Climate Informatics Conference 2023

# Physics-Constrained Deep Learning for Climate Downscaling

Paula Harder, Alex Hernandez-Garcia, Venkatesh Ramesh, Qidong Yang, Prasanna Sattigeri, Campbell Watson, Daniela Szwarcman, David Rolnick

# Intro

# Goal

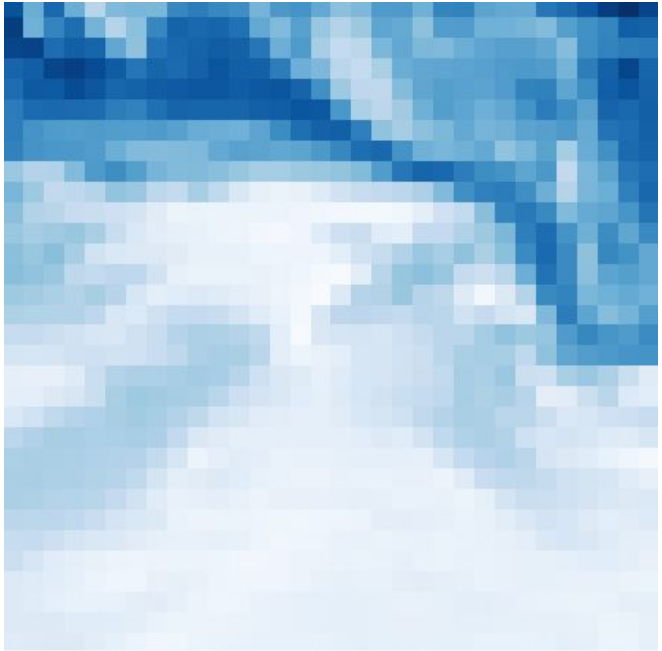
Increasing climate data’s resolution

Low-resolution (LR) input

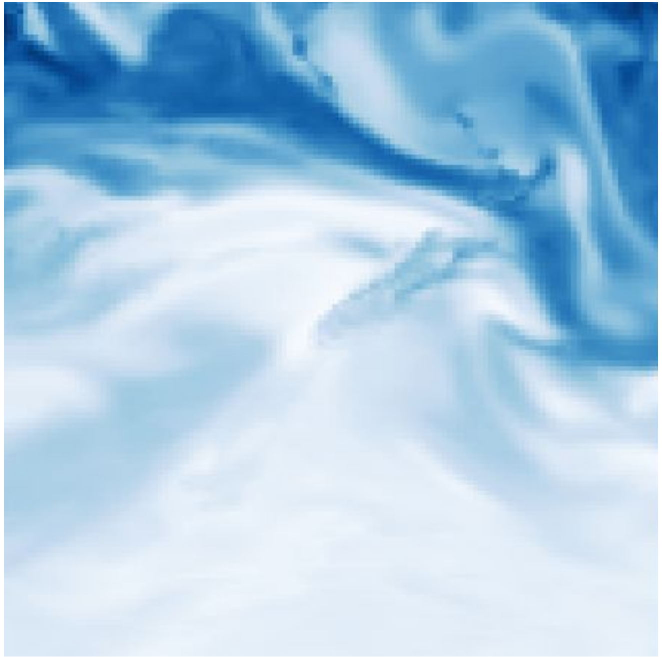
# Goal

Increasing climate data's resolution

Low-resolution (LR) input



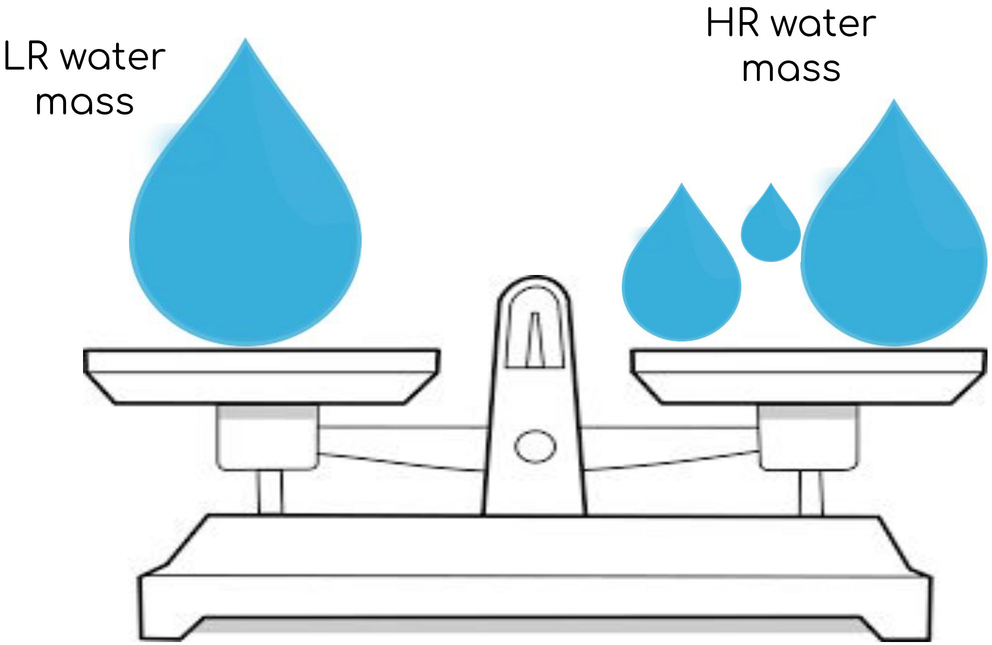
High-resolution (HR) target



# Goal

Increasing climate data's resolution ...

while obeying laws of physics



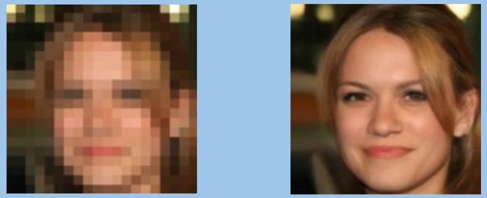
# Terminology

## Machine Learning

super-resolution

upsampling/downsampling

standard images



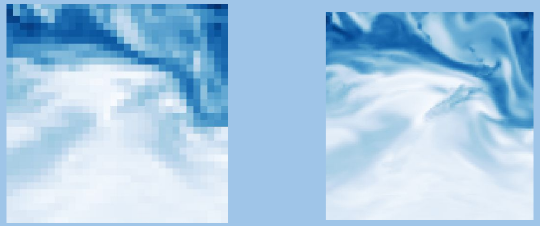
vs

## Climate Science

statistical downscaling

downscaling/upscaling

physical quantities



# Motivation

High-resolution climate data - useful, but hard to obtain

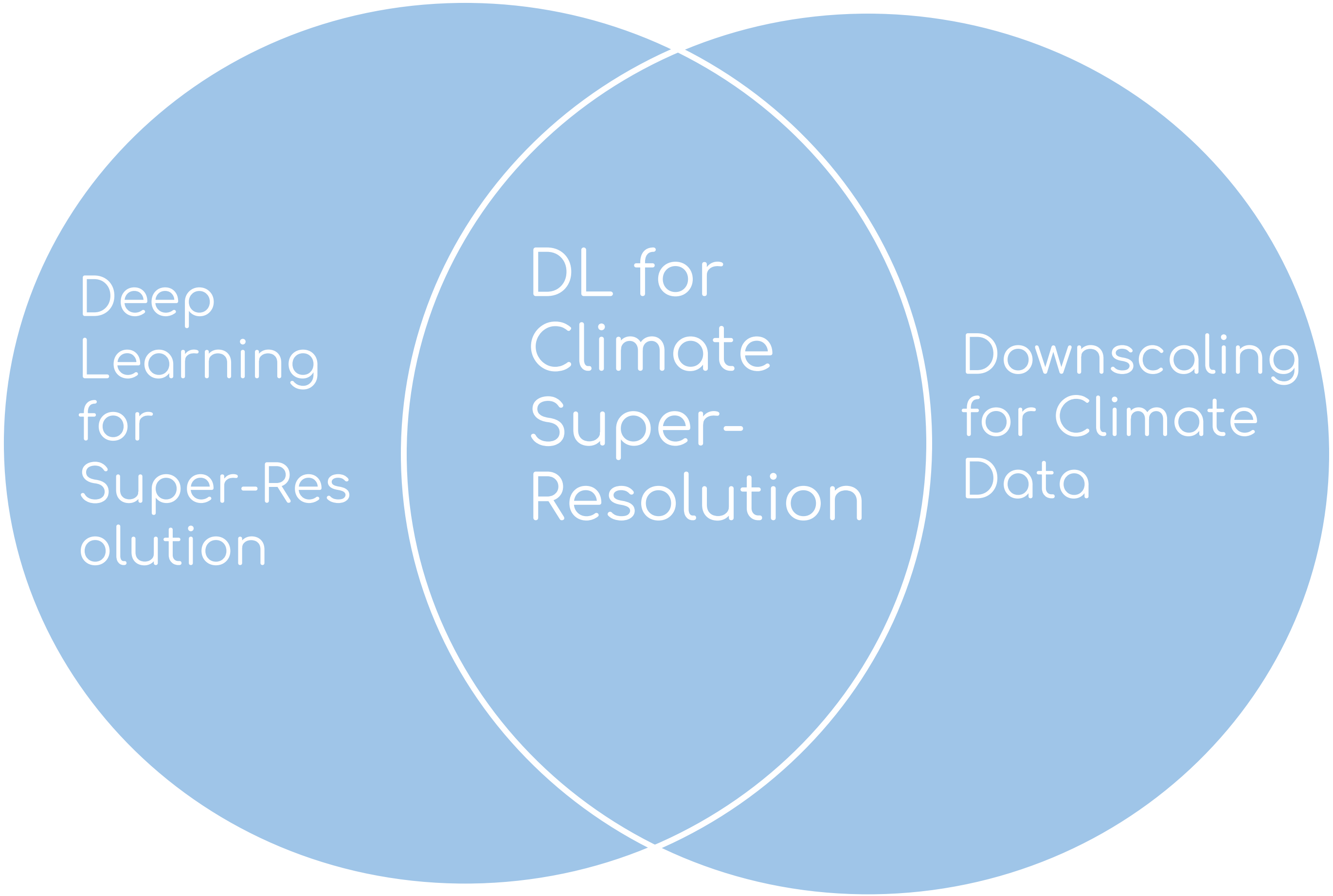
| Useful | Hard to obtain |
|---|---|
| Motivate action to combat climate change | Computationally intensive |
| Inform climate adaption locally | Long runtimes |
| Impact on agriculture, transportation etc. | High energy consumption |
| | Observation not available in some areas |

# Deep Learning for Super-Resolution

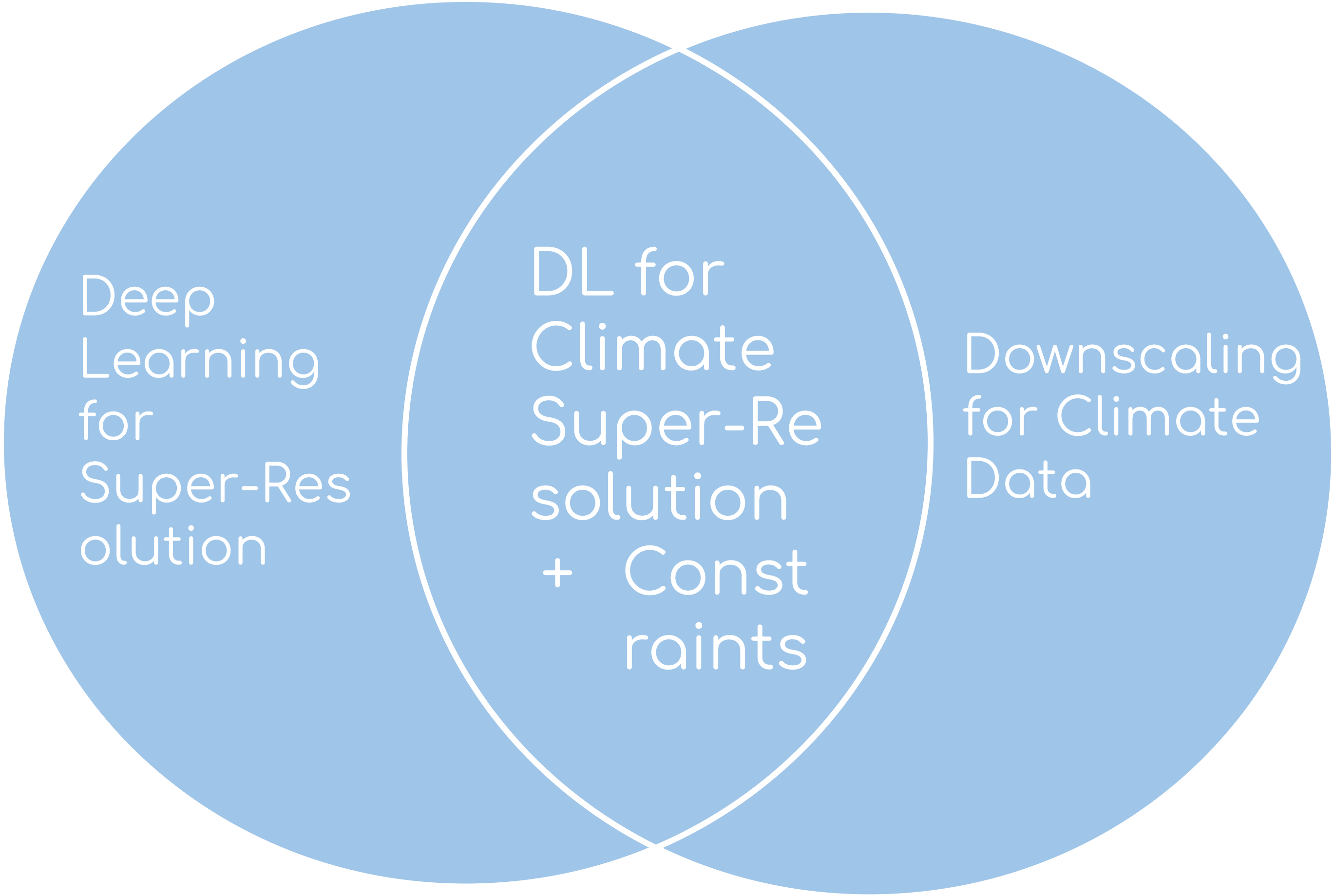
# Downscaling for Climate Data

Deep Learning for Super-Resolution

Downscaling for Climate Data



Deep Learning for Super-Resolution
DL for Climate Super-Resolution
Downscaling for Climate Data



Deep Learning for Super-Resolution
DL for Climate Super-Resolution + Constraints
Downscaling for Climate Data

# Data

# Data sets

Two main data sets

ERA5

WRF

Synthetic

Two different simulations

# Data

Climate data

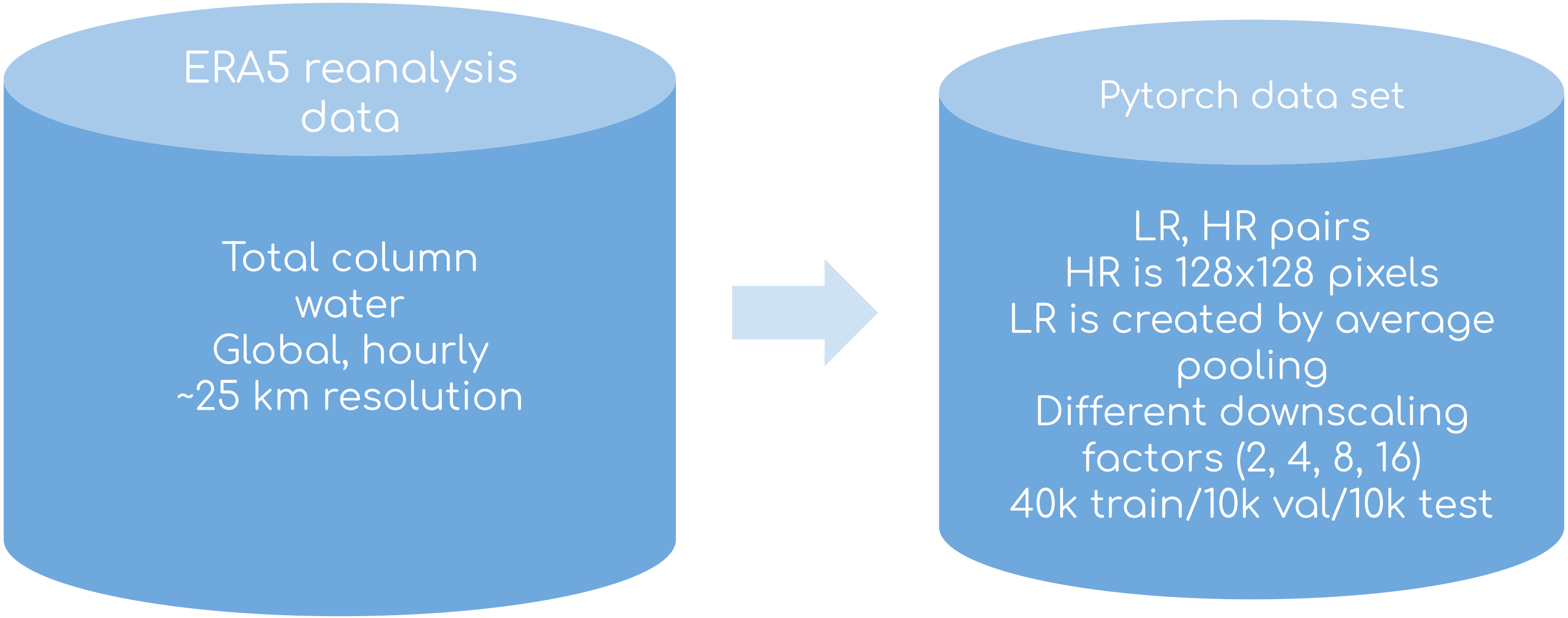
ERA5 reanalysis data

Total column water
Global, hourly
~25 km resolution

# Data

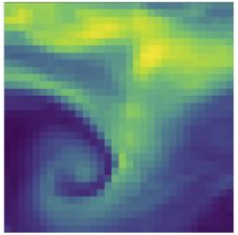
Climate data

ML ready data set

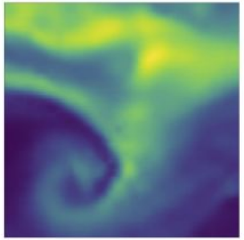


# Data sets

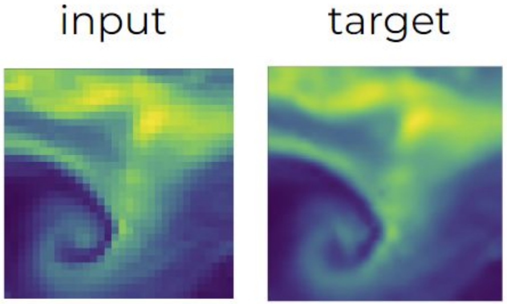
input

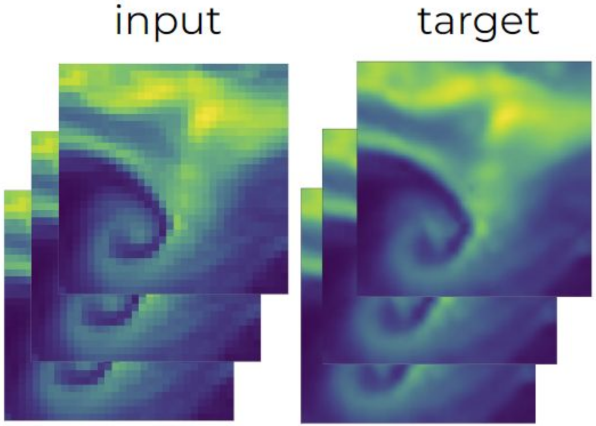


target

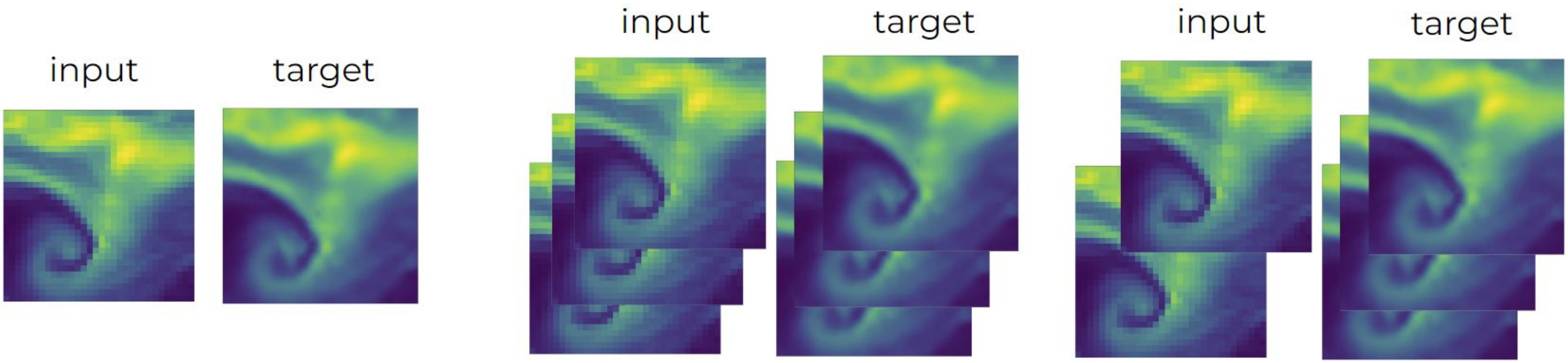


# Data sets



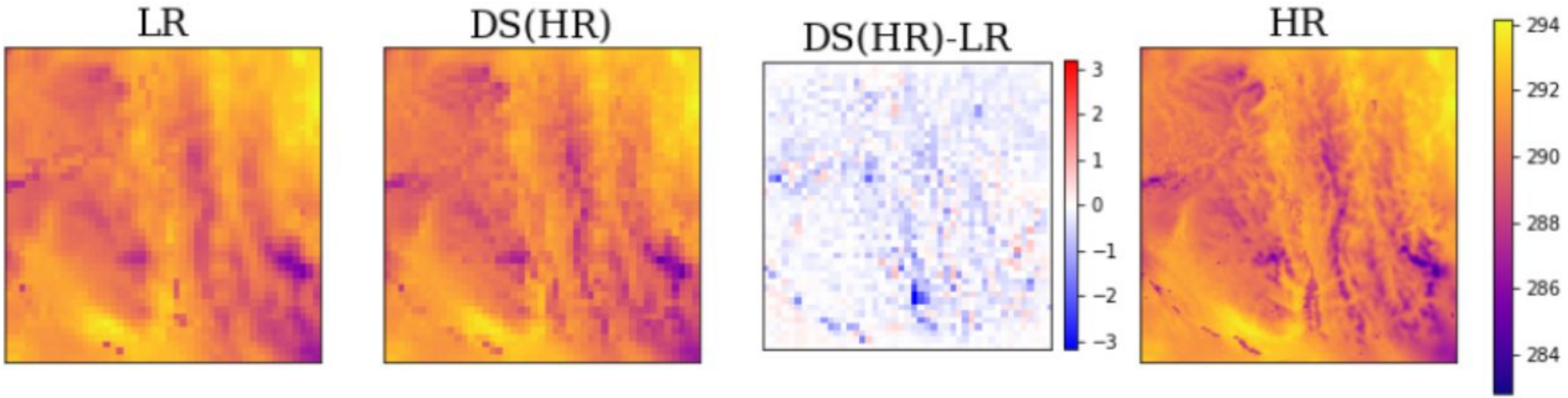



# Data sets



# Data - WRF

- Operational weather forecast
- Lake George in New York
- Hourly
- 2017-2020
- LR not created by downsampling HR, but different simulation!
- HR: 3 km resolution, LR 9 km resolution



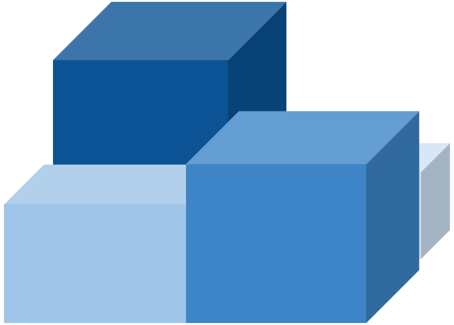
# Methodology

# Physics constraints

Predicted quantity is water mass

Want to enforce conservation of mass between low-res input and super-res prediction

Low-res water mass



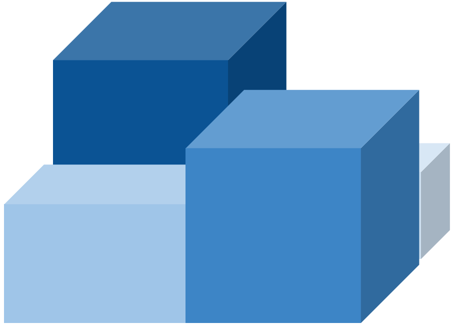
Super-res water mass

# Physics constraints

Want to enforce mass conservation between low-res input and super-res prediction

$$\frac{1}{n}\sum_{i=1}^{n} y_i = x.$$

Low-res water mass



Super-res water mass

# Soft constraining

First idea: Add regularization term to the loss function

$$\text{Loss} = (1-\alpha)\cdot\text{MSE} + \alpha\cdot\text{Constraint violation}.$$

$$\text{Constraint violation} = \text{MSE}\left(\frac{1}{n}\sum_{i=1}^{n} y_i,\ x\right)$$

Problems:

- No guarantee
- Need to optimize alpha
- Can have accuracy-constraints trade-off

# Hard constraining

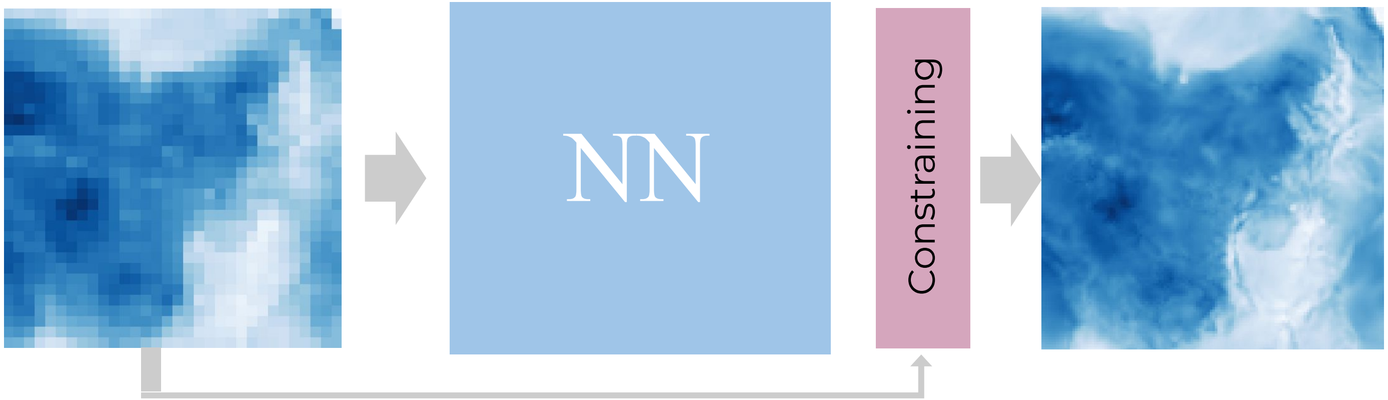
Want to enforce mass conservation between low-res input and super-res prediction

$$\frac{1}{n}\sum_{i=1}^{n} y_i = x.$$

# Hard constraining

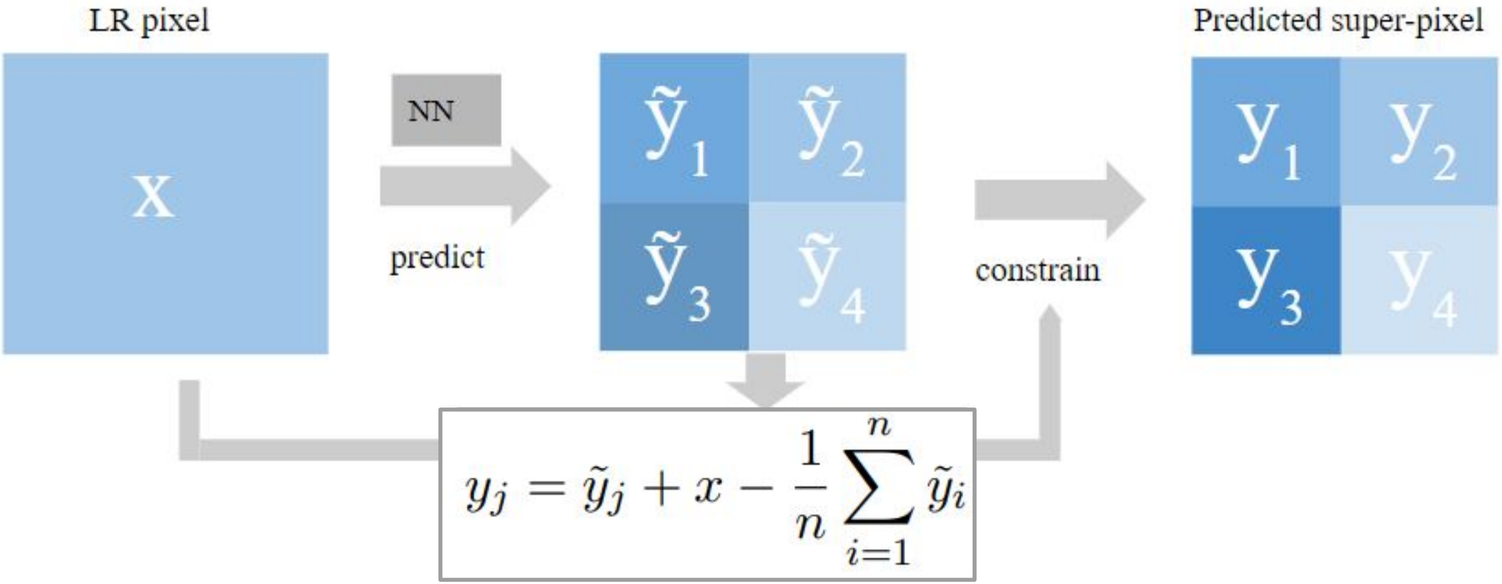
Want to enforce mass conservation between low-res input and super-res prediction

$$\frac{1}{n}\sum_{i=1}^{n} y_i = x.$$



# Renormalizing layer - Additive constraint layer

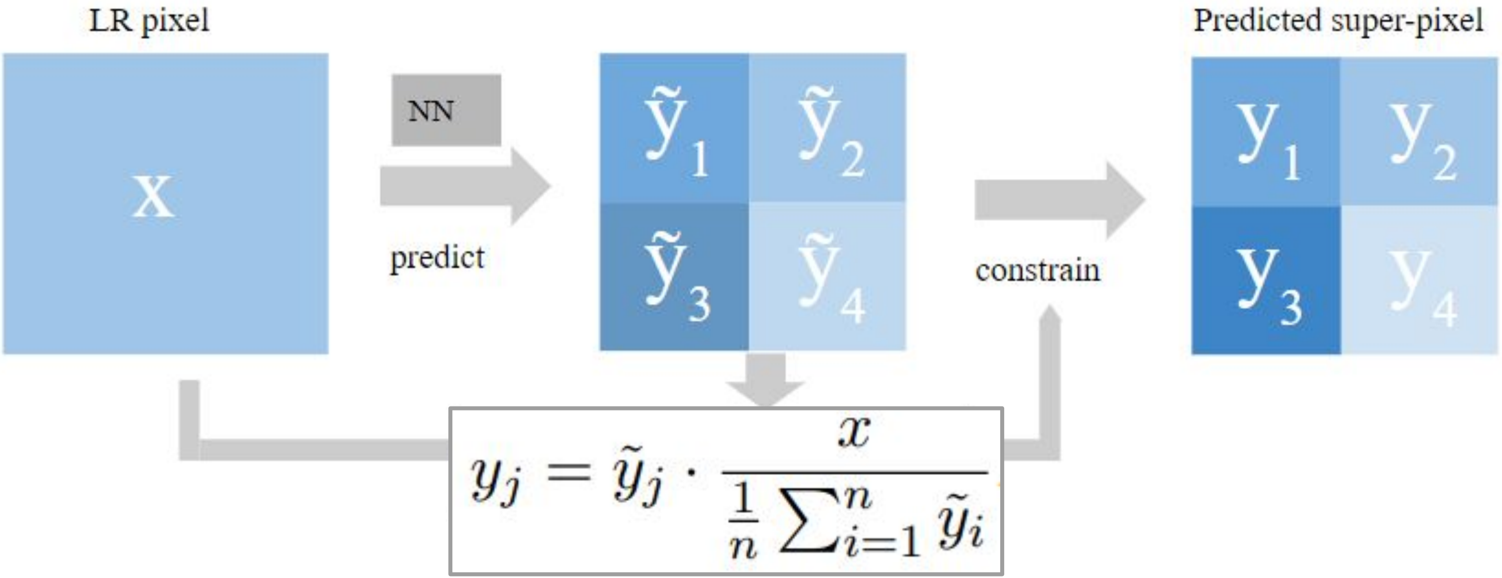
The additive constraint layer (AddCL) adds a term to the intermediate output and with that guarantees conservation of mass




$$y_j = \tilde{y}_j + x - \frac{1}{n}\sum_{i=1}^{n}\tilde{y}_i$$

# Renormalizing layer - Multiplicative constraint layer

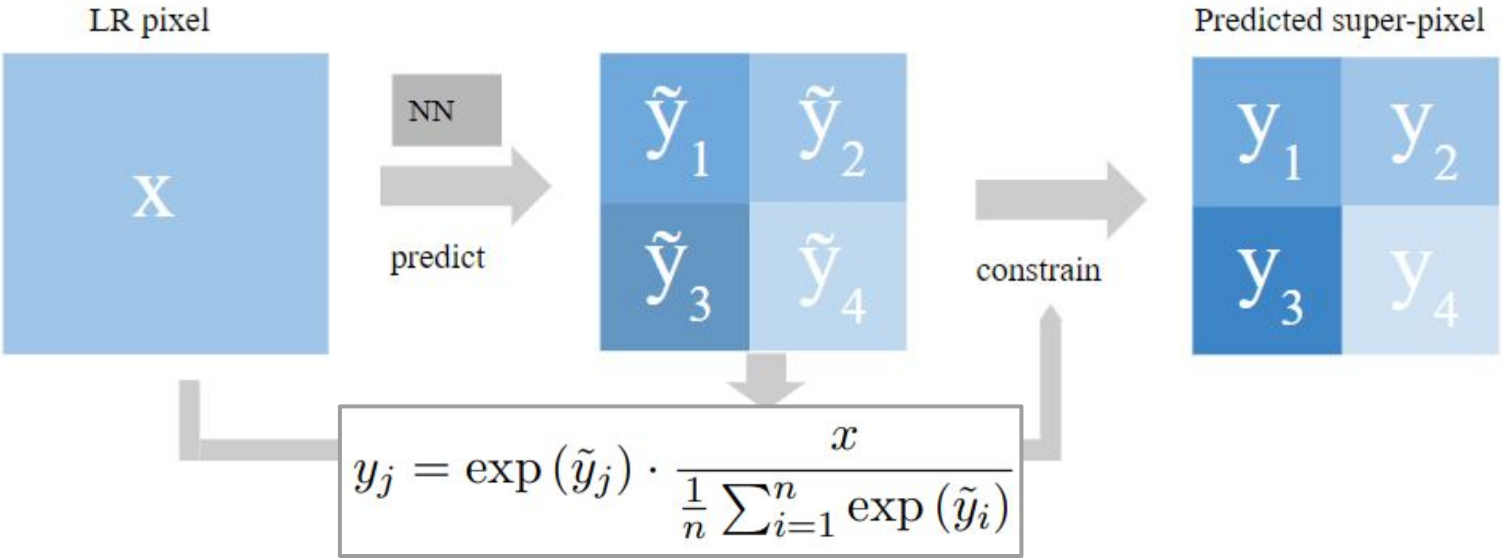
The multiplicative constraint layer (MultCL) multiplies a factor to the intermediate output and with that guarantees conservation of mass




$$y_j = \tilde{y}_j \cdot \frac{x}{\frac{1}{n}\sum_{i=1}^{n} \tilde{y}_i}$$

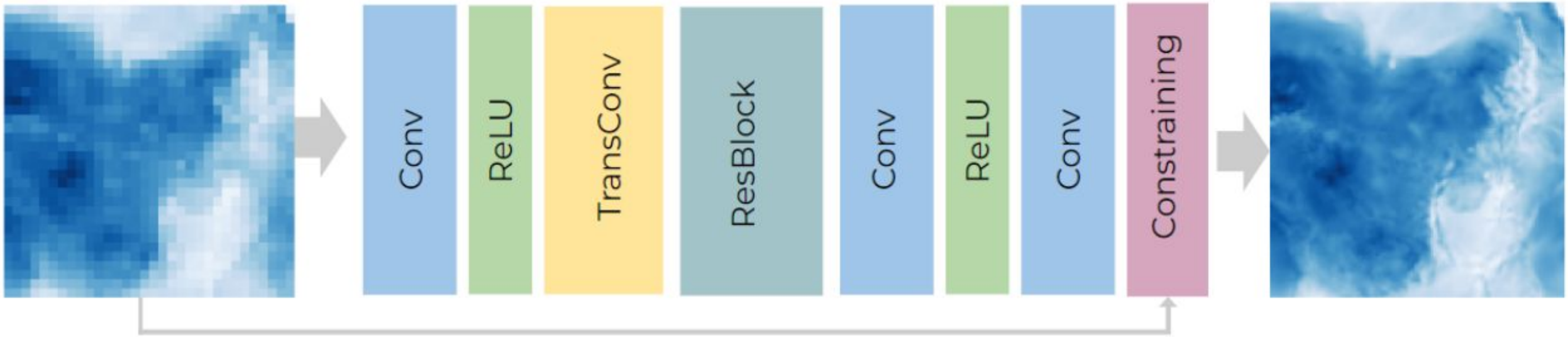
# Renormalizing layer - Softmax constraint layer

The softmax constraint layer (SmCL) applies a scaled softmax and guarantees conservation of mass and positivity



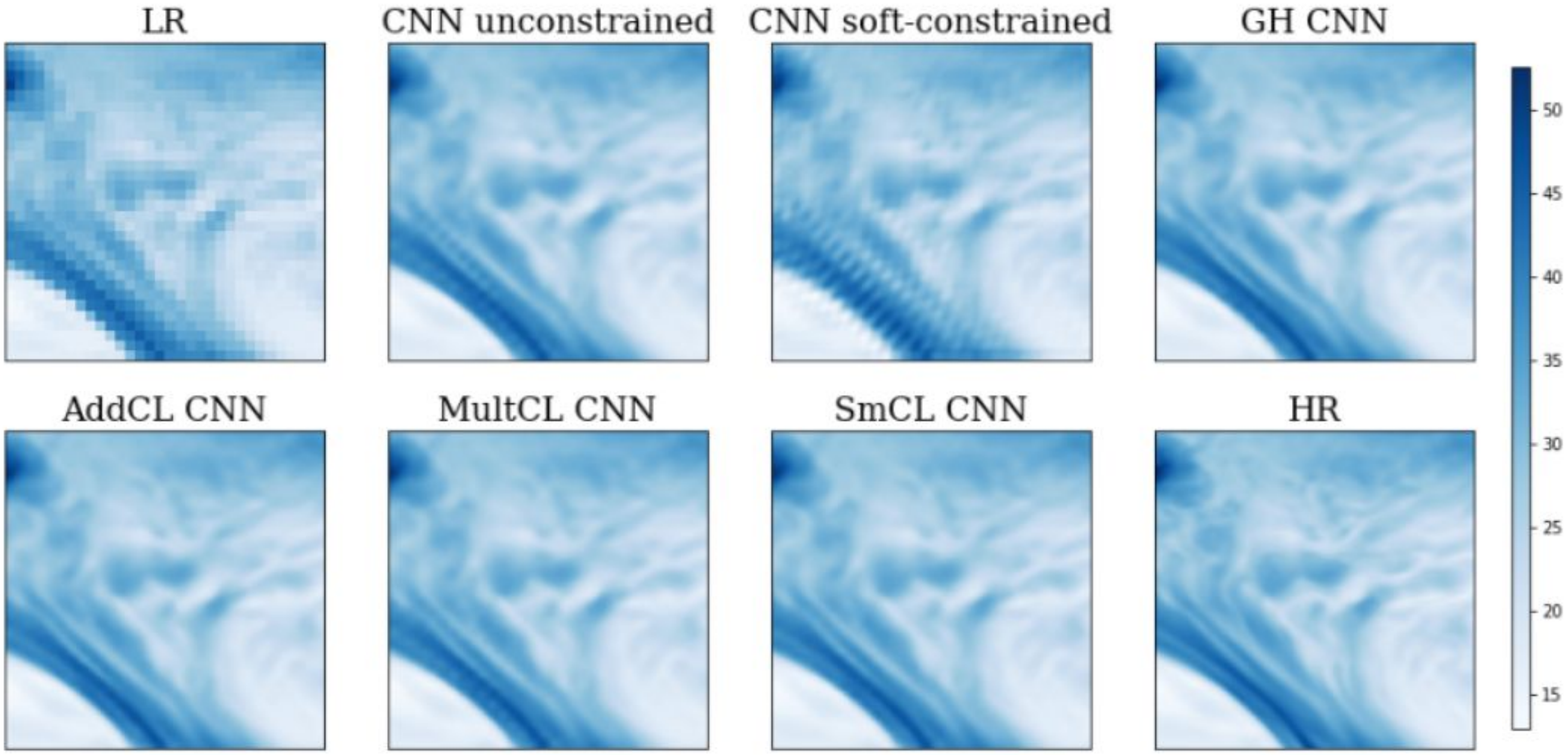

$$y_j = \exp(\tilde{y}_j) \cdot \frac{x}{\frac{1}{n}\sum_{i=1}^{n} \exp(\tilde{y}_i)}$$

# Enforcing constraints - architecture

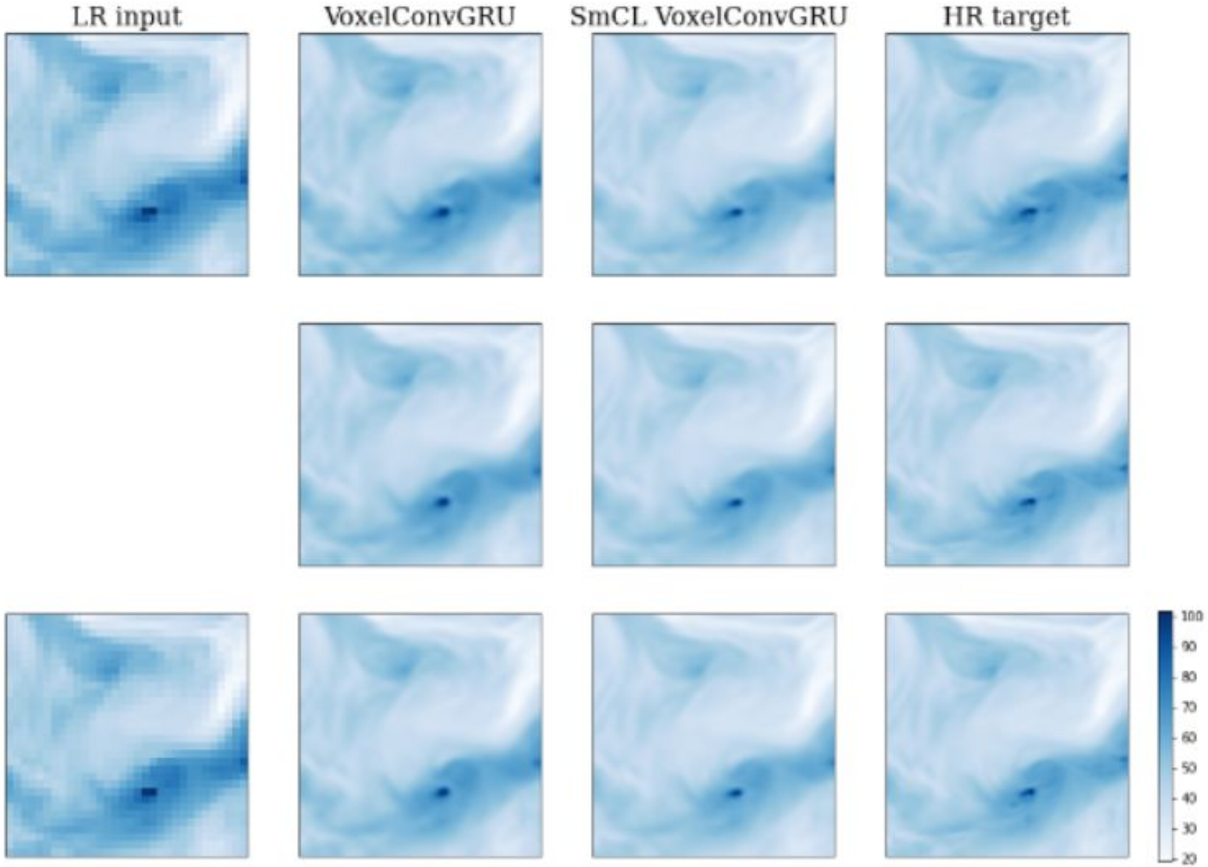


# Results

# Results - CNN water content 4x

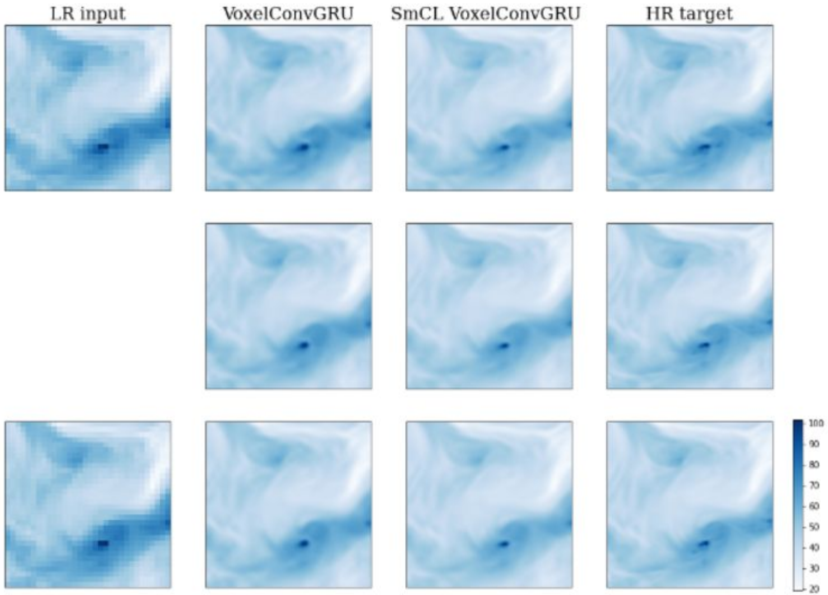


# Results - Spatial-temporal super-resolution

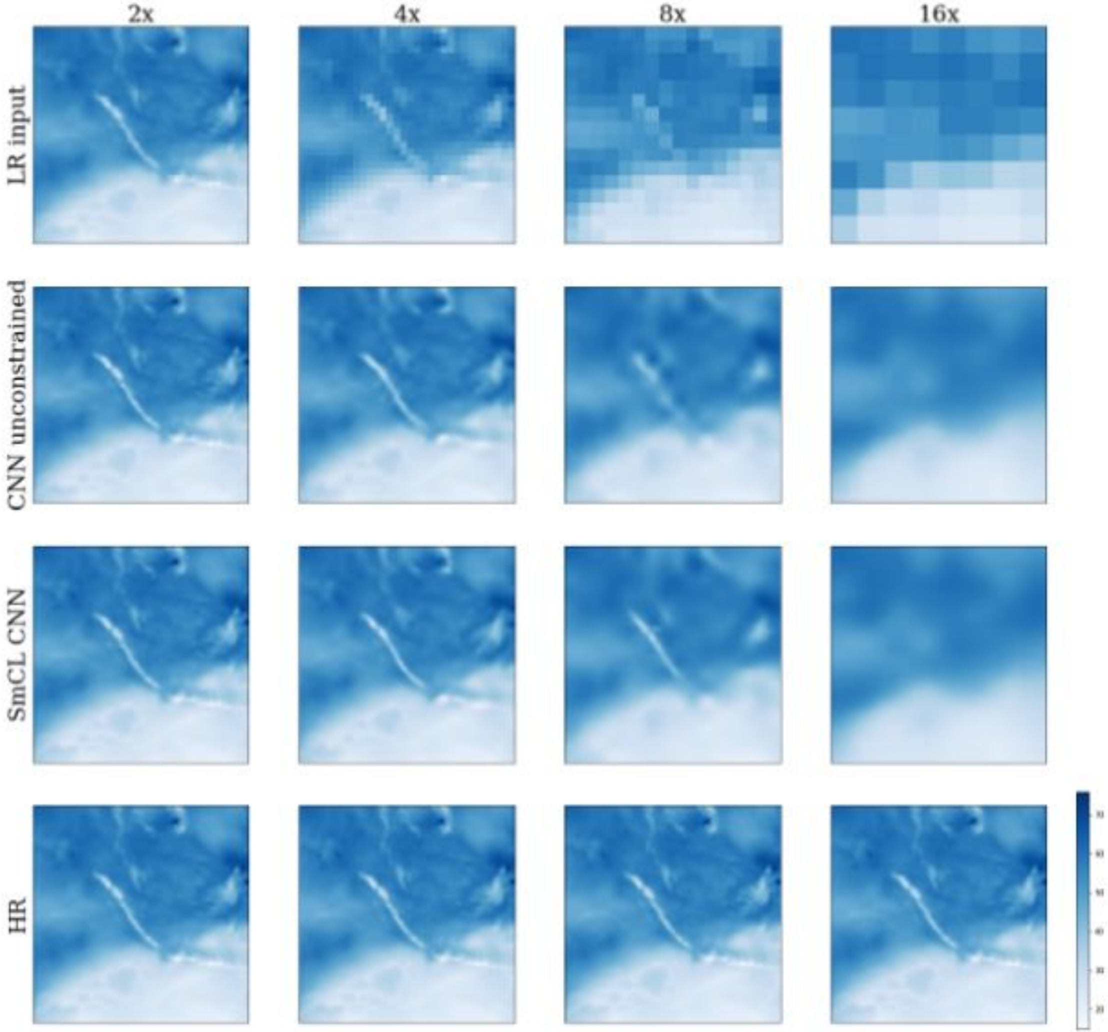


# Results - Spatial-temporal super-resolution

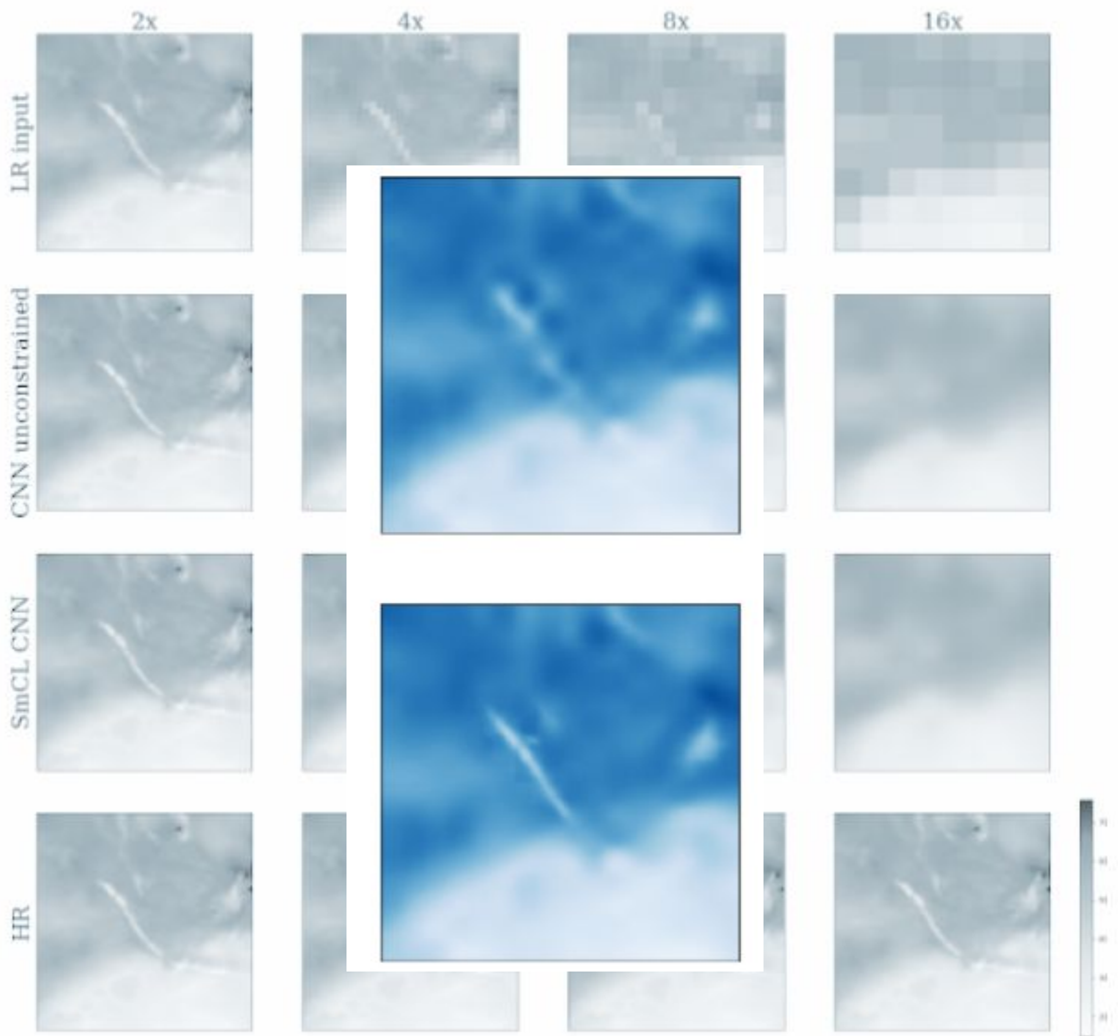
| Model | unconstrained | Hard-constrained (SmCL) |
| --- | --- | --- |
| RMSE | 0.673 | **0.514** |
| MAE | 0.352 | **0.276** |
| SSIM | 99.40 | **99.62** |



# Results - different upsampling factors

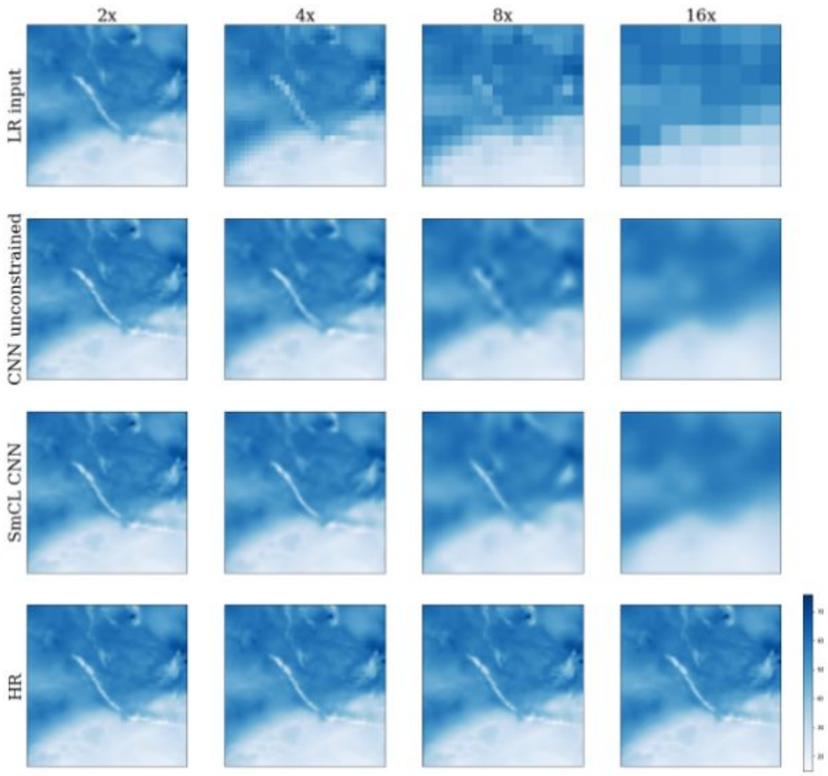


# Results - different upsampling factors

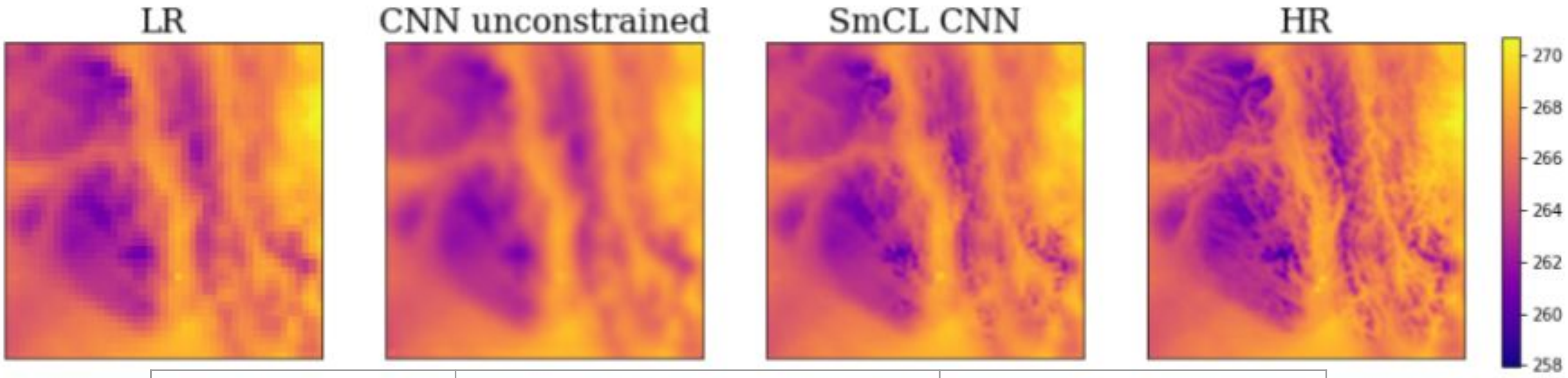


# Results - different upsampling factors

| Factor | unconstrained | Hard-constrained (SmCL) |
|---|---|---|
| 2 x | 0.251 | **0.215** |
| 4 x | 0.657 | **0.582** |
| 8 x | 1.358 | **1.268** |
| 16 x | 2.450 | **2.368** |



# Results - WRF data




| Model | unconstrained | Hard-constrained (SmCL) |
| --- | --- | --- |
| RMSE | 0.952 | **0.950** |
| MAE | 0.618 | **0.592** |
| SSIM | 94.92 | **95.24** |

# Summary

# Summary

Applying a hard constraint layer (e.g. SmCL) to deep learning downscaling architectures (CNNs, GANs, RNNs)

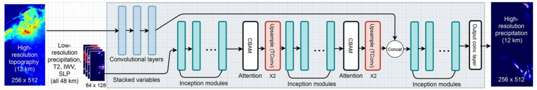
enforces physical laws in neural networks

increases predictive accuracy for downscaling

# Ongoing & future work

Explore different setups, data sets & constraints

- Include elevation
- Constraints between variables

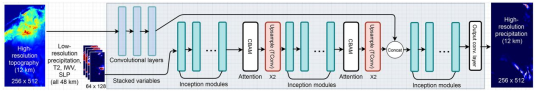



Sources: https://gmd.copernicus.org/articles/14/6355/2021/gmd-14-6355-2021.pdf,
https://agupubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1029/2021MS002954

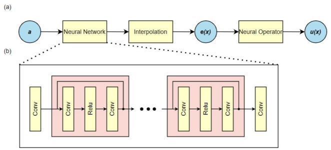
# Ongoing & future work

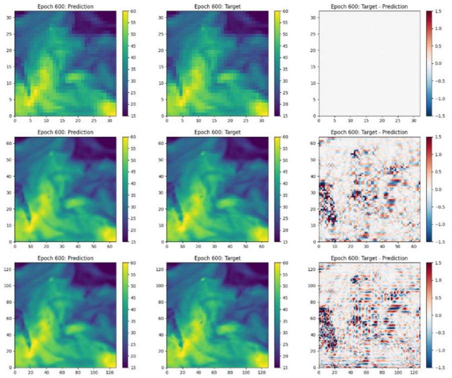
Explore different setups, data sets & constraints

- Include elevation
- Constraints between variables




Apply to different architectures:
E.g. Fourier Neural Operator



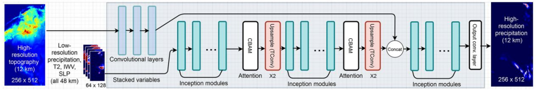




Sources: https://gmd.copernicus.org/articles/14/6355/2021/gmd-14-6355-2021.pdf, https://agupubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1029/2021MS002954

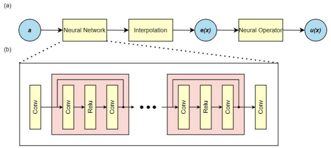
# Ongoing & future work

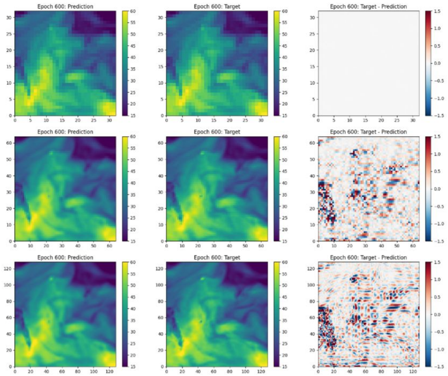
Explore different setups, data sets & constraints

- Include elevation
- Constraints between variables

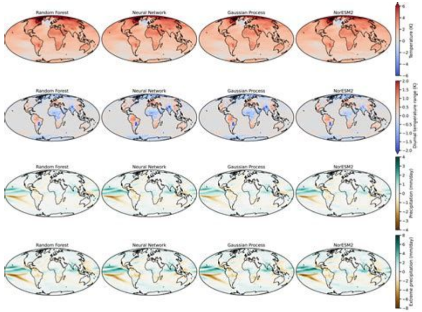



Apply to different architectures:
E.g. Fourier Neural Operator




Apply outside of downscaling:
E.g. for climate emulation




Sources: https://gmd.copernicus.org/articles/14/6355/2021/gmd-14-6355-2021.pdf, https://agupubs.onlinelibrary.wiley.com/doi/pdfdirect/10.1029/2021MS002954

# Thanks for your attention!

Preprint available