Downscaling climate projections using single-image super-resolution

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Final Project
CSE 803 Computer Vision
Professor Xiaoming Liu
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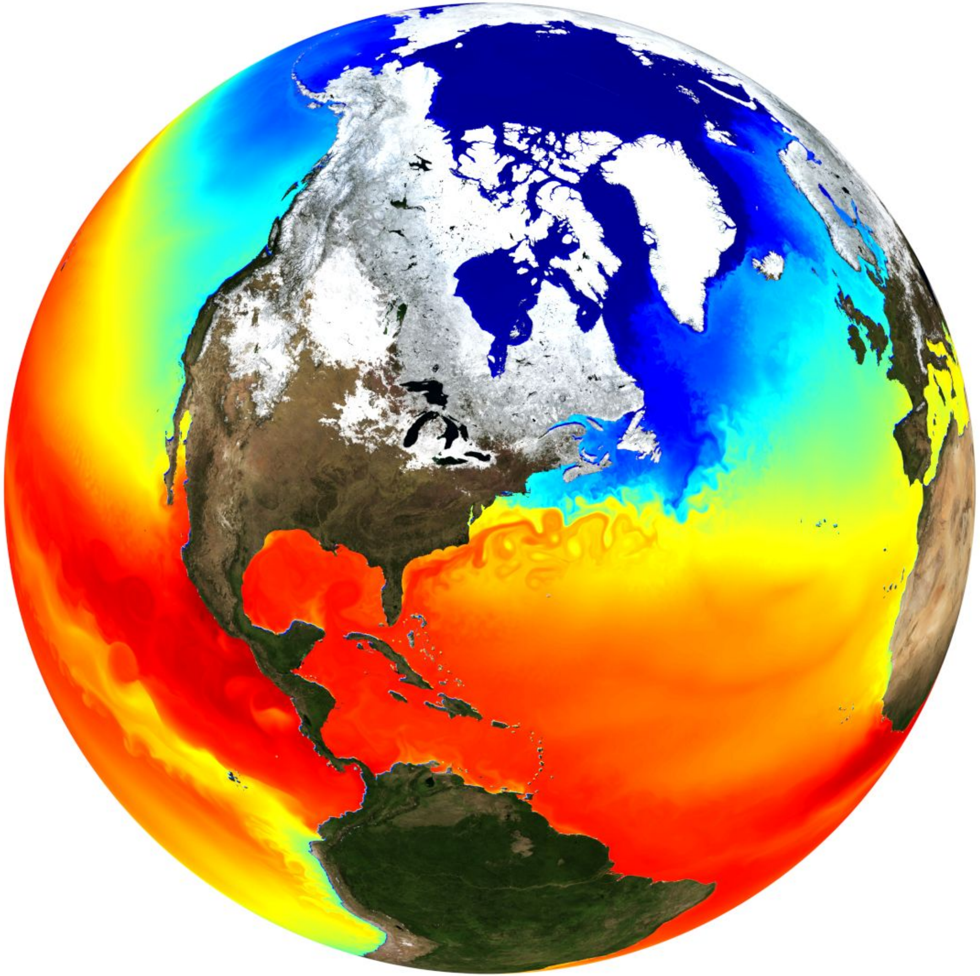
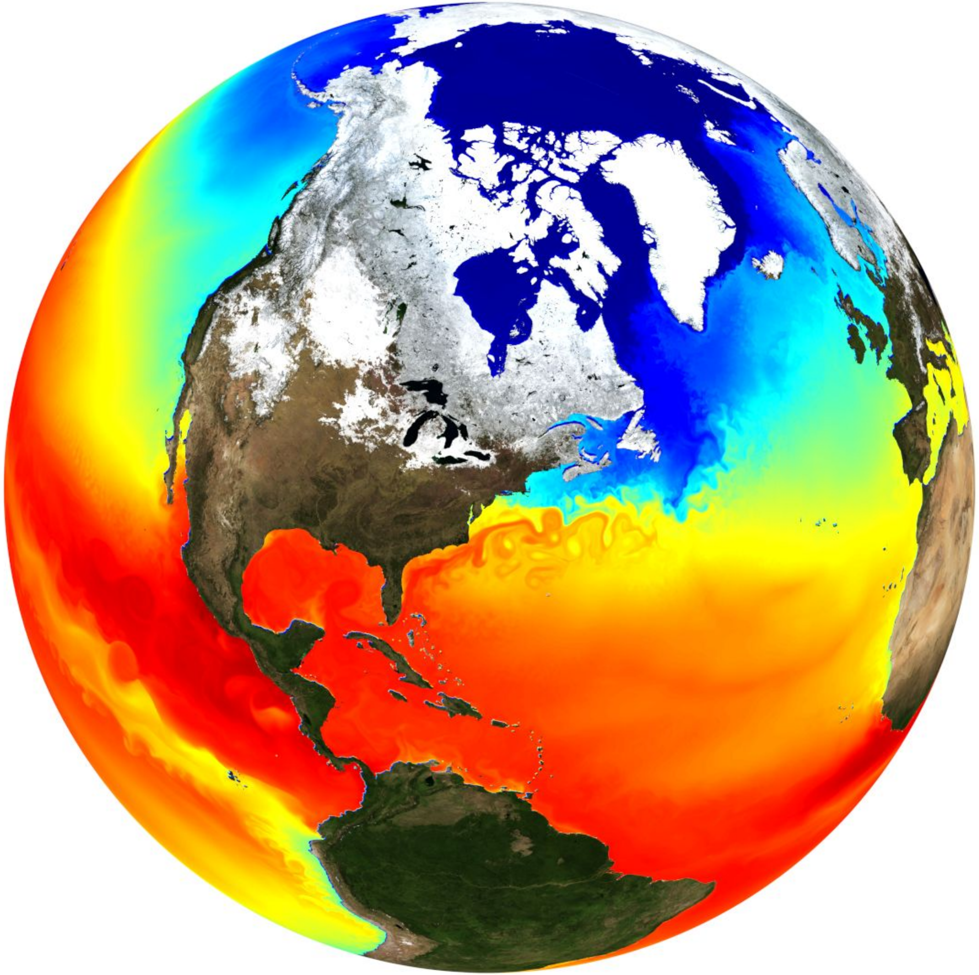
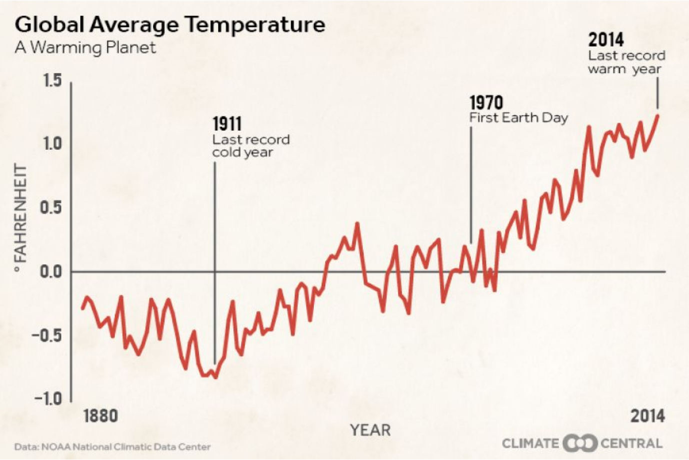


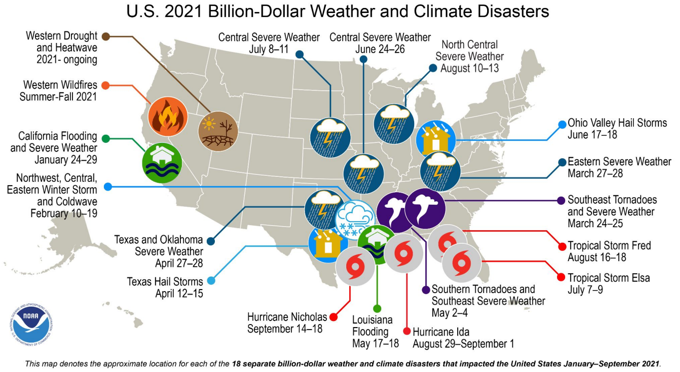
Outline



1. Introduction

- CO_2 → Stronger greenhouse effect
- Stronger greenhouse effect → global warming and climate change
- How will broad-scale changes in the climate system play out on a local level?
- What do climate model projections actually mean?
- How should we plan and invest for a future under climate change?
- Downscaling allows us to understand the local effects of climate change

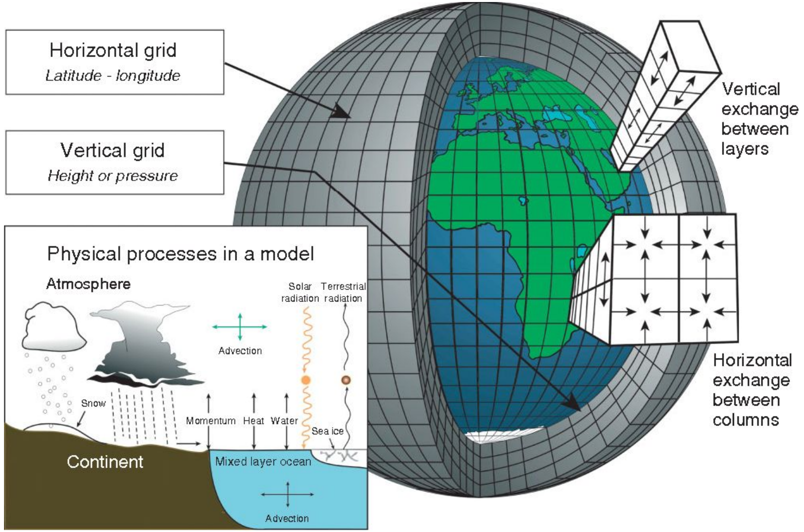


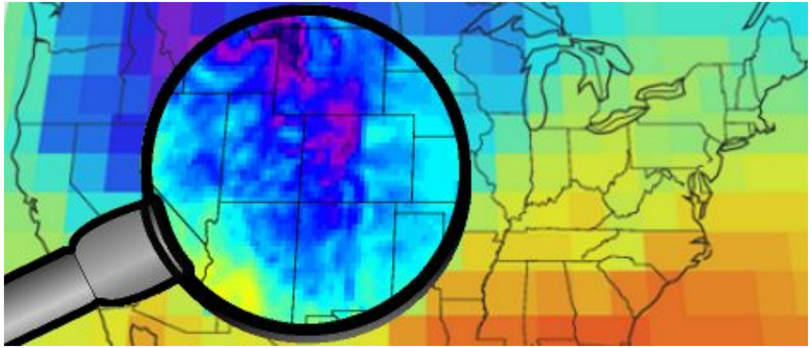


2. Problem Statement

- Downscaling: mapping low-resolution climate data to high-resolution
- Single-image super-resolution: mapping low-resolution images to high-resolution
- We can think of climate data as images, with the channel dimension representing physical variables instead of RGB
- Goal: learn a mapping f_θ for which

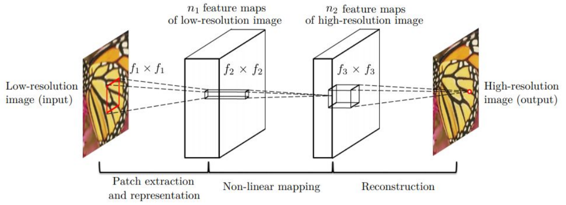
$$f_\theta(\mathbf{X}_L) = \mathbf{X}_H$$

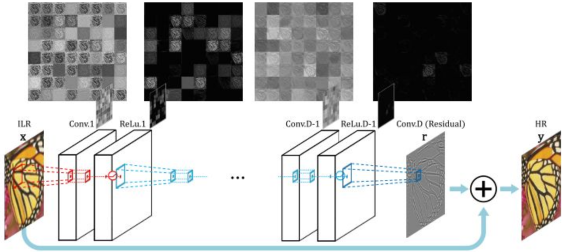




3. Related Work

- SISR
  - SRCNN (Dong 2014)
  - VDSR (Kim 2016)
  - SRResNet (Ledig 2017)
  - + many more
  - Review (Yang 2019)



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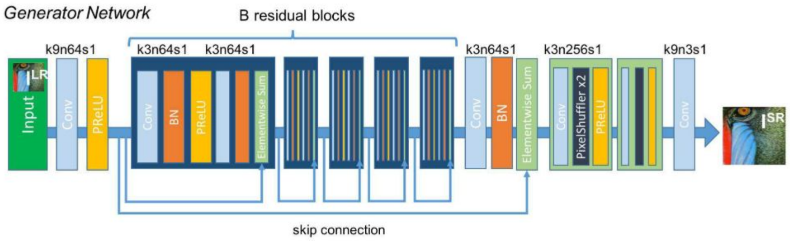
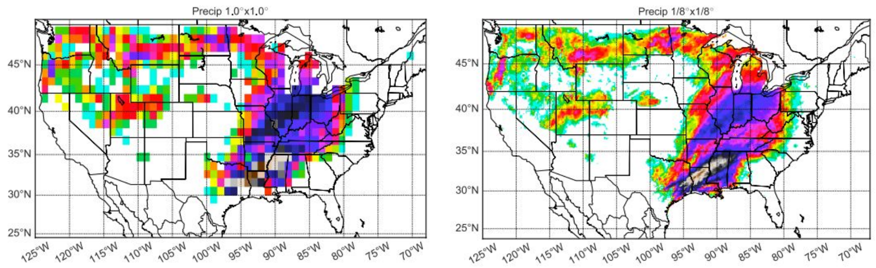
Deep Learning for Single Image Super-Resolution: A Brief Review

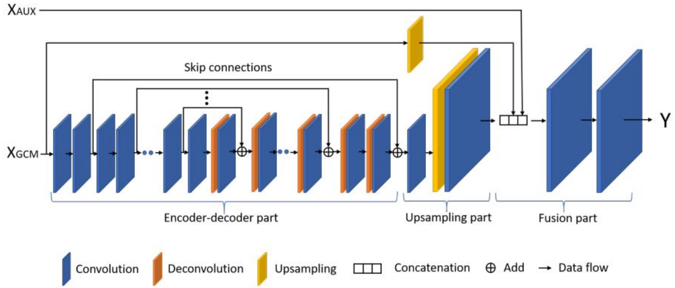
Wenming Yang, Xuechen Zhang, Yapeng Tian, Wei Wang, Jing-Hao Xue, and Qingmin Liao

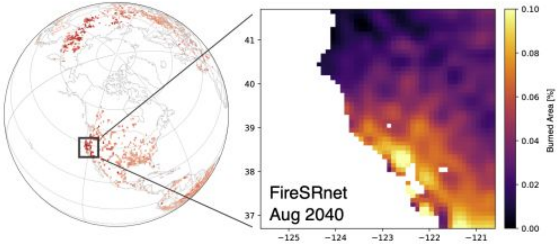


3. Related Work

- Deep Learning for Downscaling
  - DeepSD (Vandal 2017)
  - YNet (Liu 2020)
  - FireSRNet (Ballard 2020)
  - + many more
  - Climate Change AI Workshops @ ICLR, ICML, NeurIPS
  - EarthVision Workshops @ CVPR





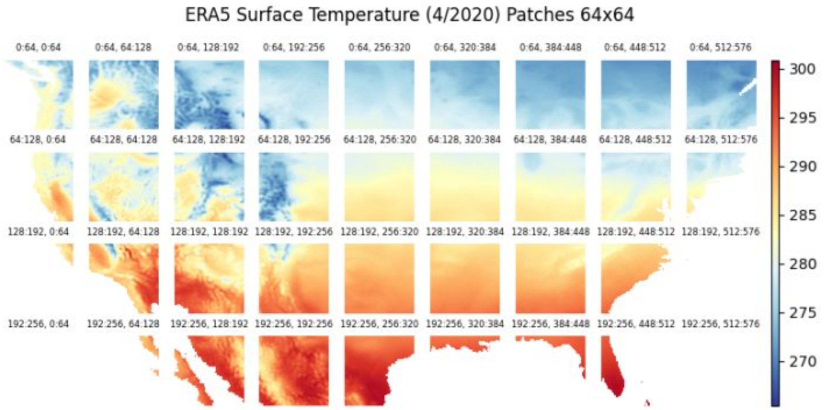


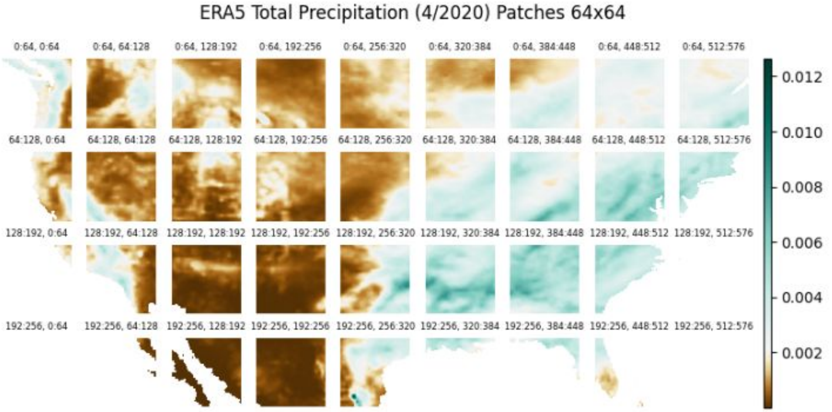
Climate Change AI

EARTH VISION

4.1 Data

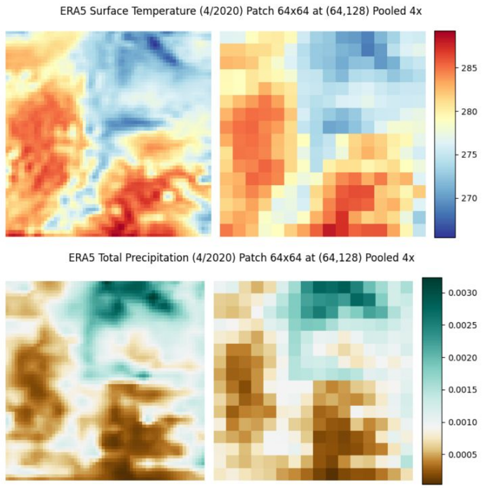
- ERA5 Reanalysis Project
  - Historical data, same idea as GCMs
- Continental US @ 0.1° resolution
- Monthly average surface temperature
- Monthly total precipitation
- Data from 1950-2020 (71 years)
- 852 total images of size 2x261x611
- Partition into 2x64x64 patches
  - Easier computation
  - Data augmentation
  - Nonstationarity

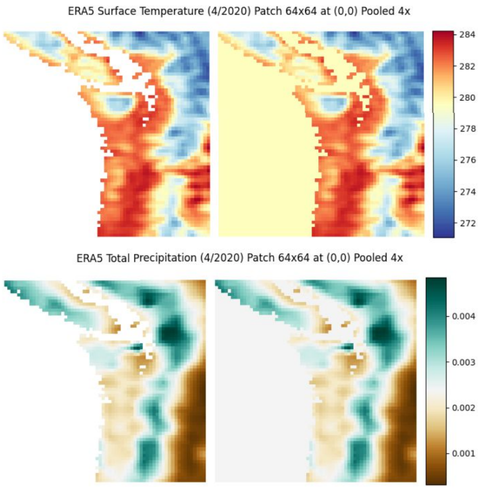




4.1 Data

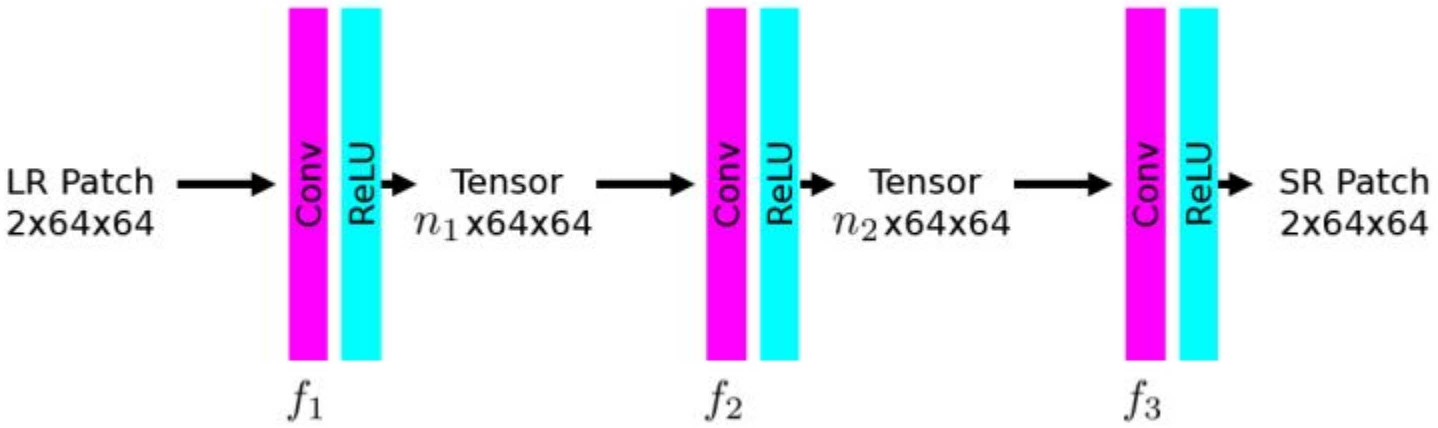
- Apply 4x4 average pooling to construct low-resolution inputs
- Fill in NaNs with patch channel-wise mean





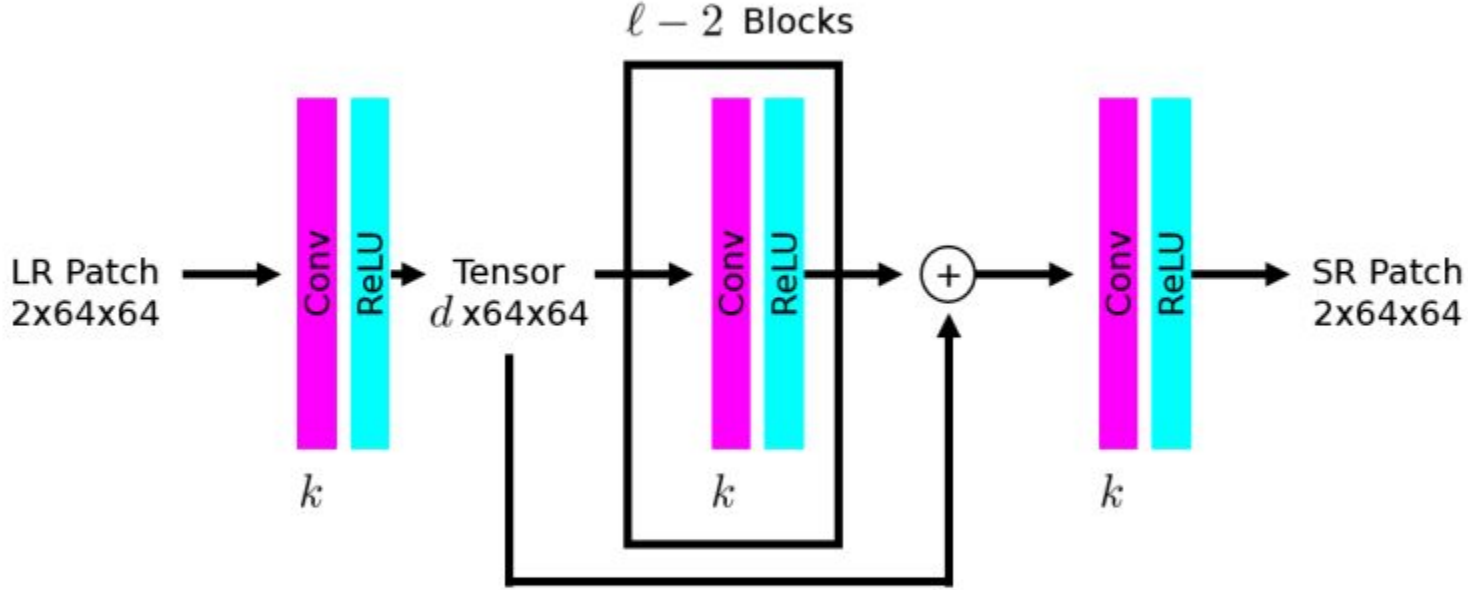
4.2 Models

- SRCNN (Dong 2014)



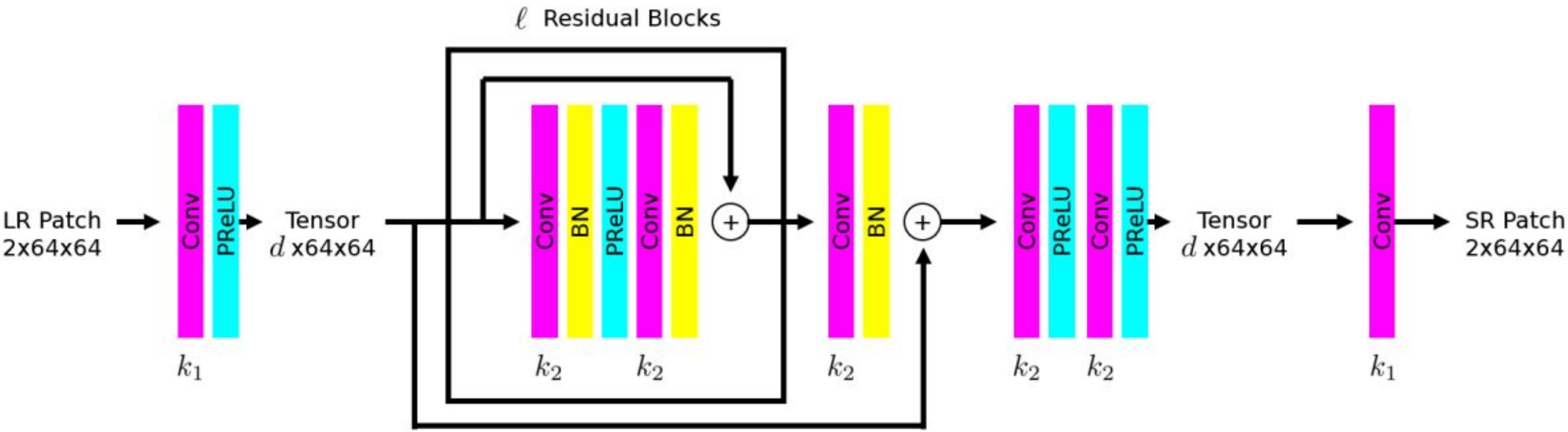
4.2 Models

- VDSR (Kim 2016)



4.2 Models

- SRResNet (Ledig 2017)

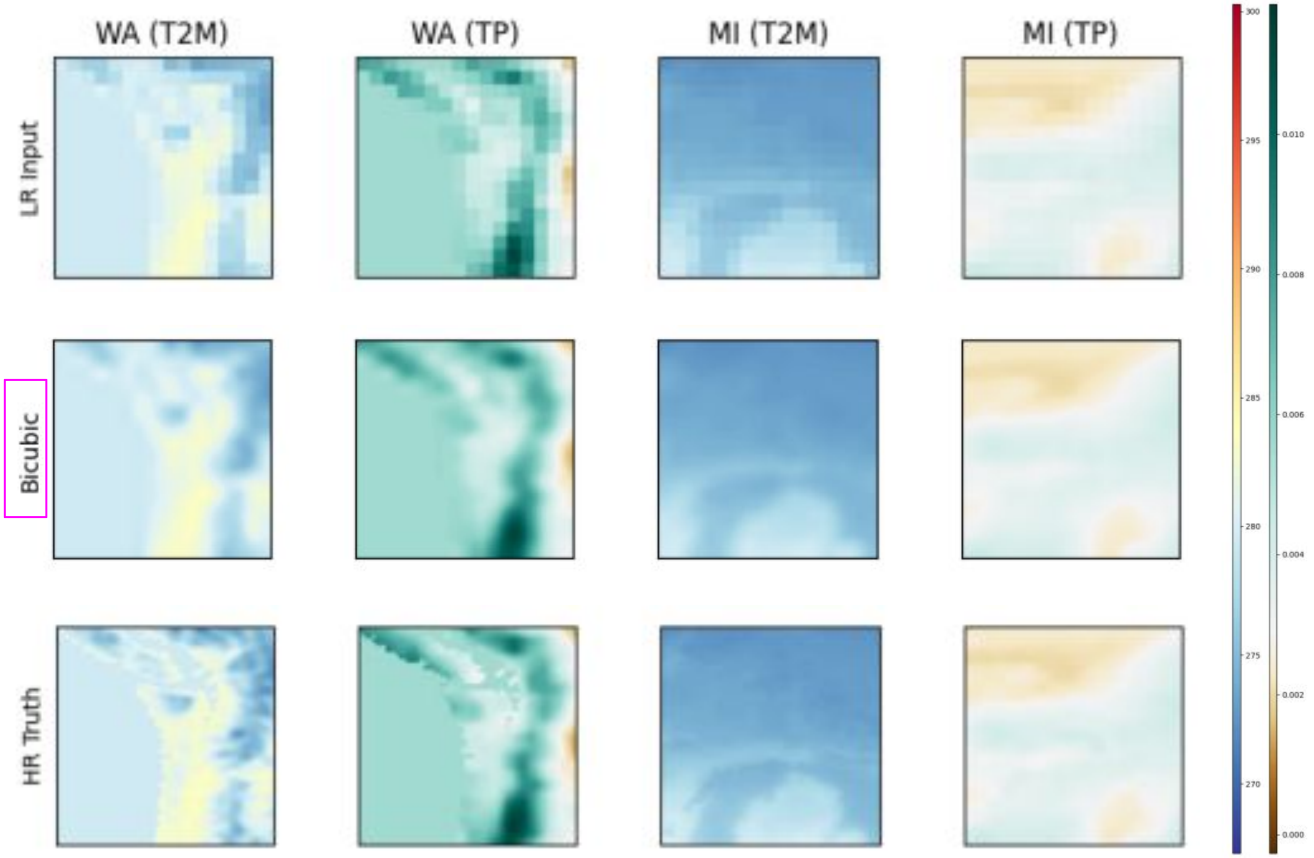


5. Results

Table 1. Comparison of model performance downscaling `t2m` and `tp` ERA5 data [11] over the continental US from 2010-2020 by a factor of $4\times$. We label metrics for which higher is better with ($\uparrow$), and metrics for which lower is better with ($\downarrow$). We indicate the first-, second-, and third-best models in each metric in gold, silver, and bronze, respectively.

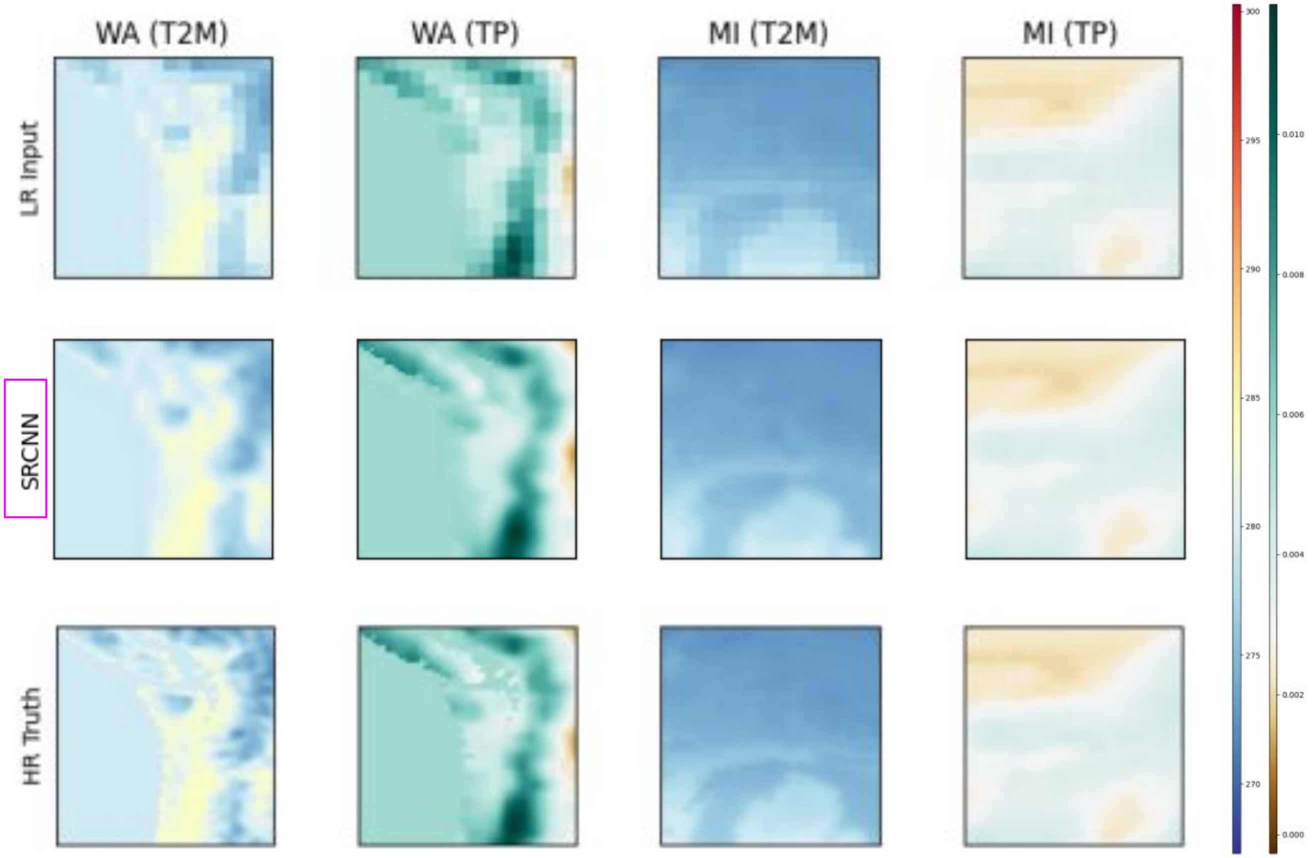
Model	MSE ($\downarrow$)	PSNR ($\uparrow$)	SSIM ($\uparrow$)	Parameters
Nearest	0.01007	30.73644	0.97682	0
Bilinear	0.00668	30.53569	0.97911	0
Bicubic	0.00484	33.16329	0.98783	0
SRCNN	0.00369	36.11259	0.98953	14,114
VDSR	0.00188	38.38477	0.99522	685,506
SRResNet	0.00155	39.11917	0.99564	1,317,525

5. Results



WA (T2M)
WA (TP)
MI (T2M)
MI (TP)
LR Input
Bicubic
HR Truth
300
295
290
285
280
275
270
0.010
0.008
0.006
0.004
0.002
0.000

5. Results



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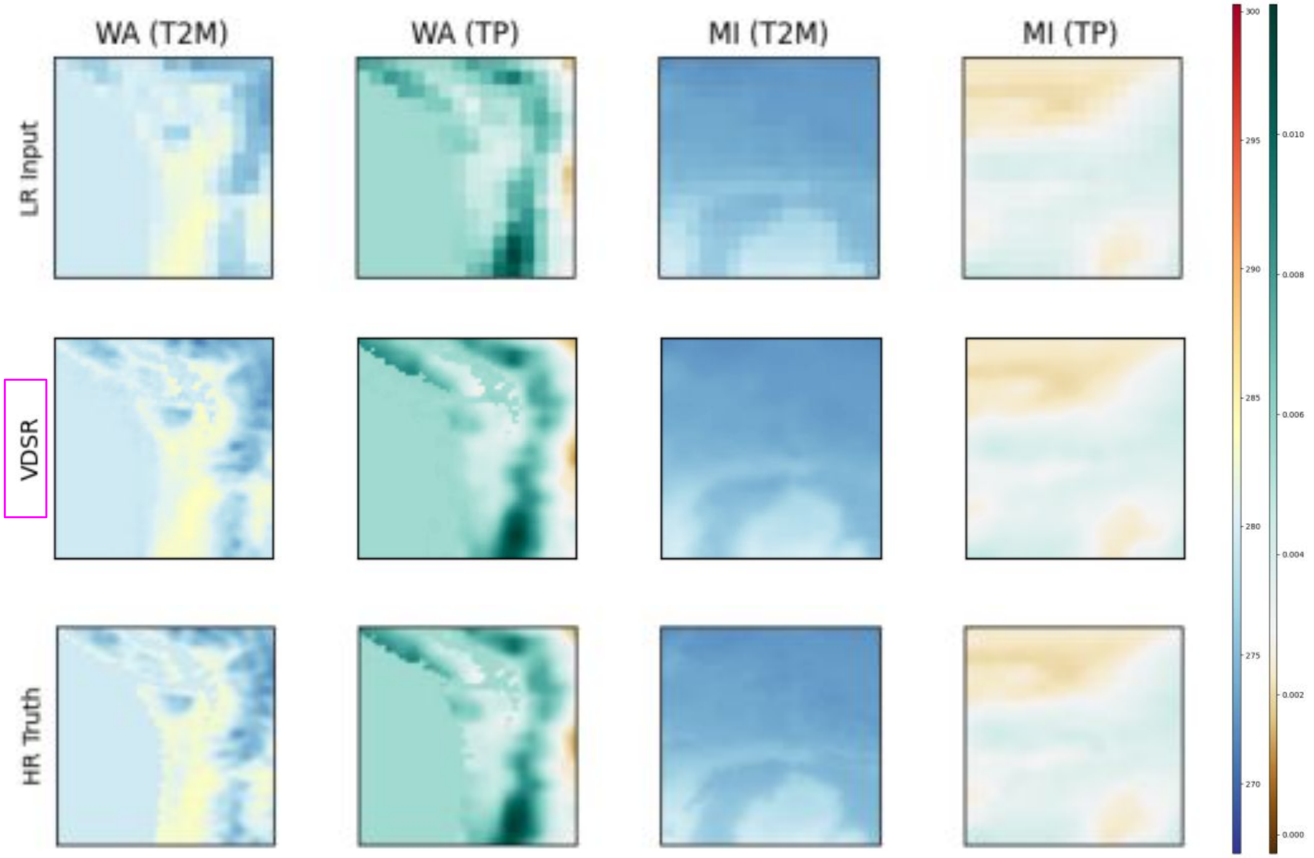
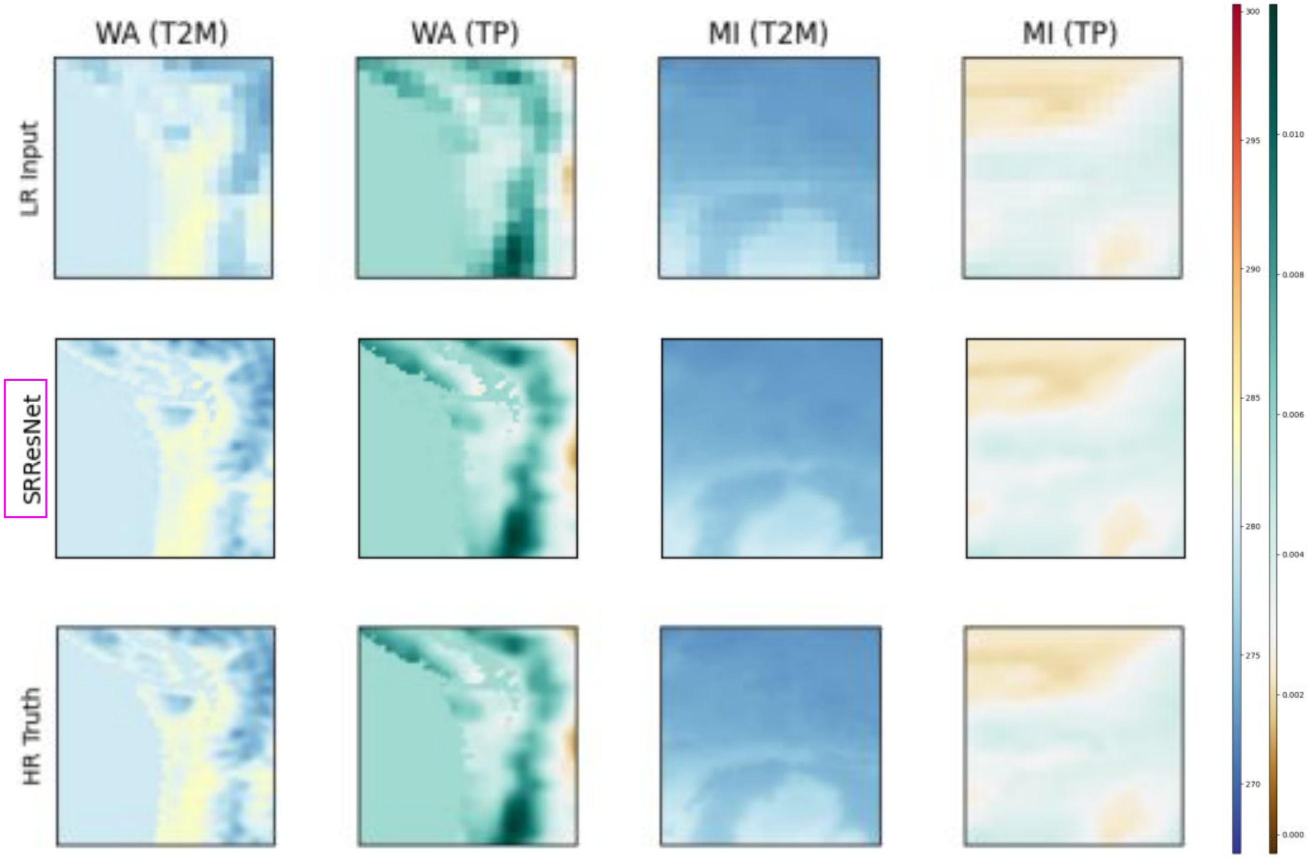


5. Results



6. Conclusions

- Takeaways
  - Outperformed nearest-neighbor, bilinear and bicubic interpolation
  - Strong quantitative results (MSE, PSNR, SSIM)
  - Strong qualitative results (blur, sharpness, structure)
- Future directions
  - Greater scale factors
  - More variables
  - Larger geographic extent
  - Application to CMIP6
- Food for thought
  - Computer vision + ML + AI can play a major role in addressing the climate crisis!

7. References

- https://github.com/andrewmcdonald27/CSE803FinalProject
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