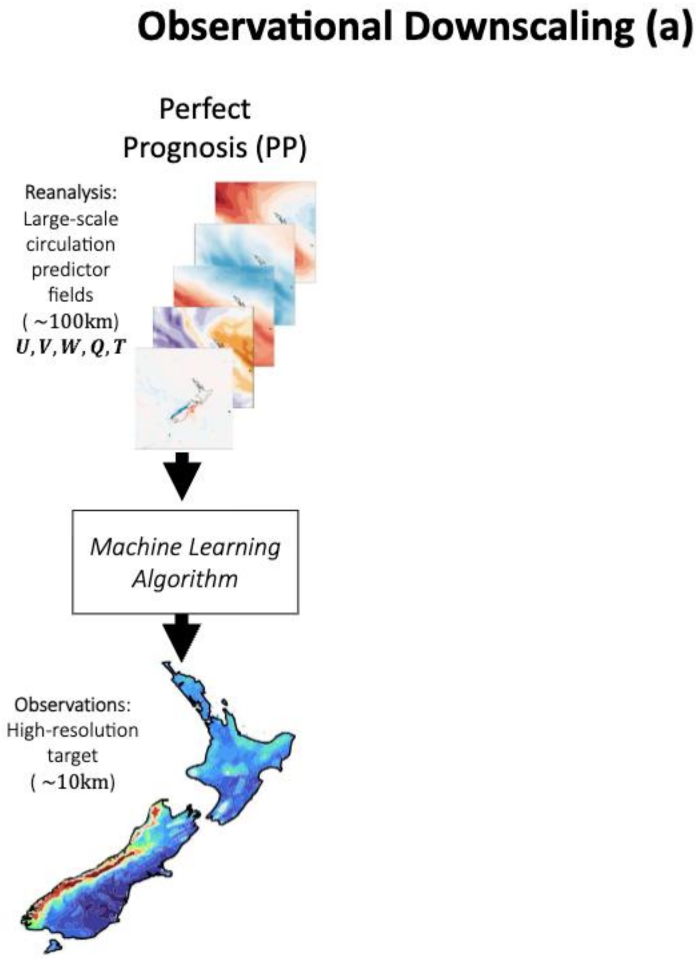
Christensen & Zanna (2022)







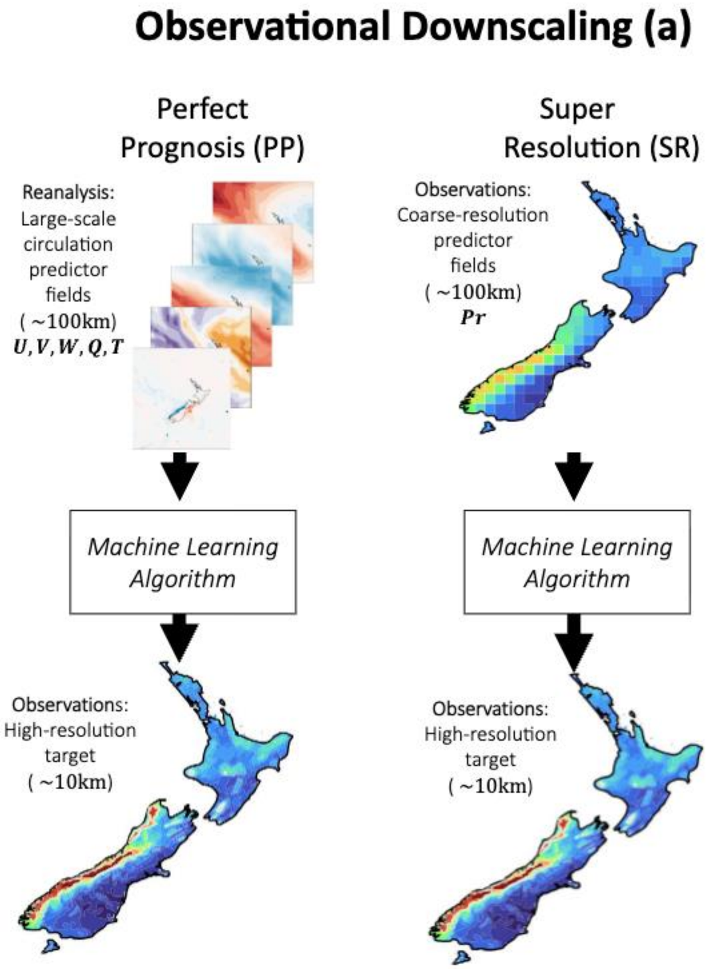
Rampal et al (2024)



aka domain adaption

Finds an optimal function between observed variables that can be applied to GCMs

Rampal et al (2024)



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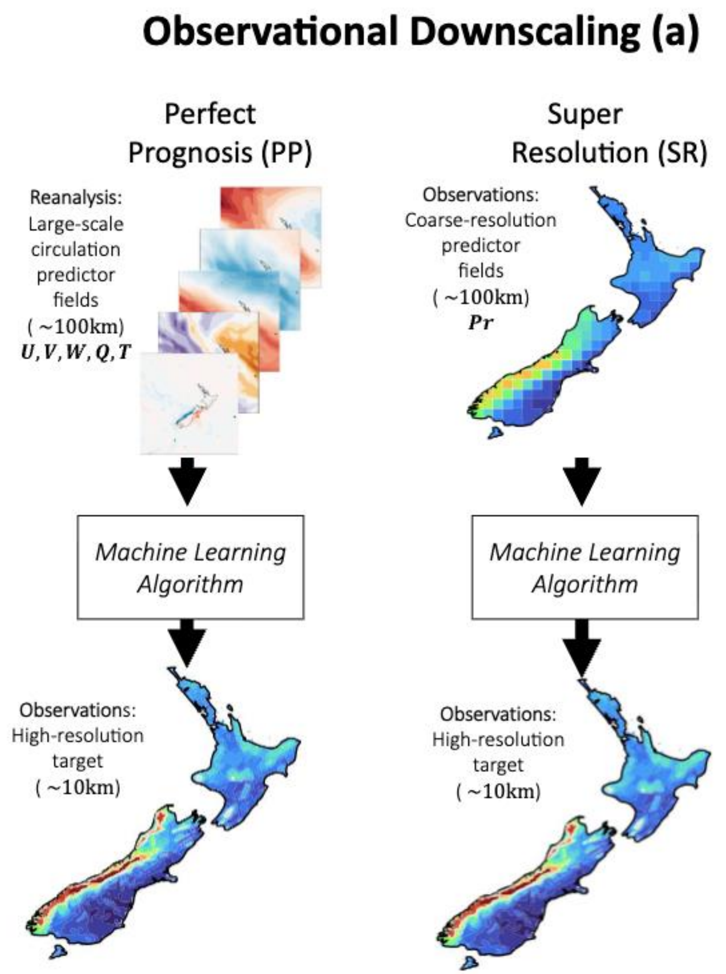
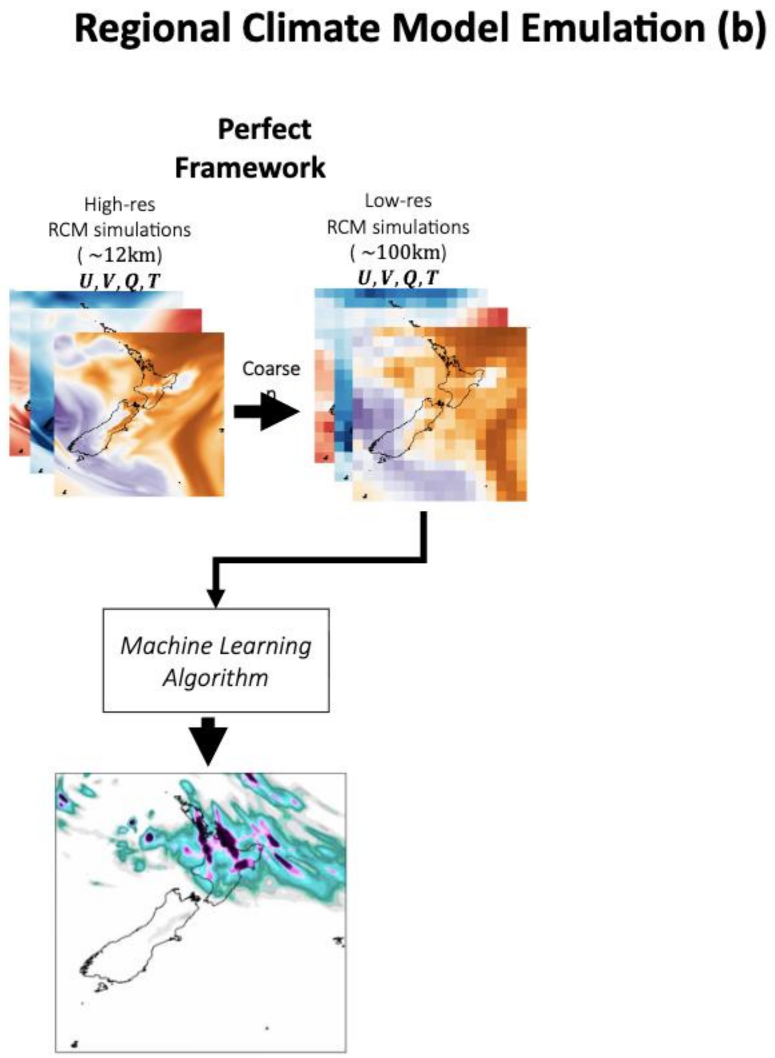
Special case of PP

Finds an optimal function between coarse observed variables and FR variables





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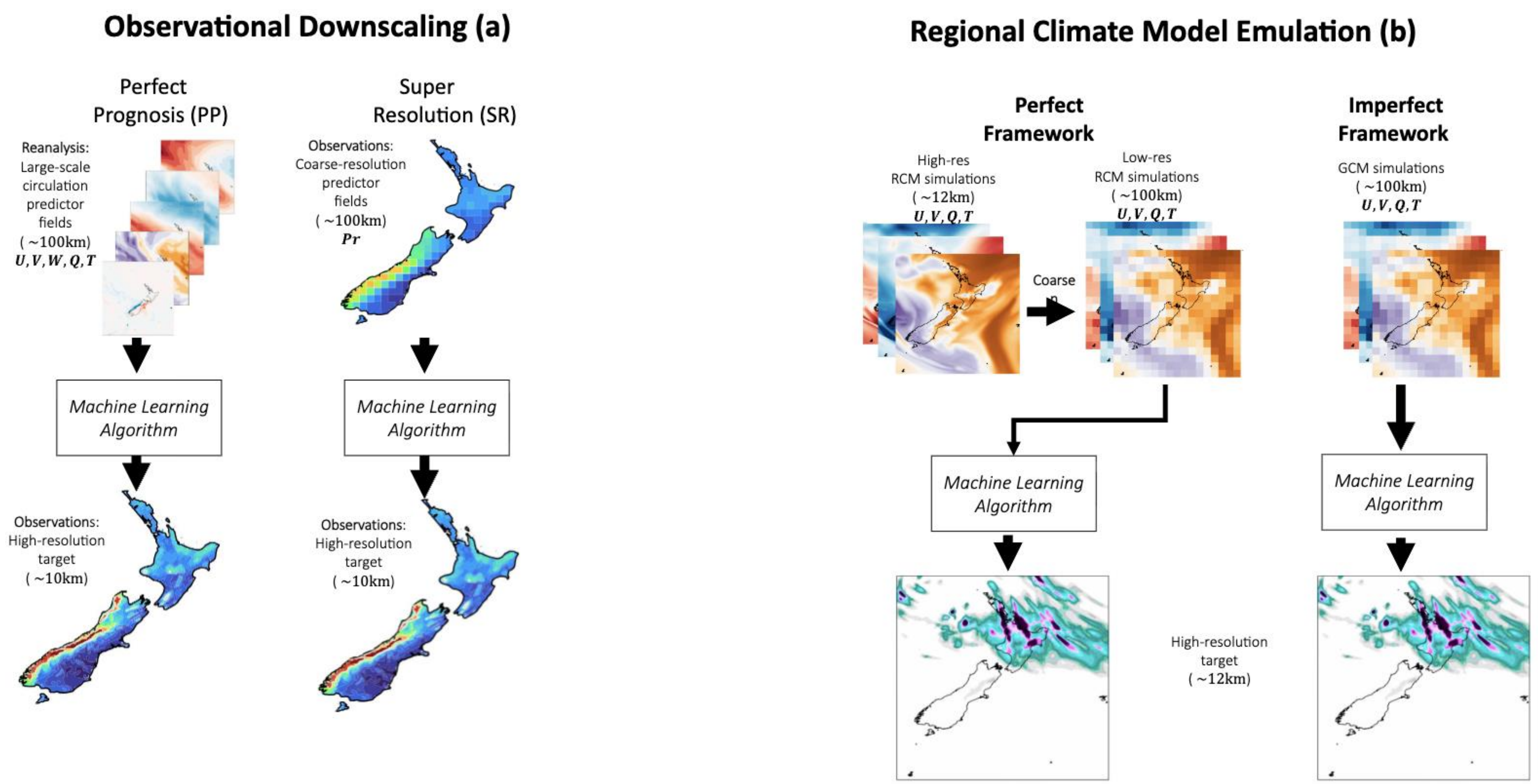
Finds an optimal function between coarse GCM-like variables and FR regional climate models



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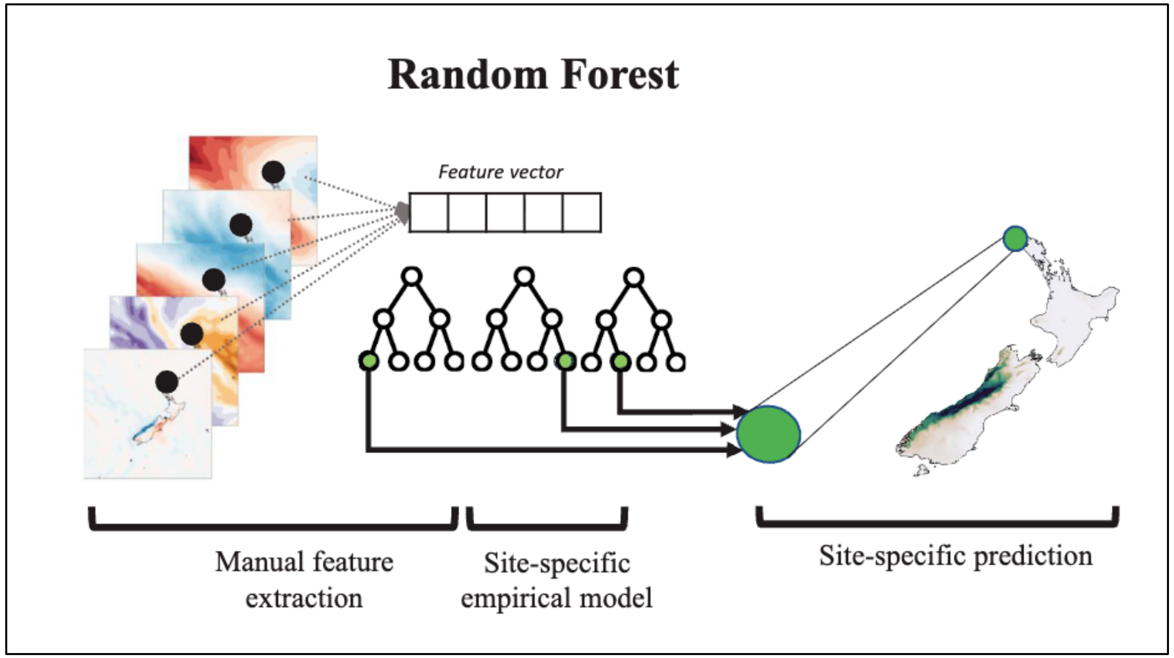
Examples of AI downscaling methods



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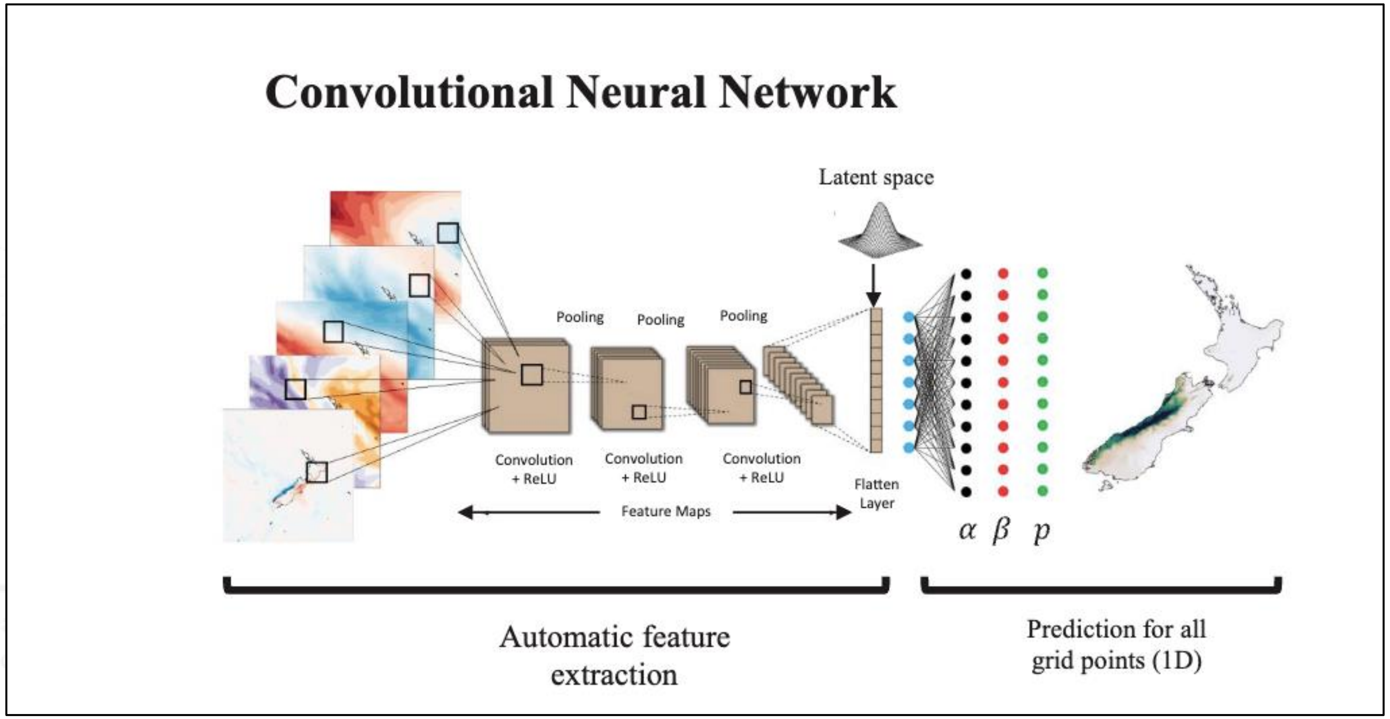

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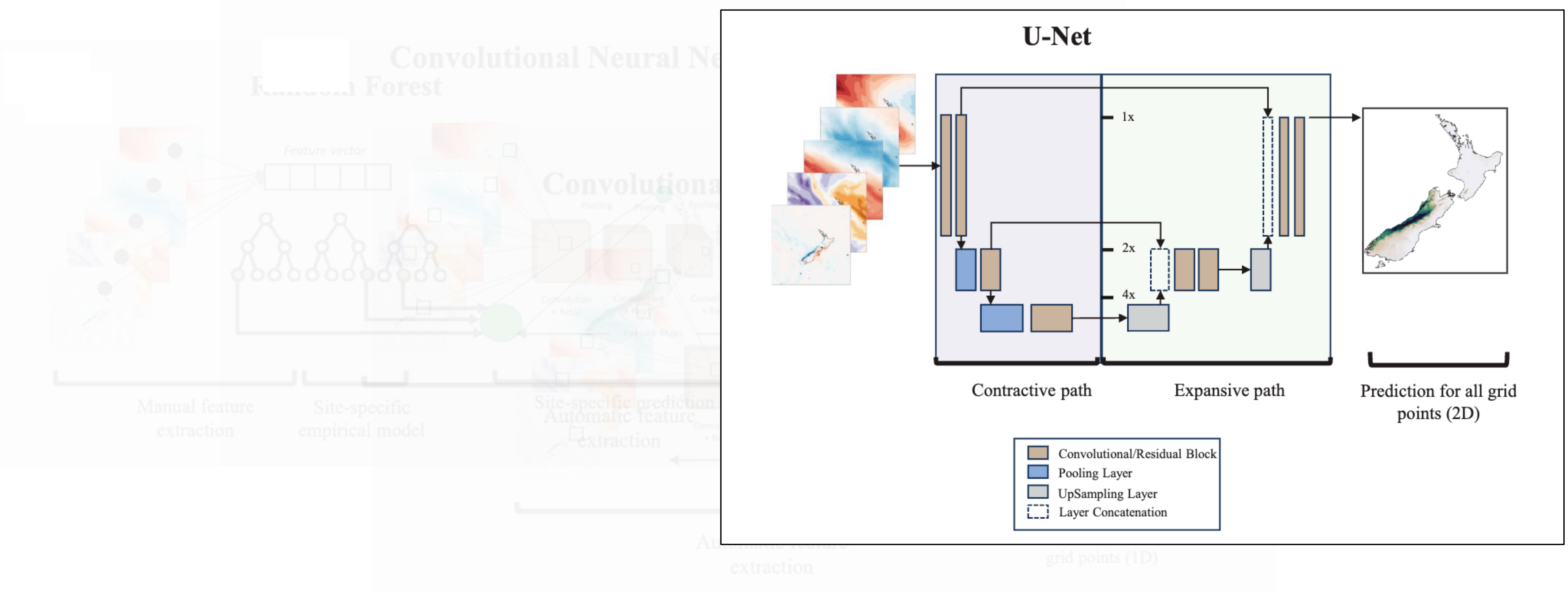

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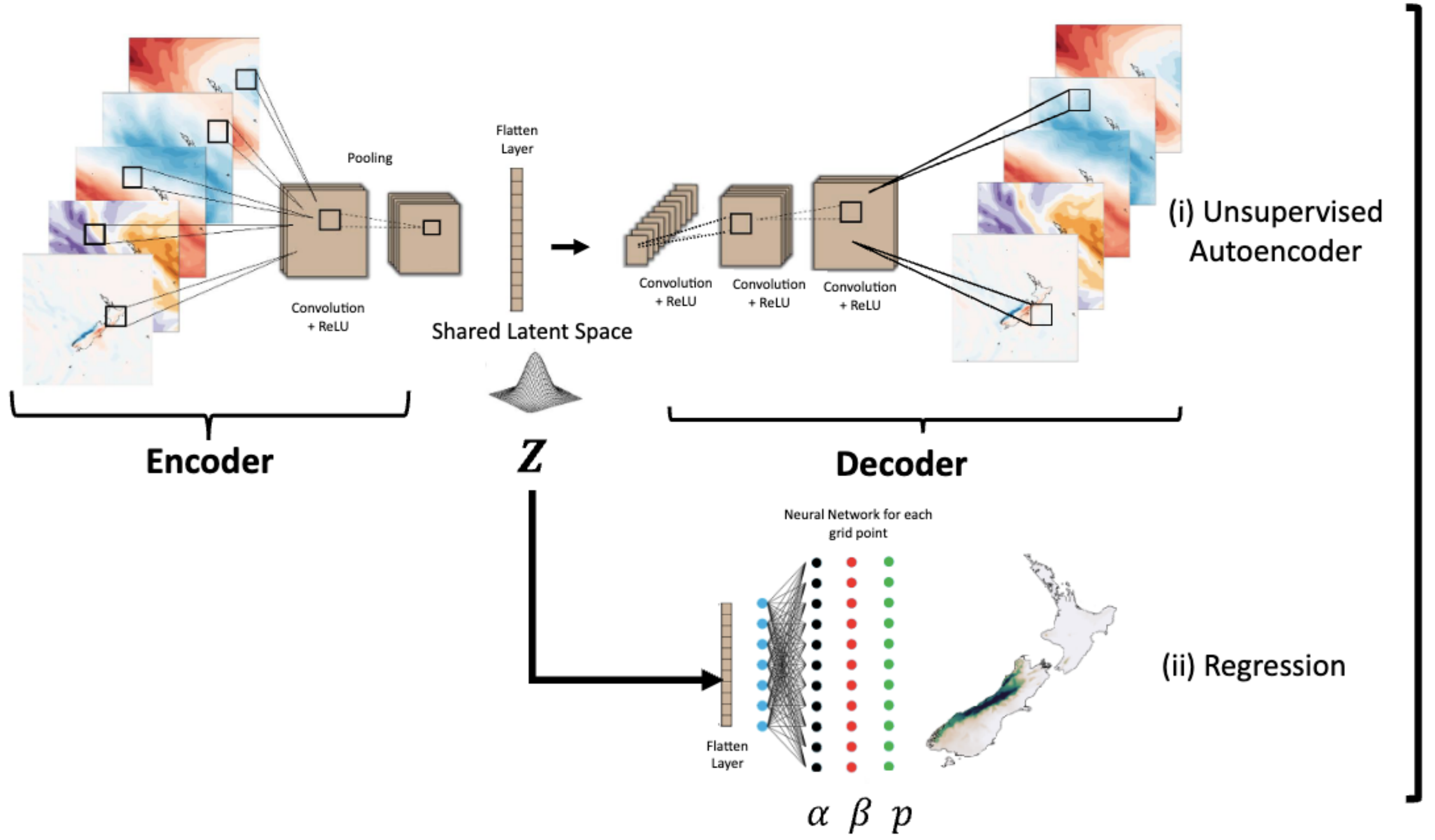

Multi-task CNN

Rampal et al (2024)

Physics informed ML

Integrates physical laws to prevent unrealistic outputs and improve generalization.

- Soft Constraints (via Loss):
  Penalizes violations of physical laws.
- Hard Constraints (via Architecture):
  Guarantees conservation by design.

Najafi et al (2026)

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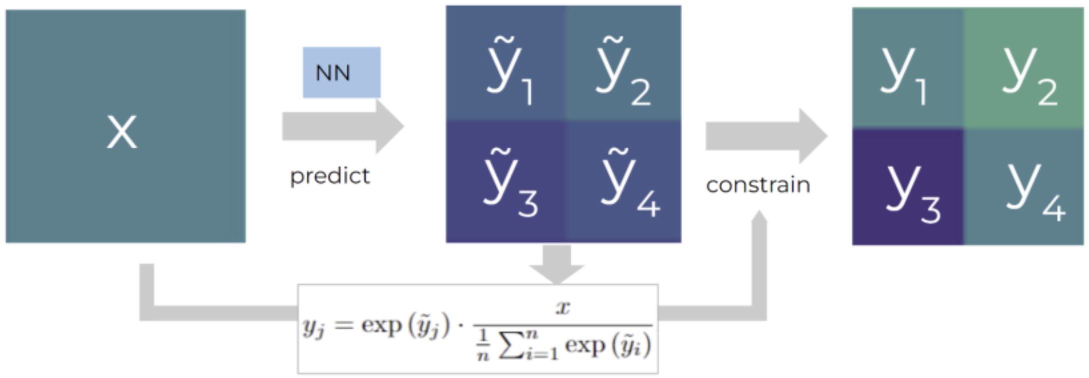

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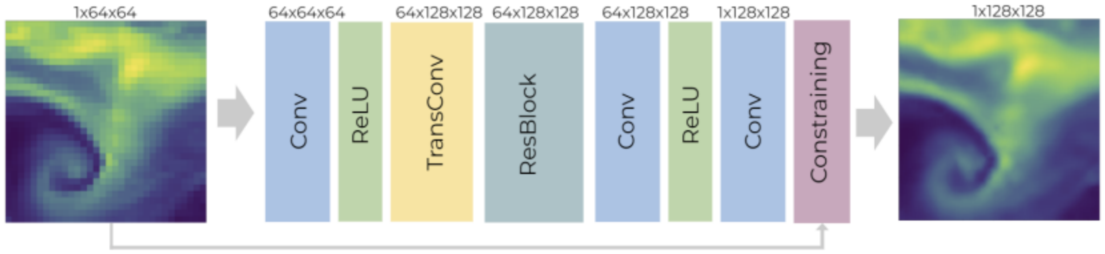

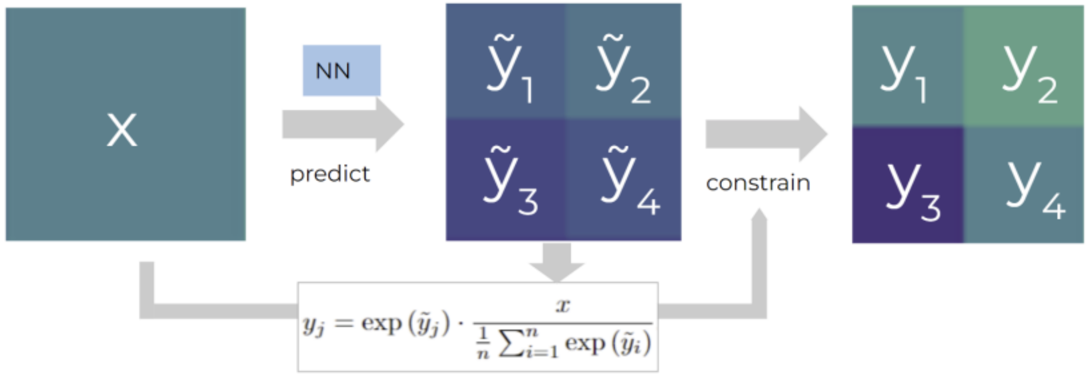

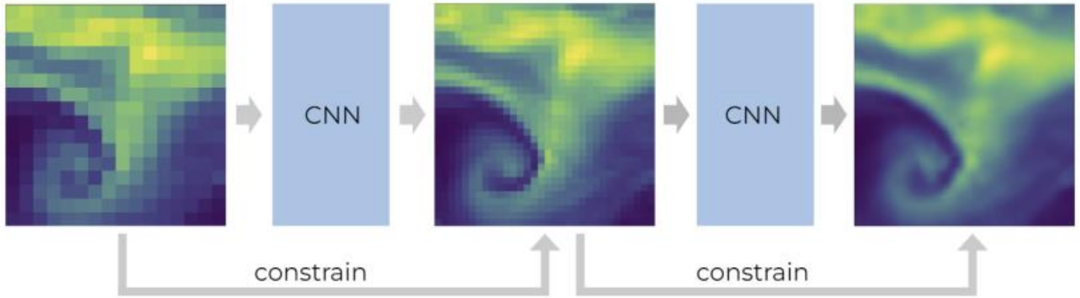

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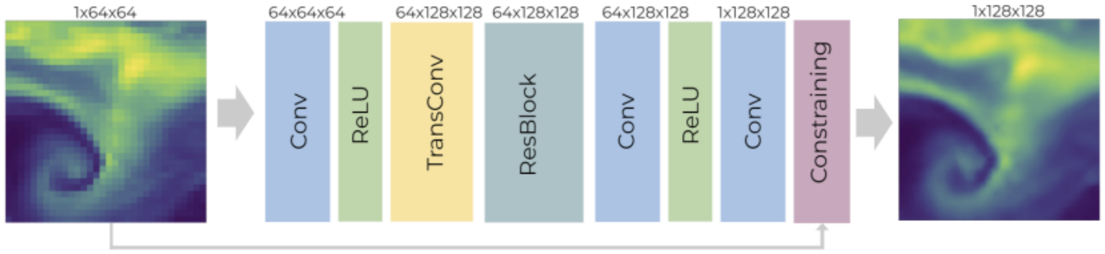

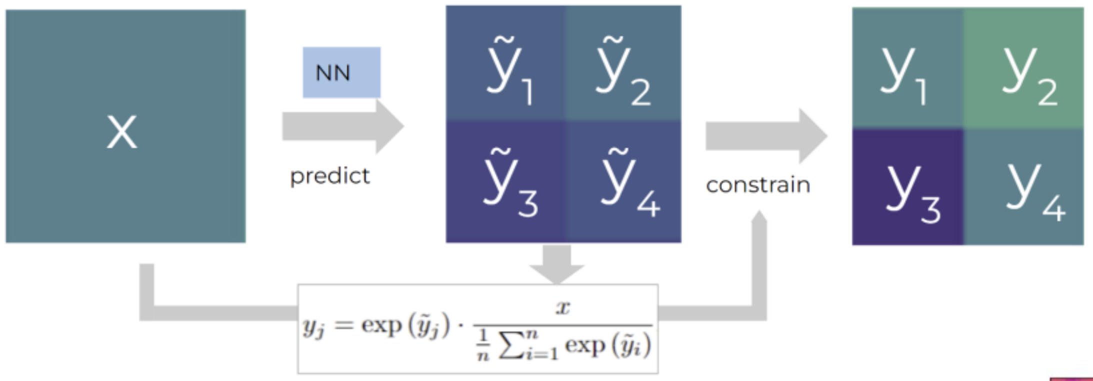

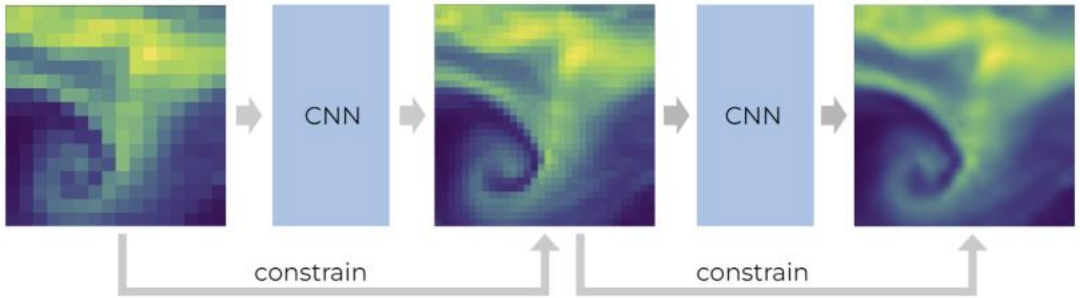

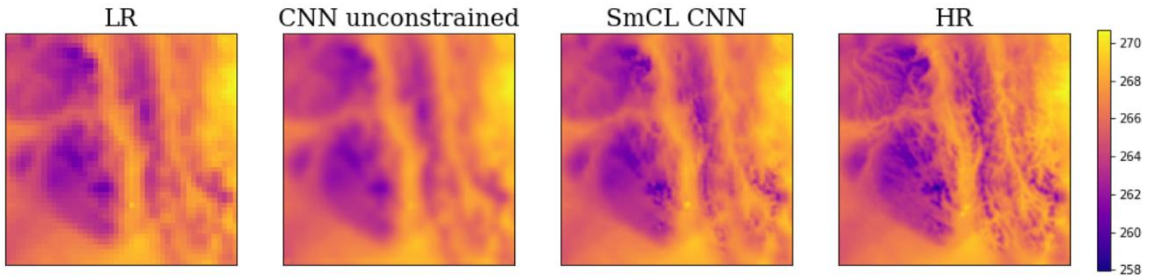

Harder et al (2024)

Enhancing extreme events

Uses specialized loss functions to address data imbalance and accurately model the tails of the distribution.

- Problem with MSE:
  Models trained on Mean Squared Error learn the conditional mean, which systematically underestimates rare, high-intensity events.
- Solution: Probabilistic Loss
  Model both occurrence (p) and intensity (α, βα, β) of precipitation using Negative Log-Likelihood of a Bernoulli-Gamma distribution.

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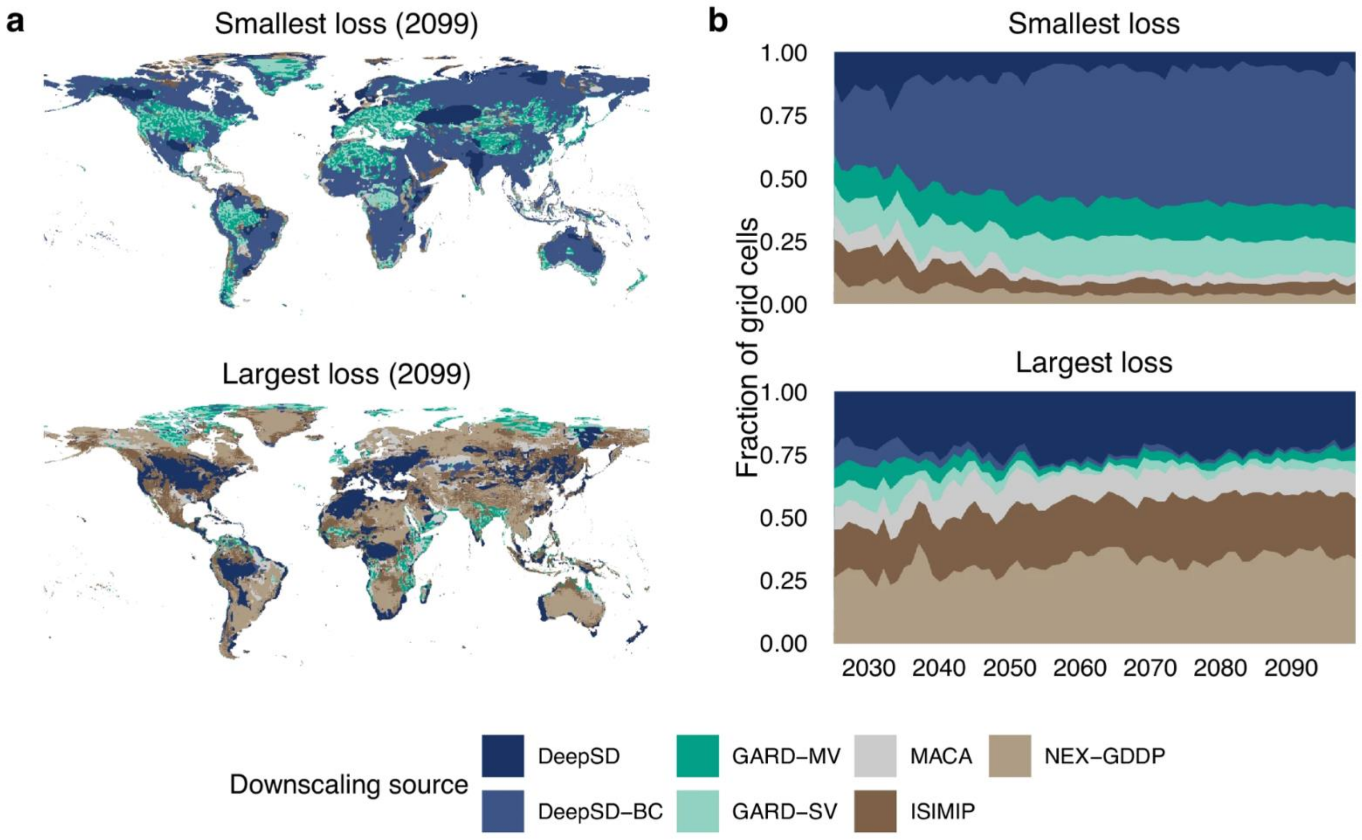
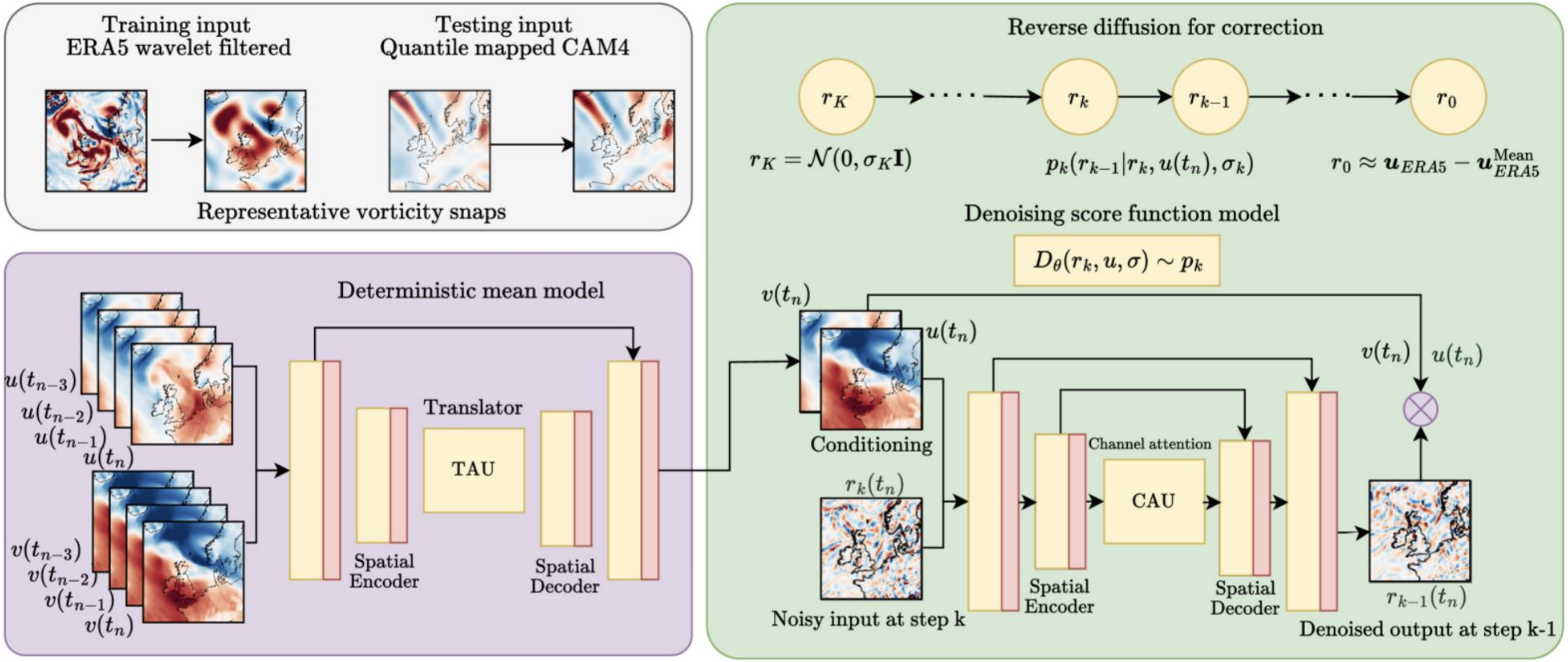


Miller et al (2025)

Enhancing extreme events

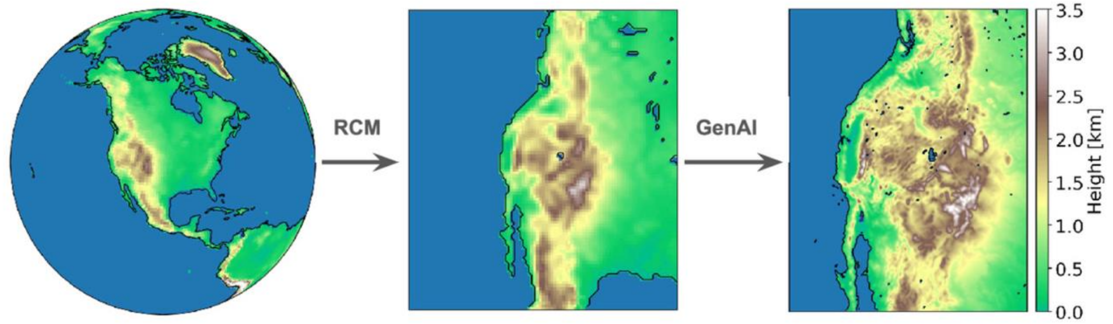
Example: quantile mapping



Sundar et al (2025)

Enhancing extreme events

Example: dynamical generative downscaling



Lopez-Gomez et al (2025)

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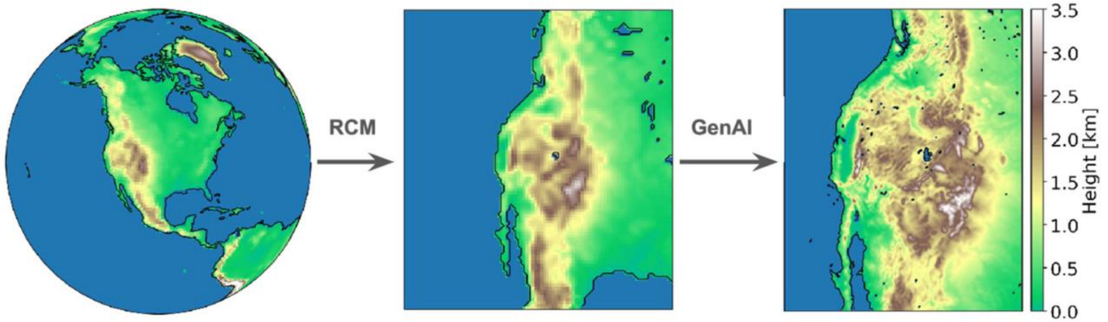
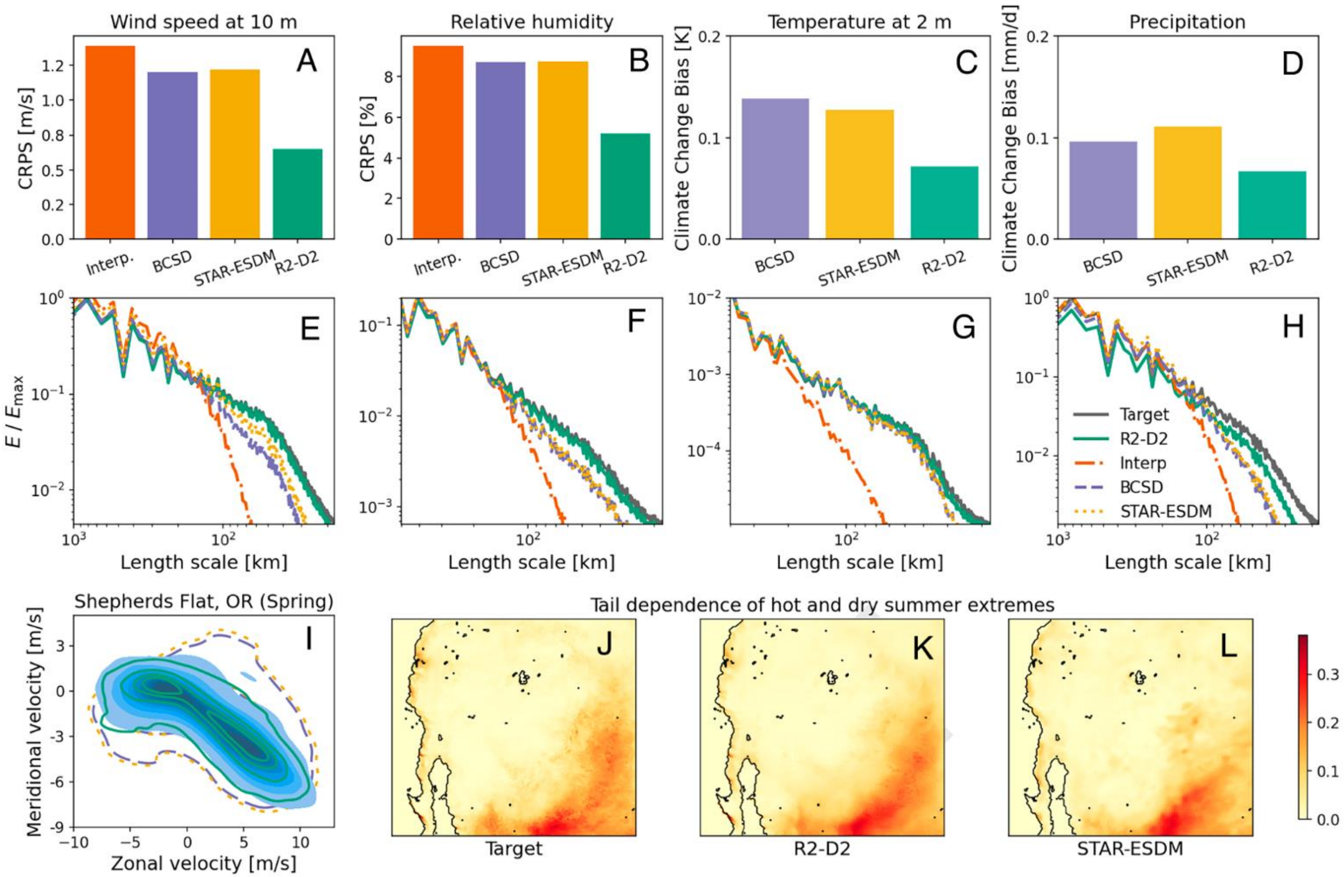
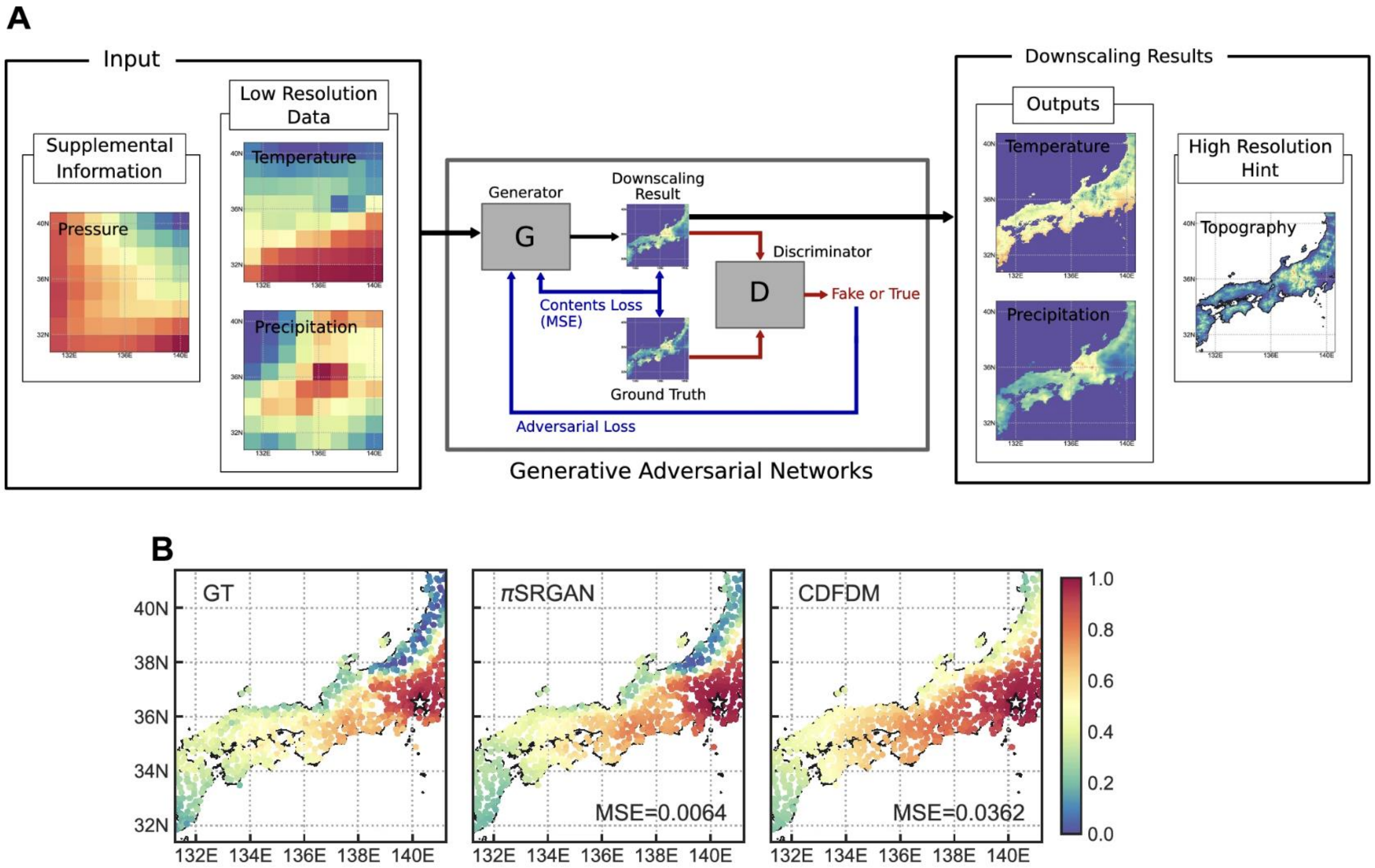




Lopez-Gomez et al (2025)

Enhancing extreme events

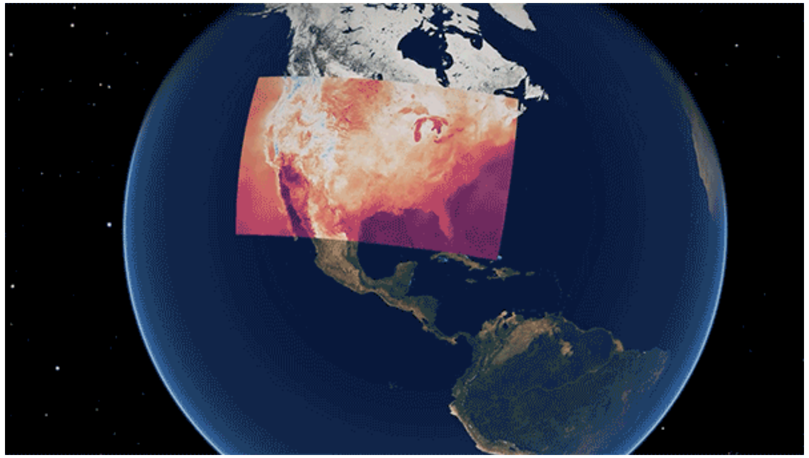
Example: GAN



Oyama et al (2023)

Enhancing extreme events

Example: regression + diffusion



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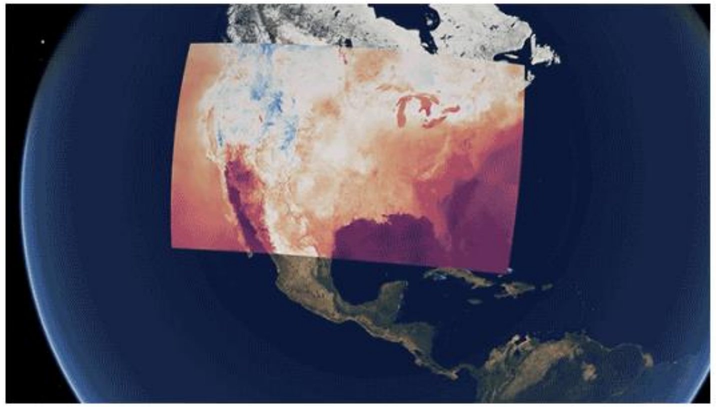

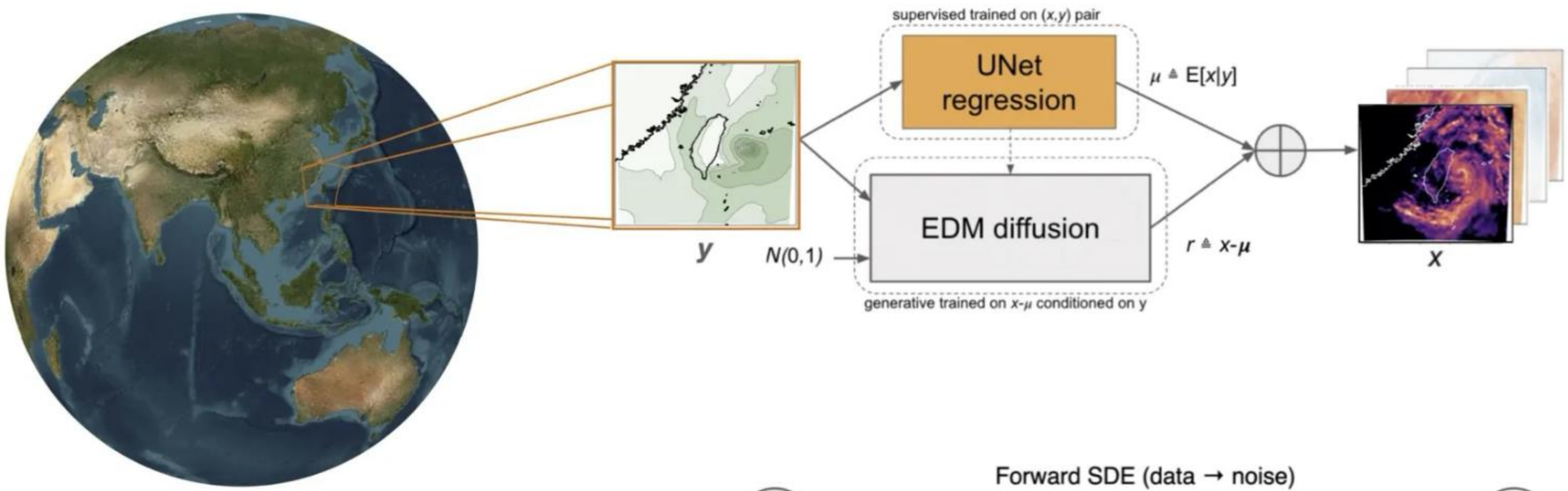

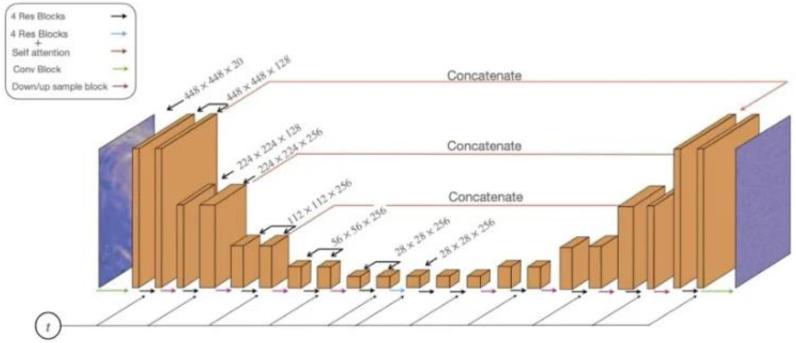

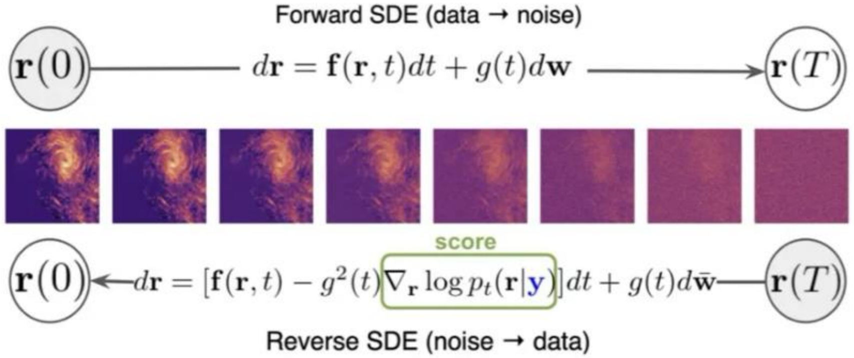

Explainable AI

Uses attribution methods to "unmask the black box," ensuring the model learns physically meaningful relationships, not spurious correlations.

- Method: Saliency Maps
  Highlights which input regions are most influential for the output prediction. Helps verify if the model is focusing on scientifically relevant areas (e.g., moisture source regions).

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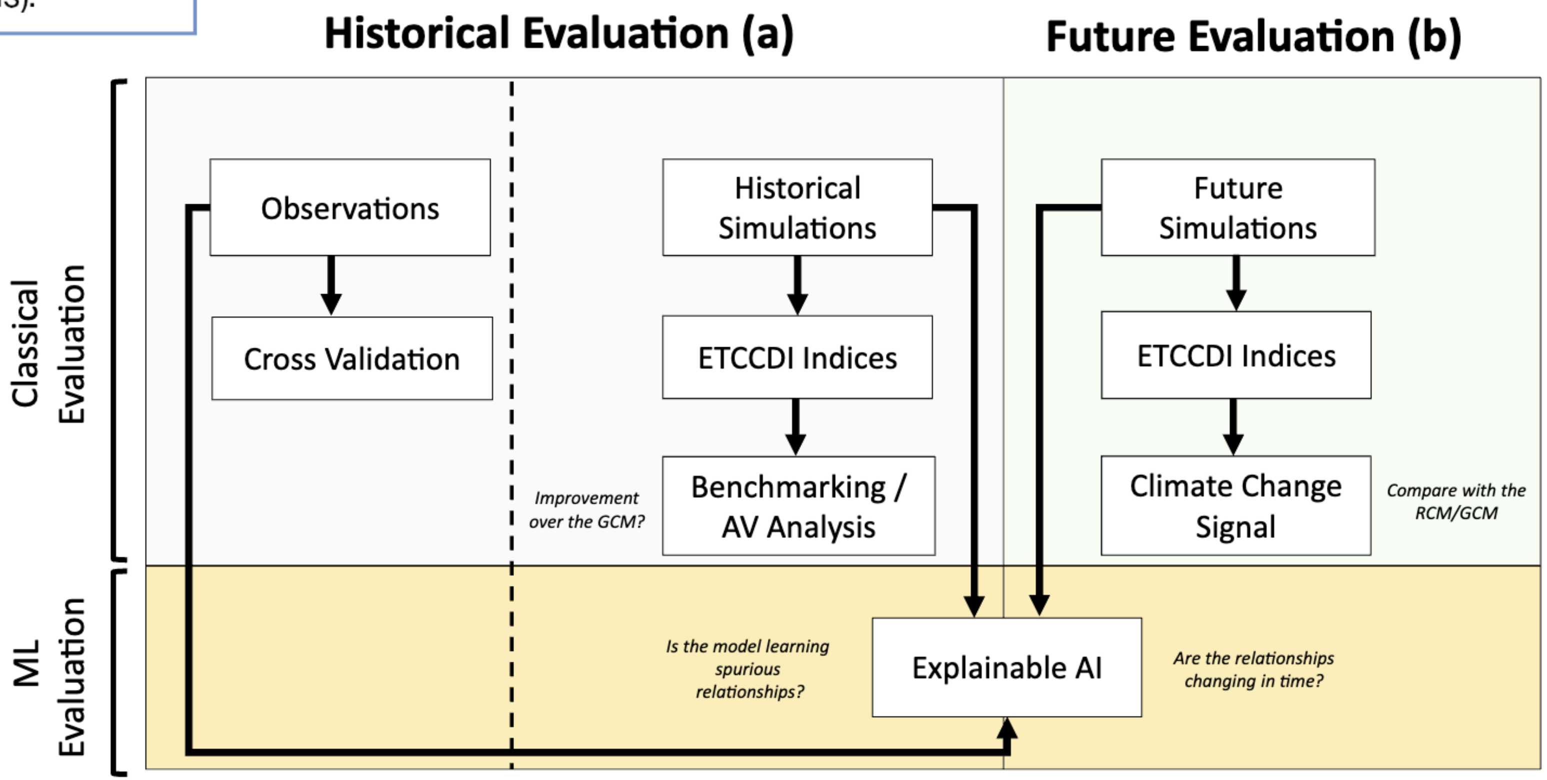

Rampal et al (2024)

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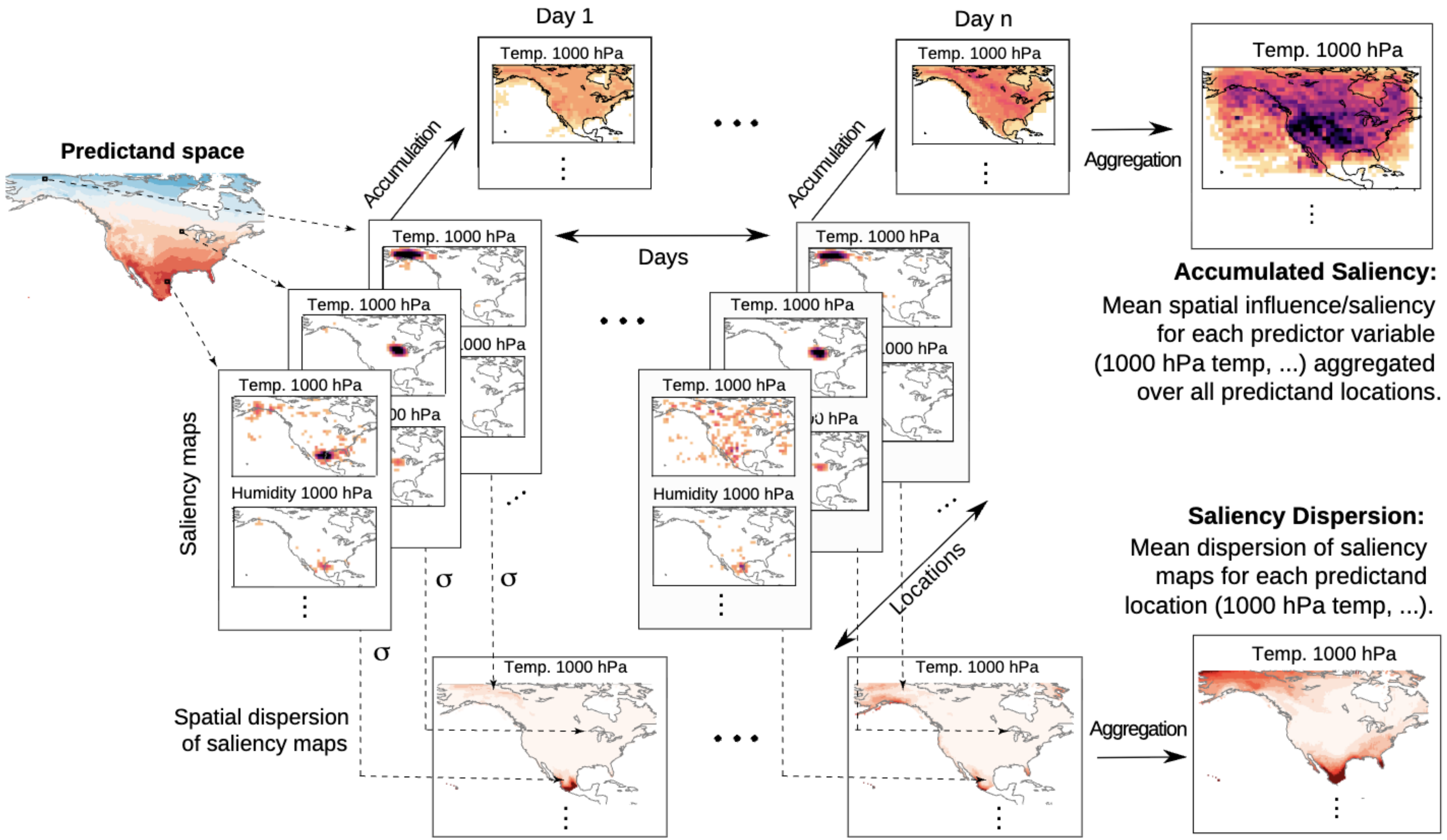

Rampal et al (2024)

Quantifying uncertainty and generalization

Moves beyond deterministic predictions to provide robust uncertainty estimates and test a model's ability to generalize to unseen data.

- Uncertainty Quantification (UQ)
  Methods like Deep Ensembles or Bayesian NNs estimate model confidence and the range of plausible outcomes.
- Out-of-Distribution (OOD) Testing
  Rigorously evaluates model performance on unseen future climates (PGW) or different GCMs to combat the "performance paradox".

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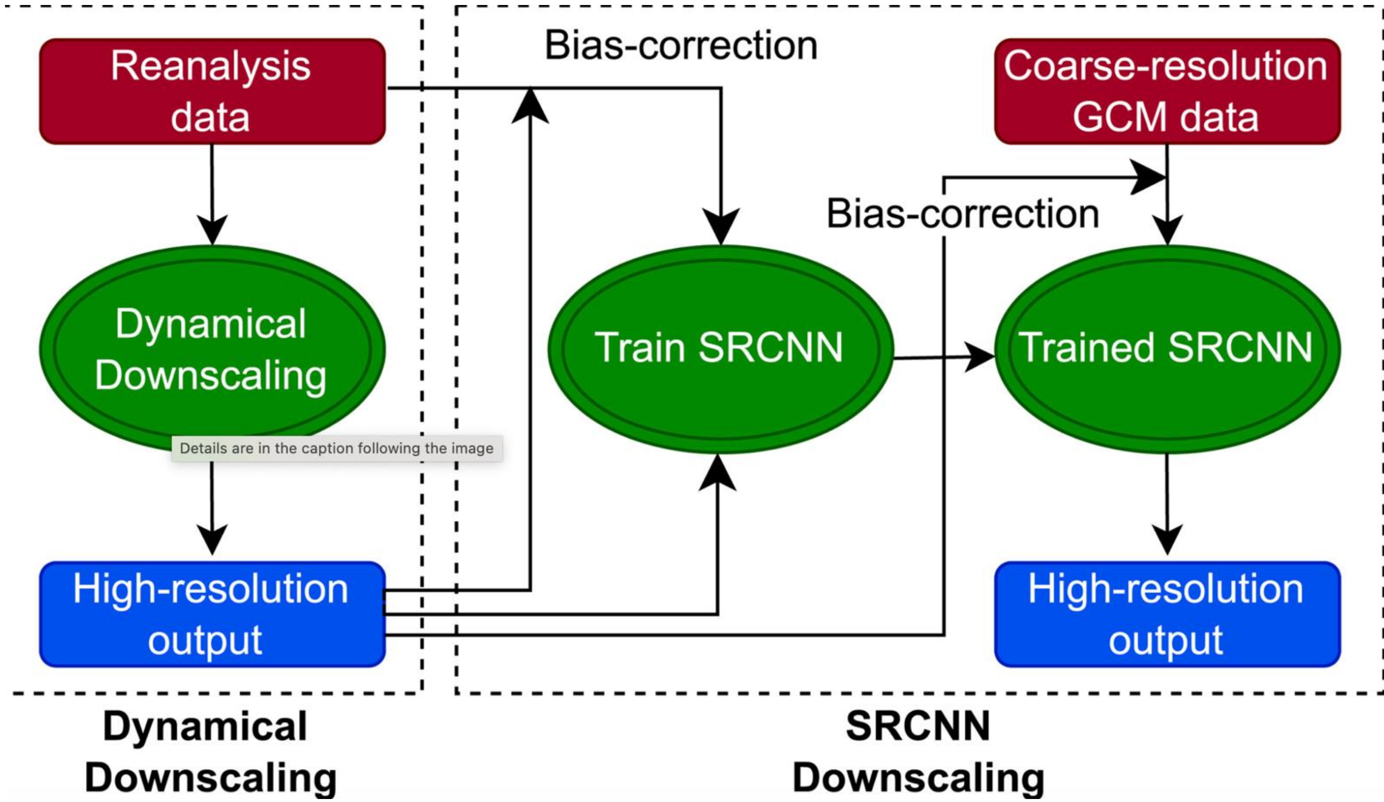
Najafi et al (2026)



Rastogi et al (2025)

Quantifying uncertainty and generalization

Moves beyond deterministic predictions to provide robust uncertainty estimates and test a model's ability to generalize to unseen data.

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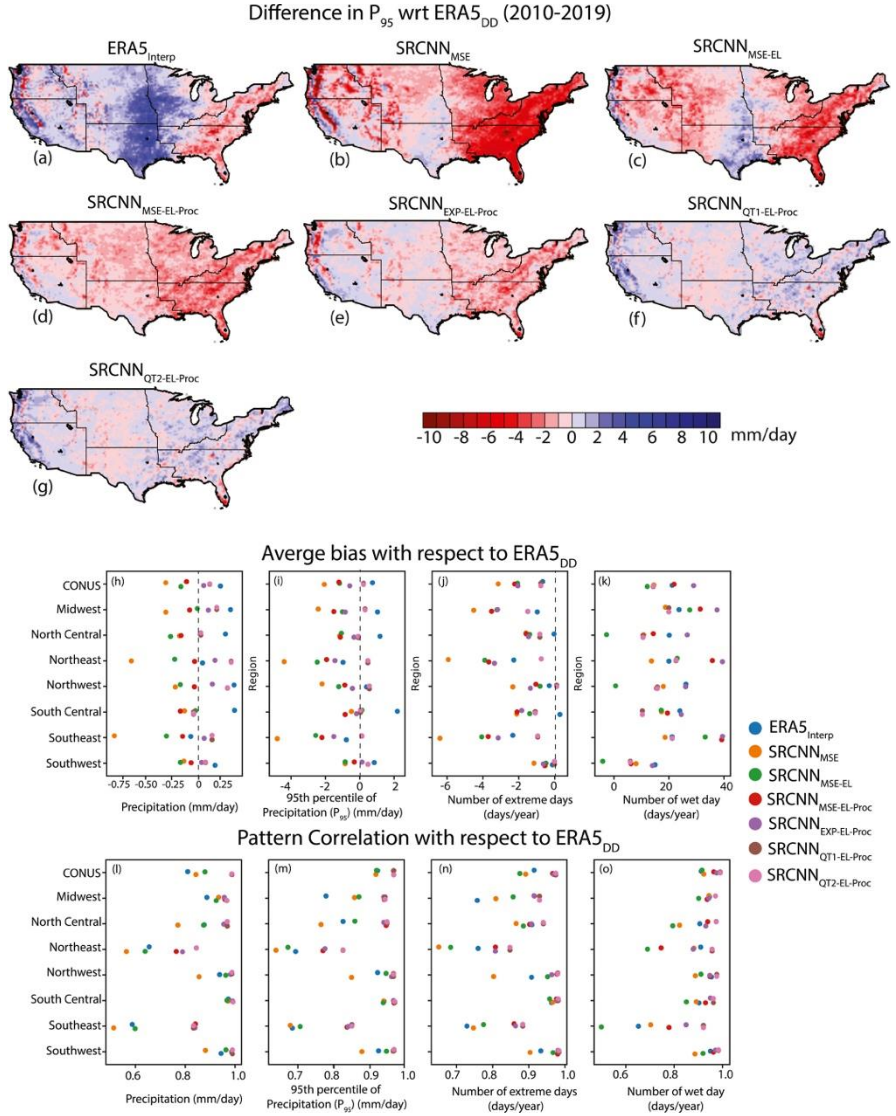

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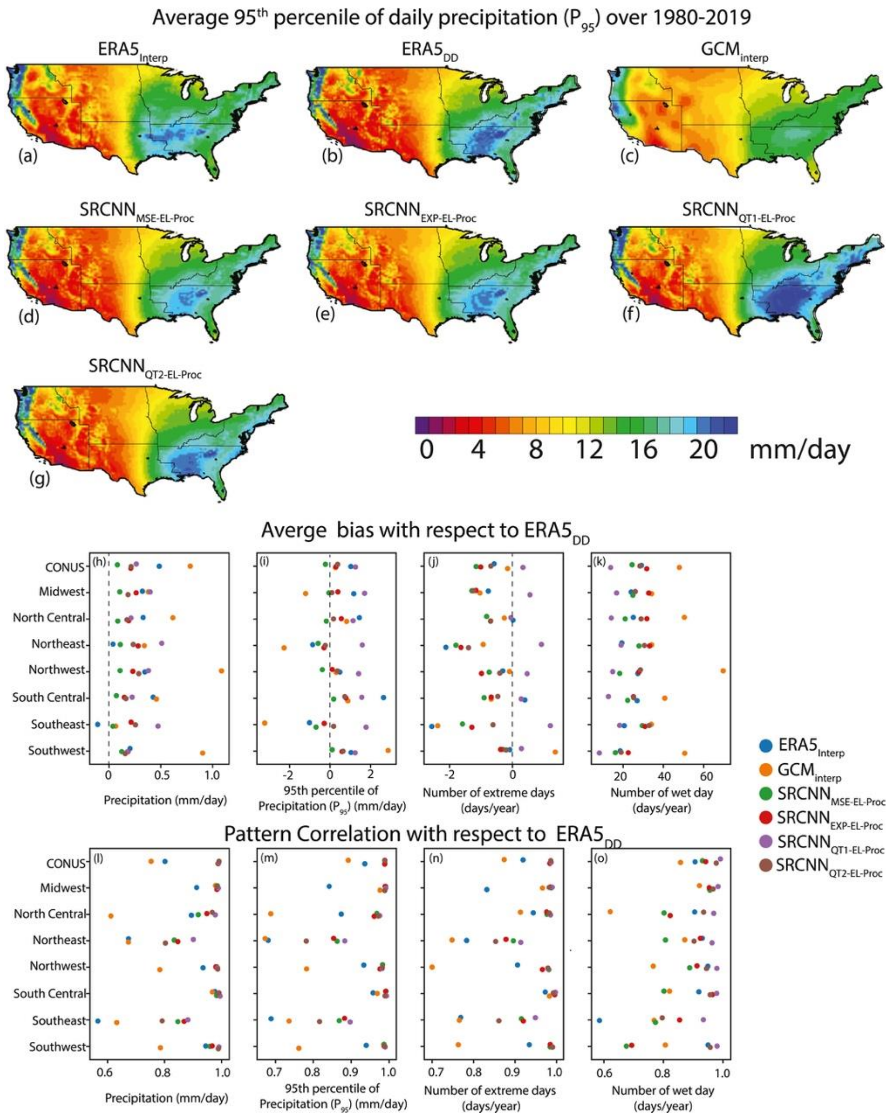

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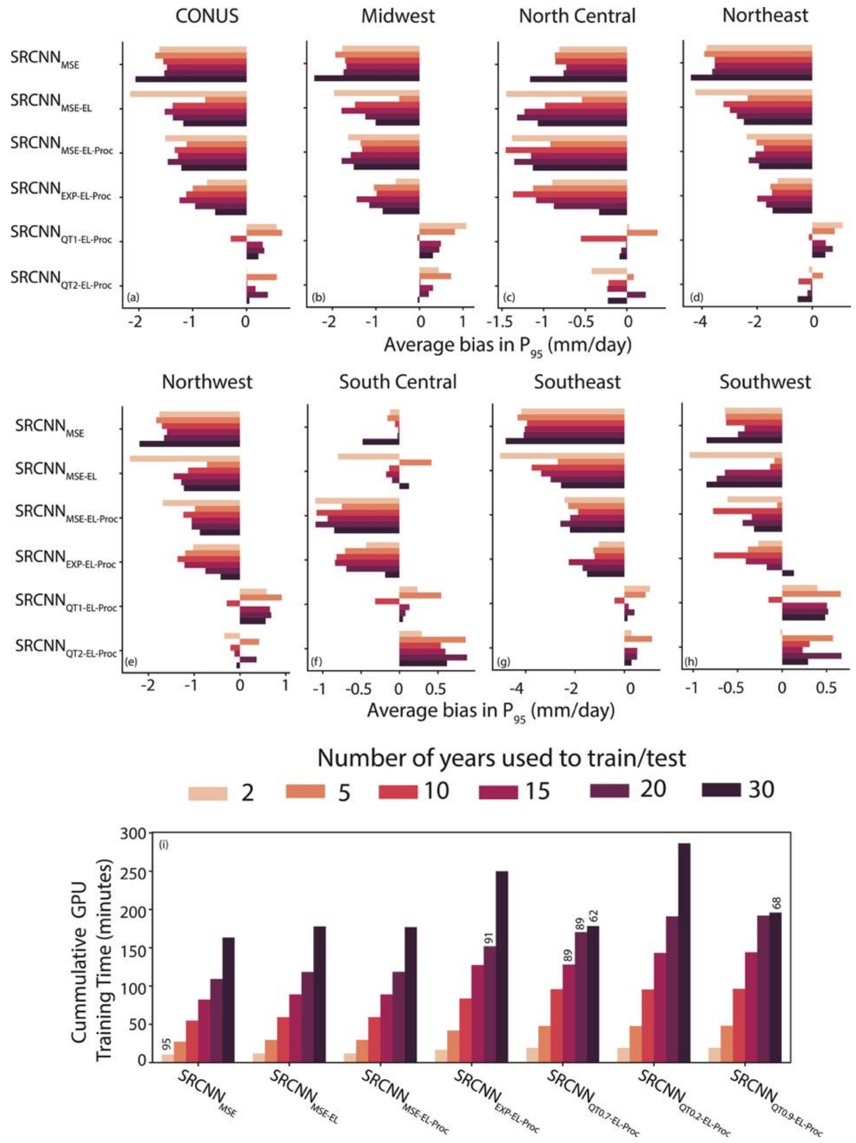

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Summary

- Super-resolution (downscaling) converts coarse climate model outputs into higher-resolution fields for finer regional climate details.
- Traditional approaches include dynamical and statistical downscaling, while modern methods use deep learning (CNNs, U-Nets, GANs, diffusion models) to better reconstruct spatial patterns.
- Key challenges include maintaining physical consistency, accurately representing extreme events, and ensuring models provide reliable, interpretable, and uncertainty-aware predictions for future climates.