Environment and Climate Change Canada
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Generative Adversarial Networks for Extreme Super-Resolution and Downscaling of Wind Fields at Convection-Permitting Scales

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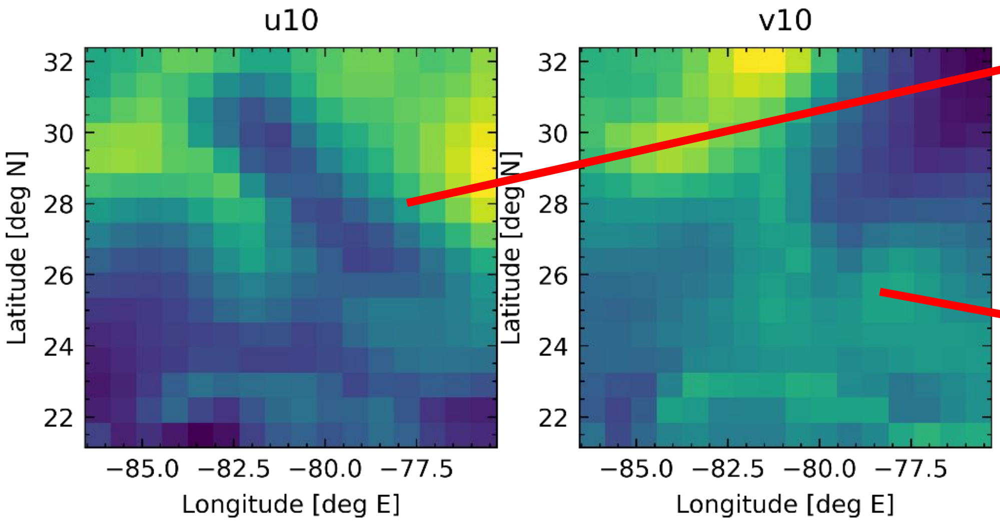
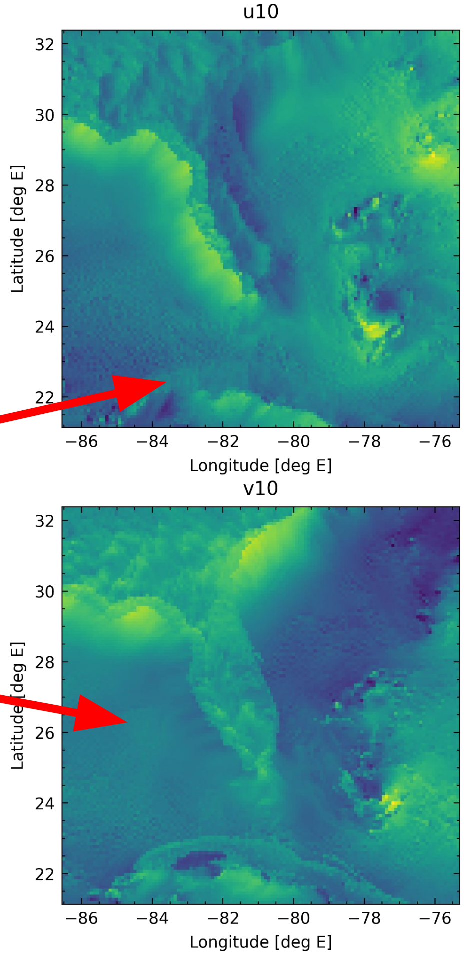
Super Resolution

- **Enhances** the resolution of an imaging system
- Aligned with statistical downscaling of gridded data
- Deep learning has achieved great success so far

Example ground truths:
2D Surface Winds Coarse (left), Fine (right)

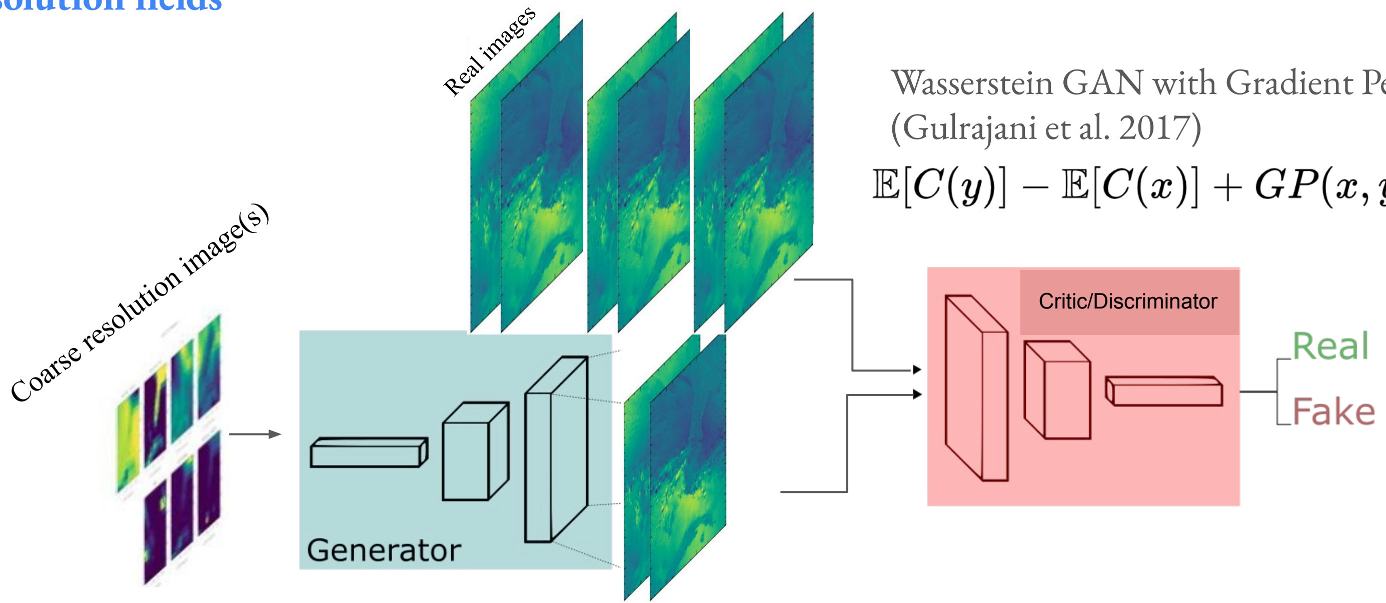




8x8 downscaling (each pixel is replaced by 64 pixels)

Conditional Generative Adversarial Networks (GANs) for Super Resolution (SRGAN framework)

- **Competing networks trained simultaneously to fool each other**
- GAN is **conditioned on a low-resolution fields** with the goal of producing **high-resolution fields**



Wasserstein GAN with Gradient Penalty (Gulrajani et al. 2017)

$$\mathbb{E}[C(y)] - \mathbb{E}[C(x)] + GP(x, y)$$

$$-\mathbb{E}[C(y)] + L_c(x, y)$$

Adversarial Loss

SR Specific Pixel-wise Content Loss (MAE/MSE)

Modified Figure: Goodfellow et al. 2014 *Generative Adversarial Networks*

GANs in climate field downscaling

Shortcomings

1. **Idealized pairings** -- i.e. coarse input is an upscaled fine scale image by predefined factor (Singh et al. 2019, Stengel et al. 2020)
2. Only focused on a **single region**
3. Limited amount of work that incorporates new advancements in GAN architectures

Image: J. Poggie 2016, Purdue University

Wind

Test GANs using surface flow *u (zonal, east-west), v (meridional, north-south)*

- **highly variable**, influenced **strongly by topography**
- Contains **multiple physical scales** within regions (synoptic to mesoscale and convection)
- Pose a difficult problem for the generator/discriminator from a computer vision perspective

Models

ERA Interim (Low-resolution coarse scale conditioning fields)

- Global reanalysis, **80km, 6 hourly, 1979 - 2019**

WRF (*"High Resolution WRF Simulations of the Current and Future Climate of North America"*)

- Convection permitting model at **4km, hourly, 2000 - 2013, regridded to 10km**

WRF is **synchronous** with ERA Interim (concurrent) ✅

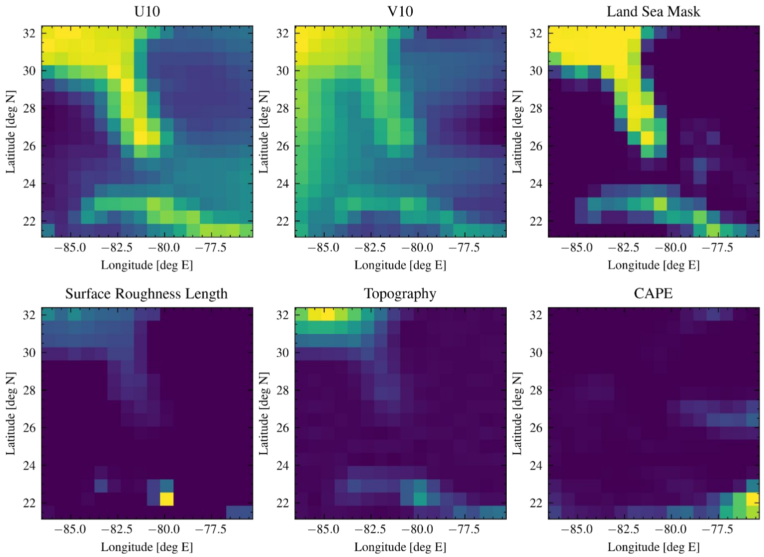
WRF **driven** by ERA Interim BC **and** IC ✅

WRF is kept **dynamically consistent at coarse (80km) scales** with ERA (spectral nudging)✅

GAN SR **deterministic** regression using climate fields

Coarse **covariate conditioning fields that correlate with wind, a priori**

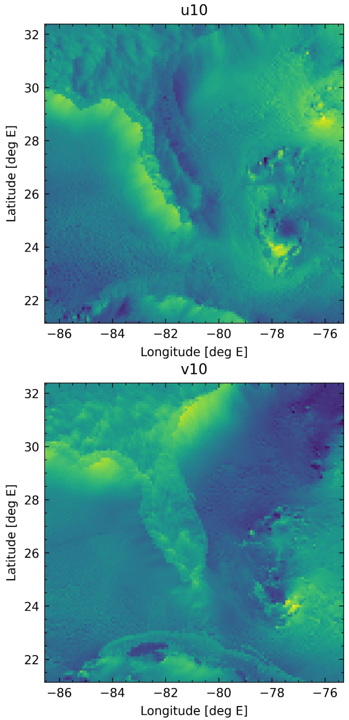
a. **U, V wind fields**
b. **Land sea mask (time invariant)**
c. **Topography (time invariant)**
d. **Surface roughness length**
e. **Convective Available Potential Energy (CAPE, ERA5 re-gridded to 80km)**
   i. **CAPE is unavailable at 6 hourly in ERA Interim**

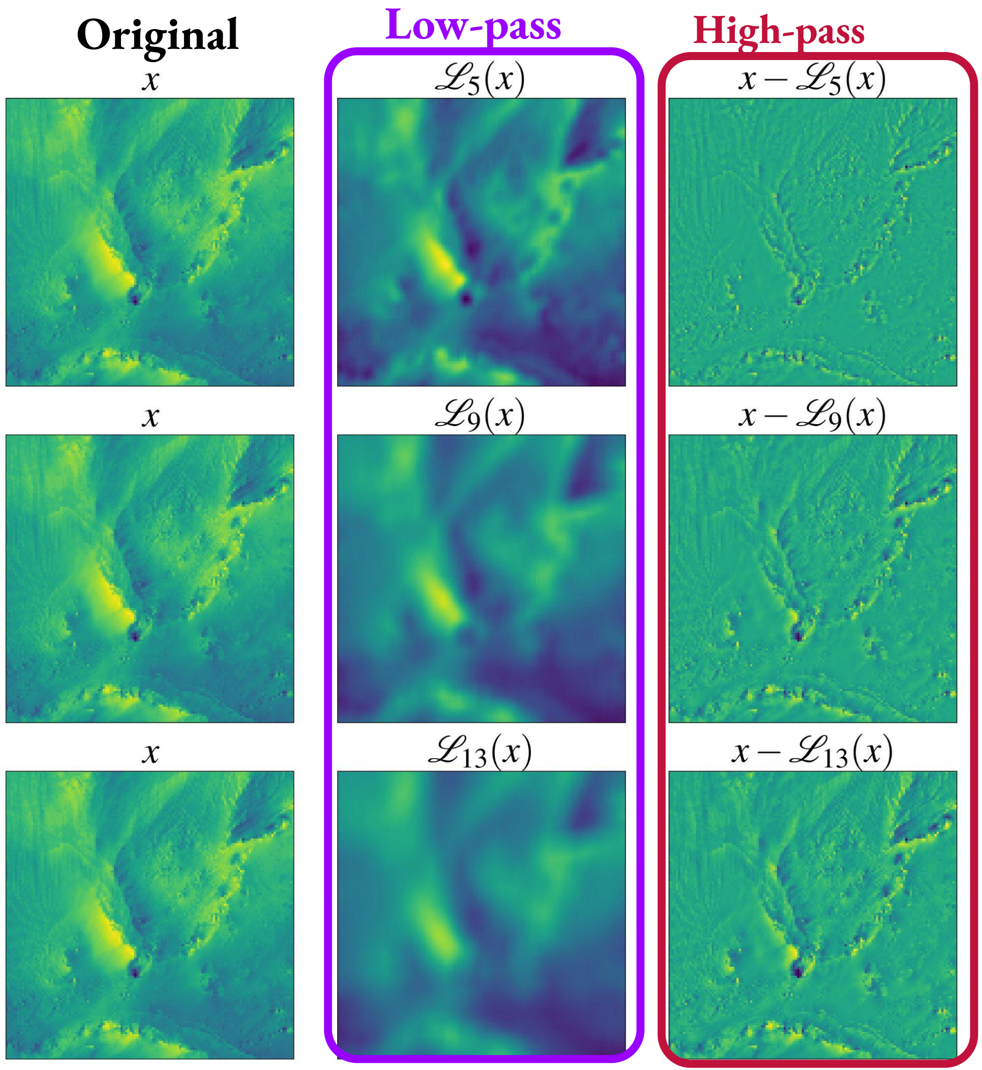


16 x 16 to 128 x 128
Each pixel is replaced with 64 pixels

For Generator

For Discriminator





Frequency Separation

Average 2D Pool Kernel example

1/N	1/N	1/N	1/N	1/N
1/N	1/N	1/N	1/N	1/N
1/N	1/N	1/N	1/N	1/N
1/N	1/N	1/N	1/N	1/N
1/N	1/N	1/N	1/N	1/N

N=25
stride=1
k5x5

$$\boxed{-\mathbb{E}[C(y)]} + \boxed{L_c(x, y)}$$

Frequency separation can help deal with noisy images

(**Fritsche et al. 2019,** *Frequency Separation for Real-World Super-Resolution)*

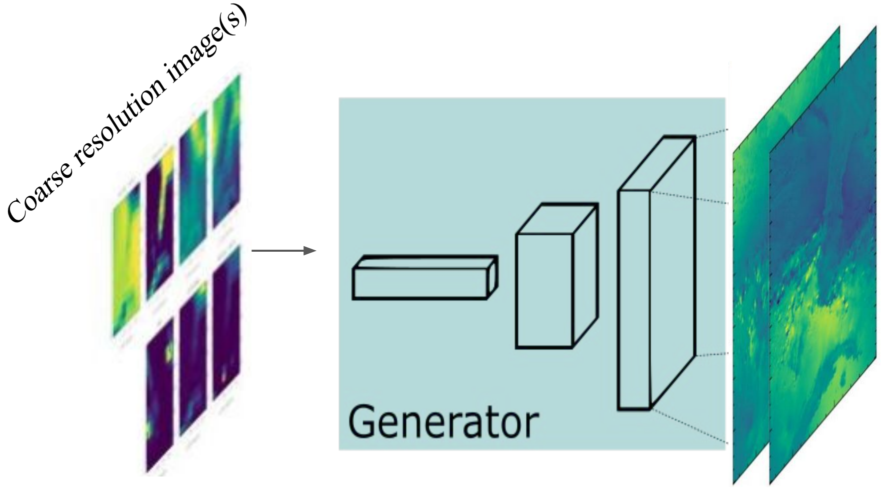
Larger kernels = lower frequency cutoff = smoother low pass

Smaller kernels = higher frequency cutoff = sharper low pass

Build on the successes of each of the objective function terms

Convolutional Neural Network Baseline (i.e. Non-GAN)

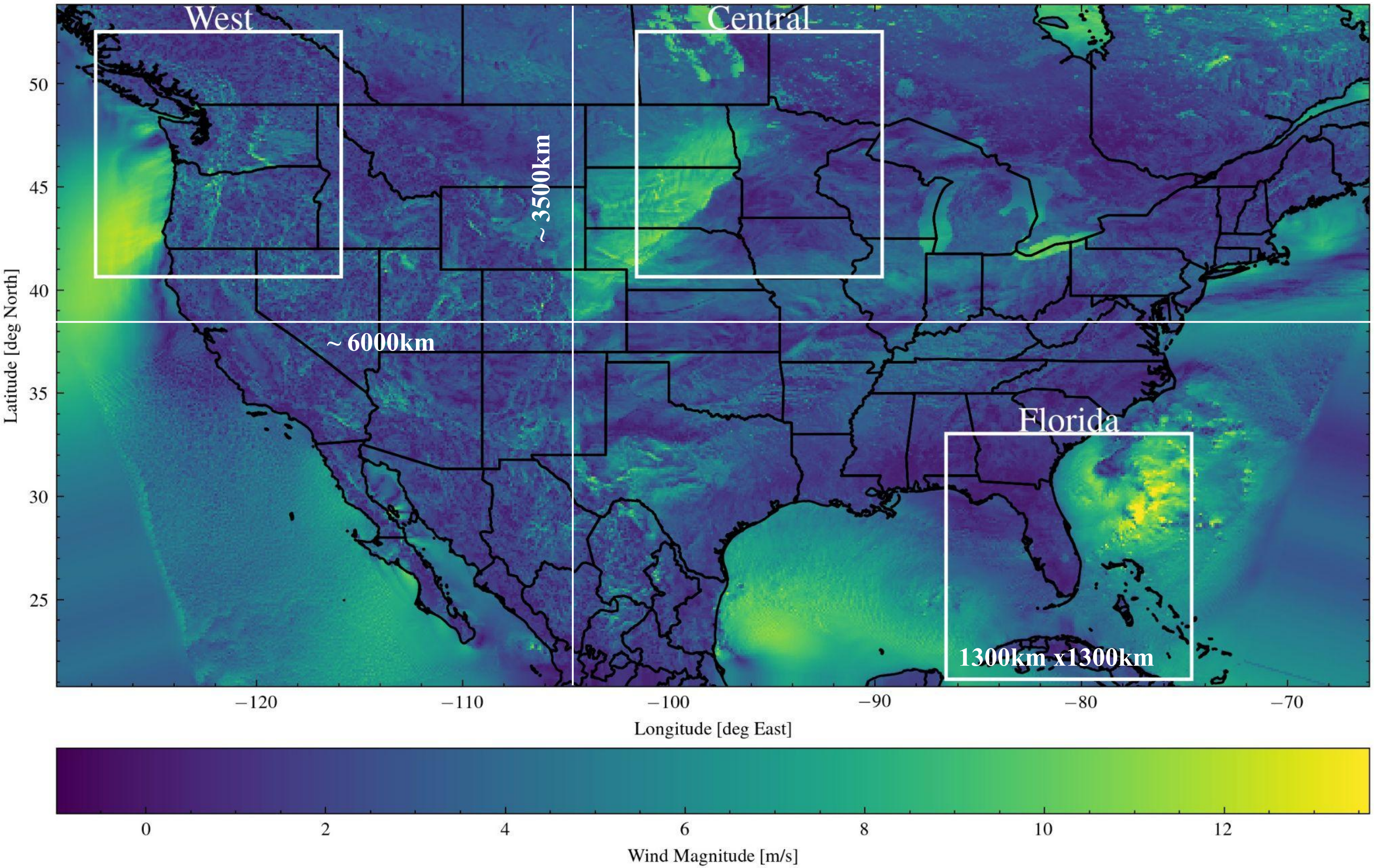
- CNN is **conditioned on a low-resolution rendering** of a high resolution pair
- Introduced so we can see **what impact the discriminator has on results**
- Optimized using **Mean Absolute Error**



$$L_c(x, y)$$

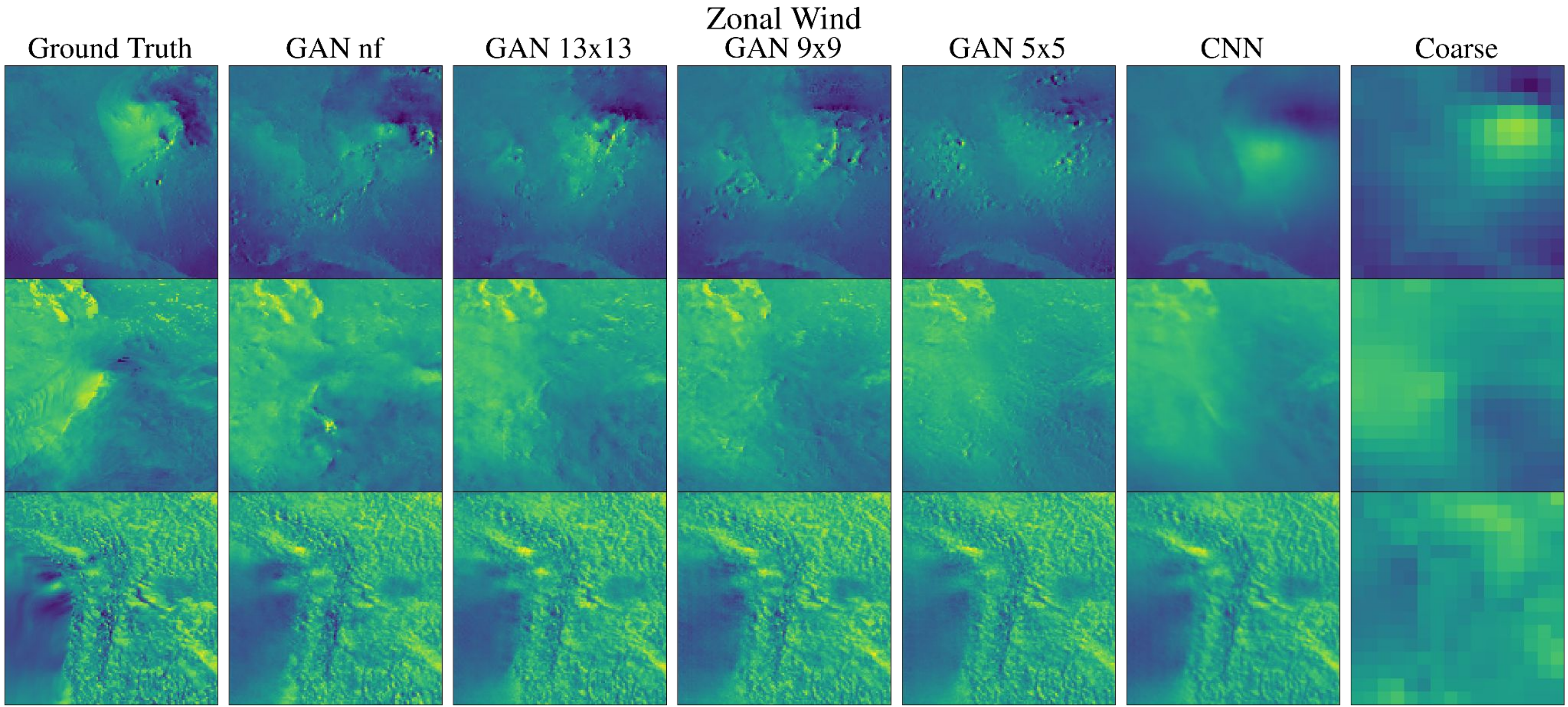
(Content loss = Mean Absolute Error)

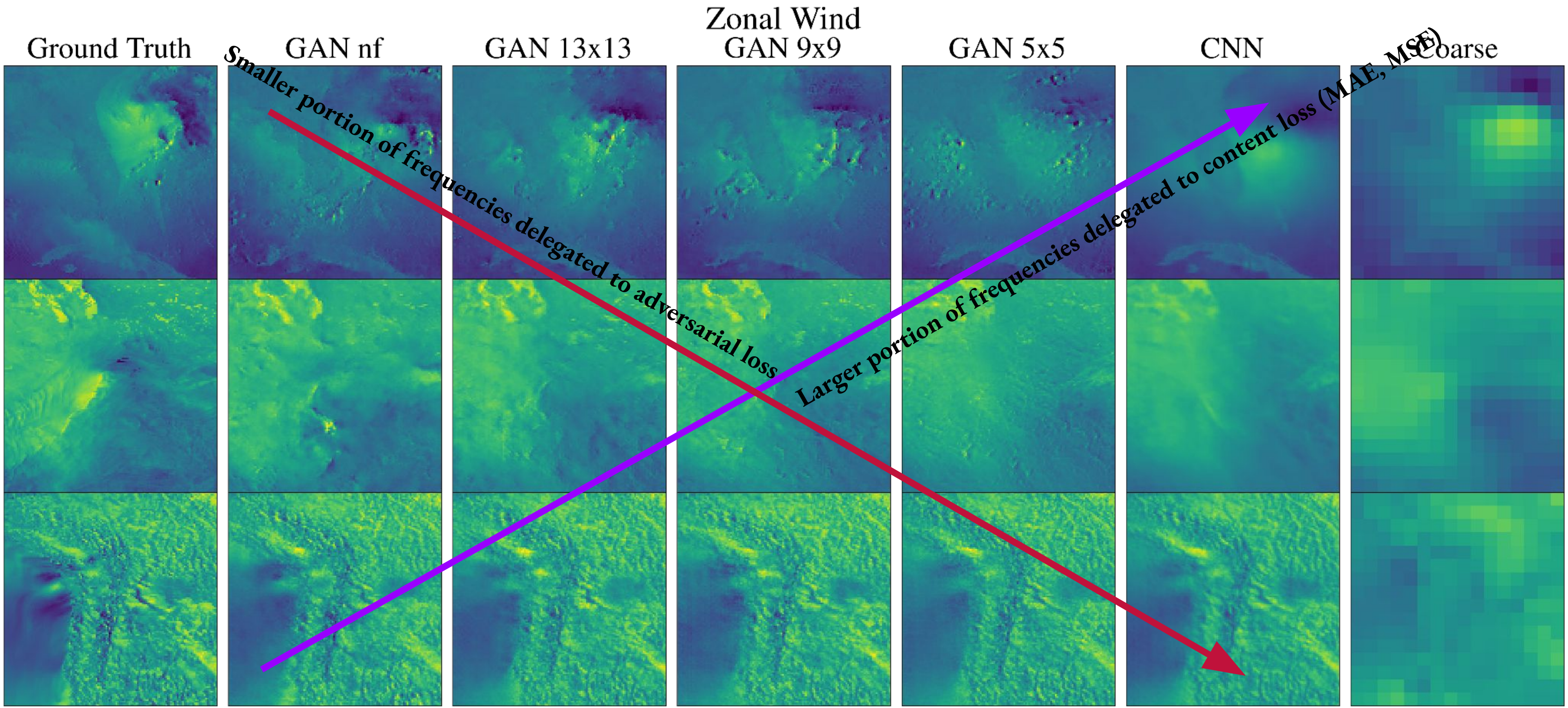
WRF Over North America (HRCONUS)

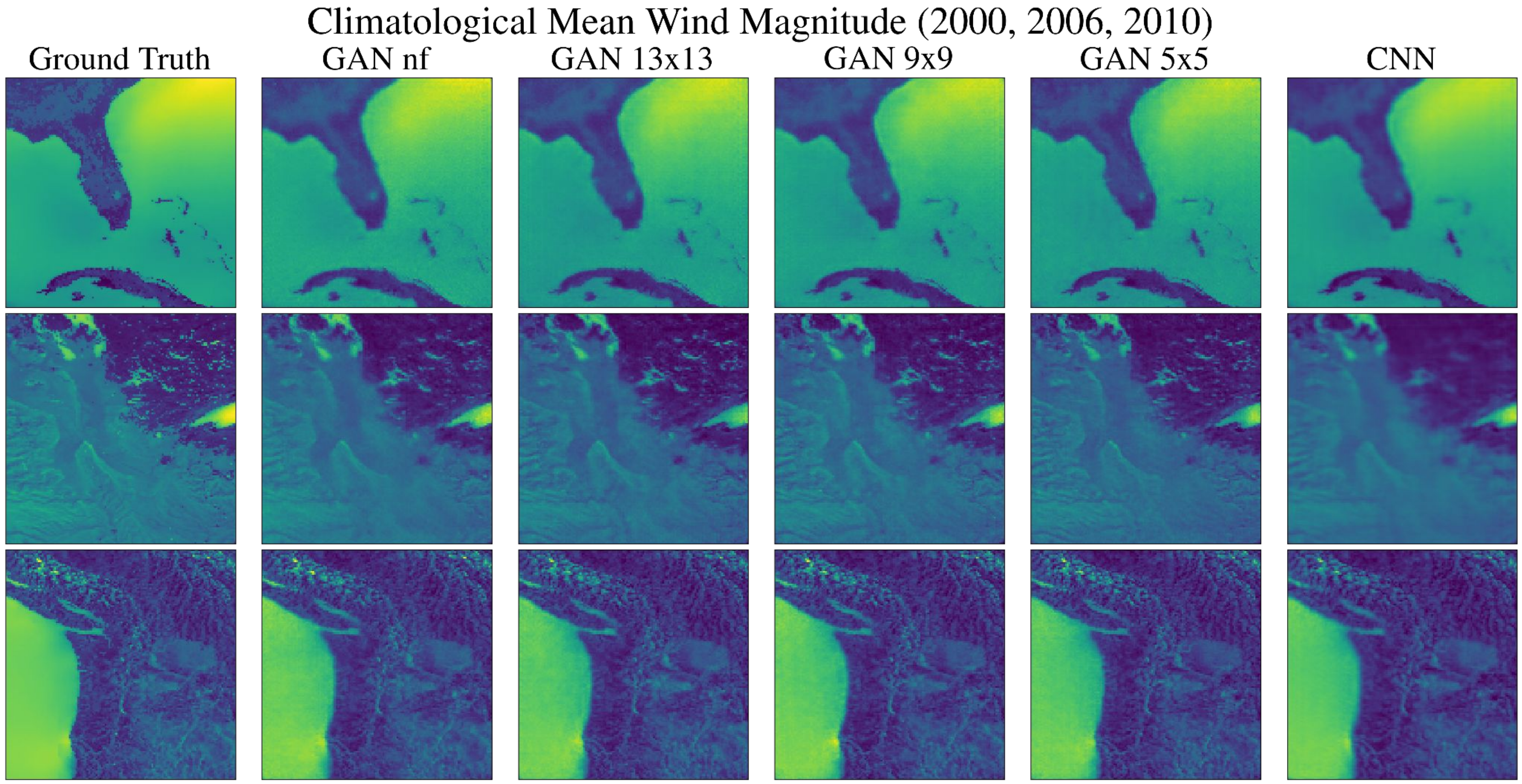


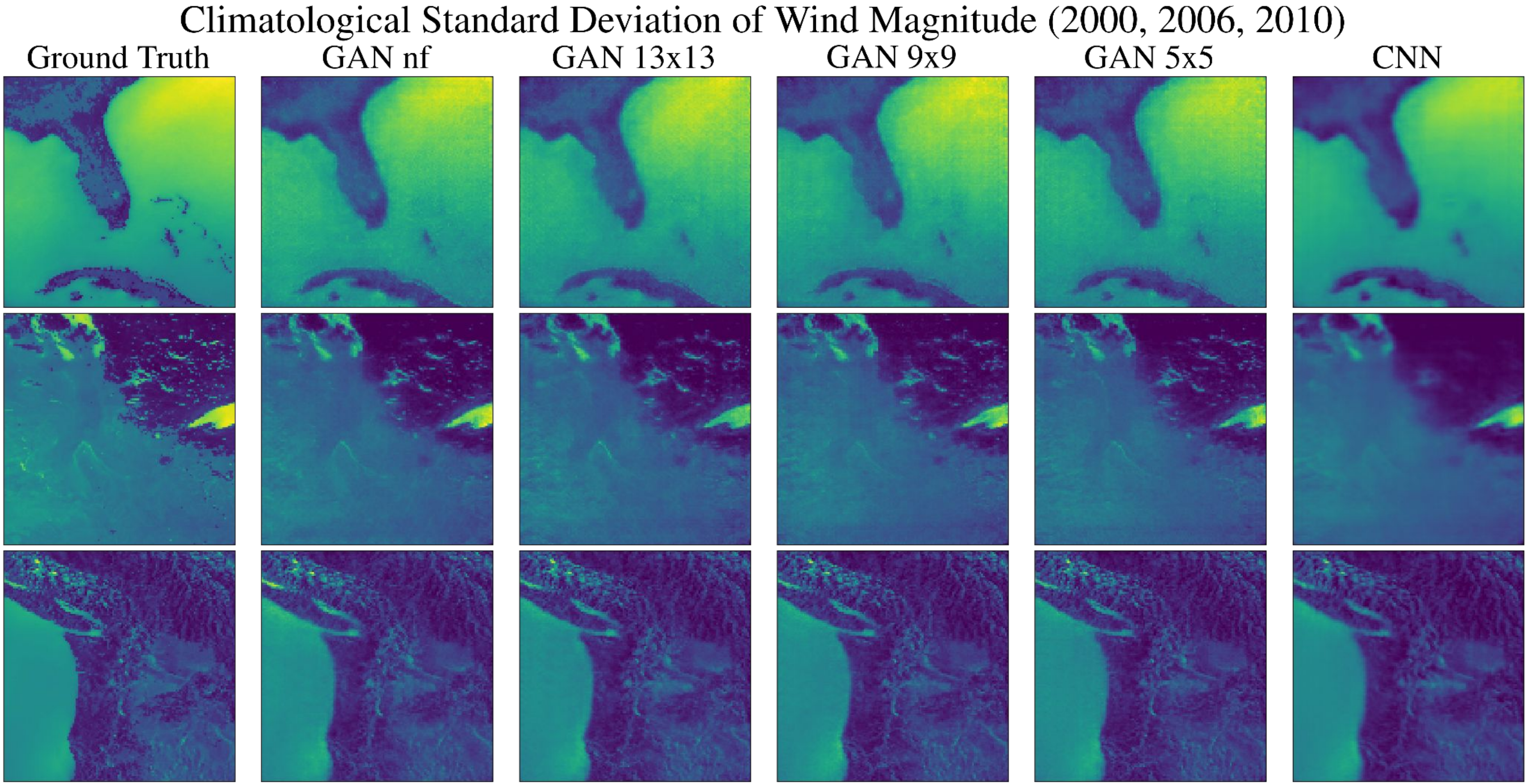
Results

- Training takes **~2 - 3 days per GAN** depending on GPU and region
  - NVIDIA GeForce GTX 1060 **6GB**
- Complete years **2000, 2006, and 2010** are completely **omitted from training**
  - Results in a roughly 80% to 20% ratio between train and test sets
  - **18901** training samples, **3287** testing samples
- All following results are from **test set**

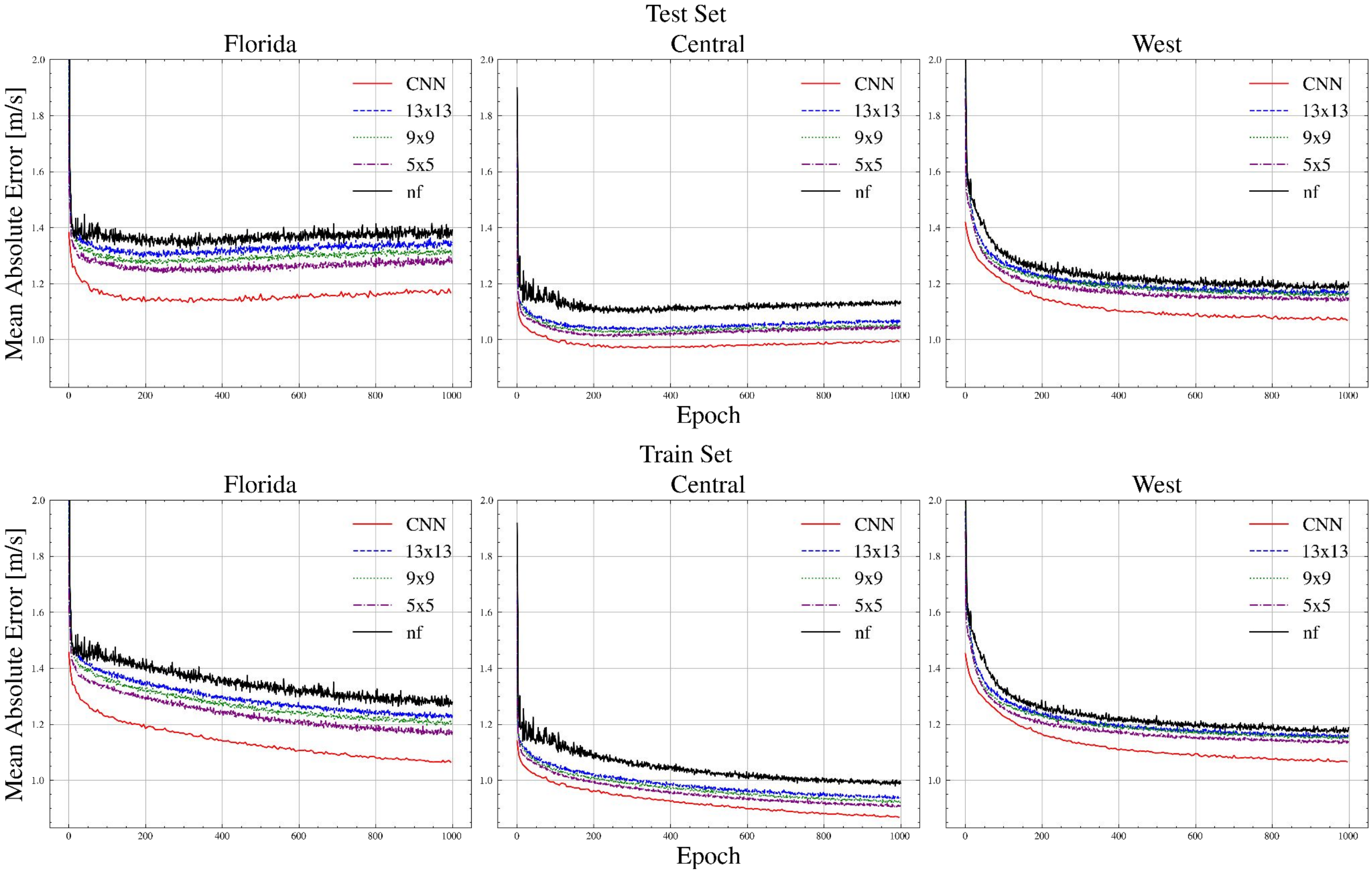

Zonal Wind
Ground Truth
GAN nf
GAN 13x13
GAN 9x9
GAN 5x5
CNN
Coarse


Zonal Wind
Ground Truth
GAN nf
GAN 13x13
GAN 9x9
GAN 5x5
CNN
Coarse
Smaller portion of frequencies delegated to adversarial loss
Larger portion of frequencies delegated to content loss (MAE, MSE)


Climatological Mean Wind Magnitude (2000, 2006, 2010)
Ground Truth
GAN nf
GAN 13x13
GAN 9x9
GAN 5x5
CNN


Climatological Standard Deviation of Wind Magnitude (2000, 2006, 2010)
Ground Truth
GAN nf
GAN 13x13
GAN 9x9
GAN 5x5
CNN

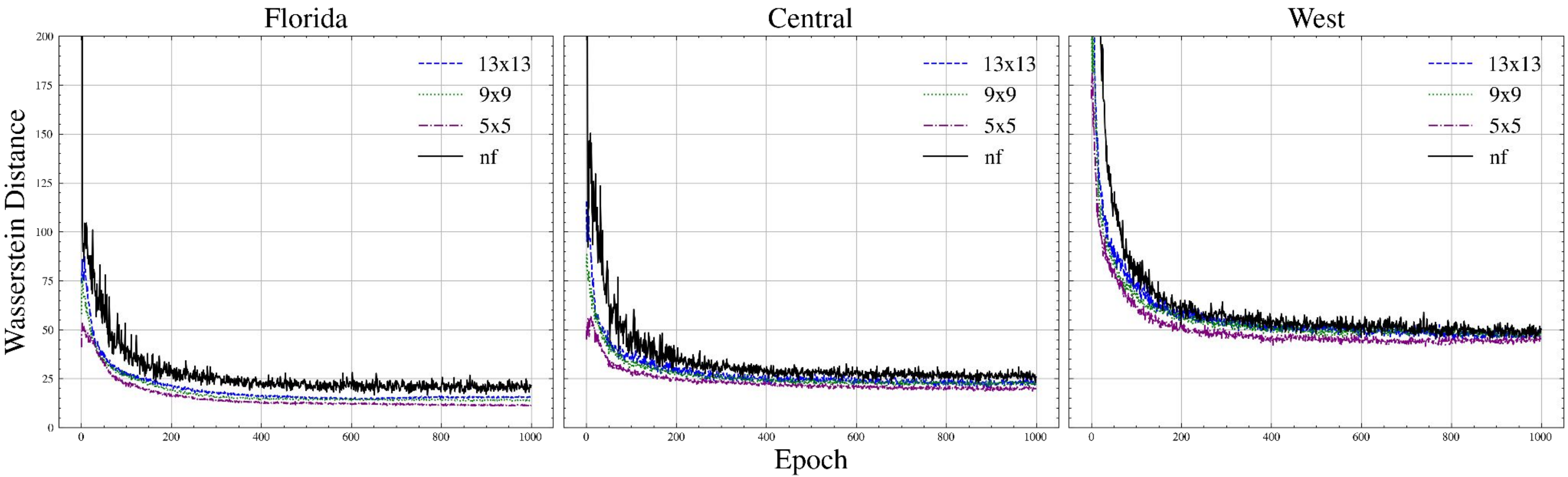
Mean Absolute Error Evolution



Similar results:

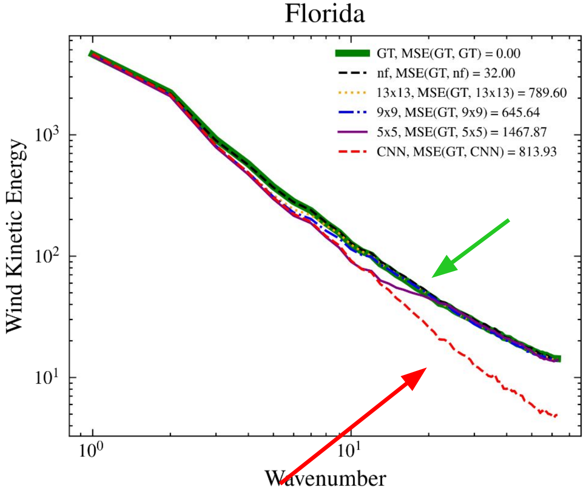
1. MS-SSIM
2. MSE

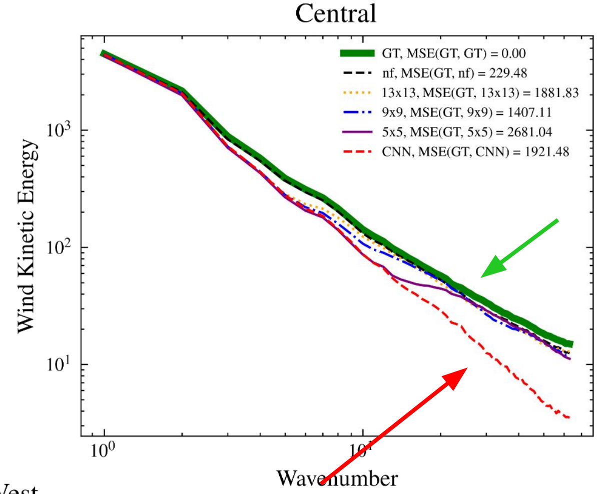
Test Set Wasserstein Distance Evolution



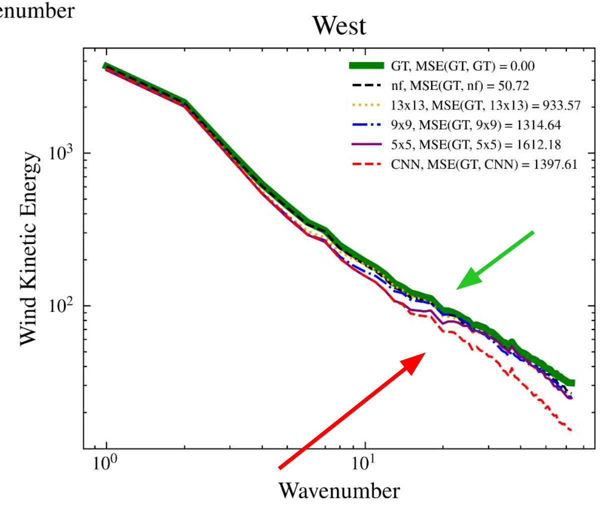
1. Models generalize nicely
2. No sign of overfitting in Wasserstein loss on test set
3. WGAN-GP is very stable

Kinetic Energy Spectrum

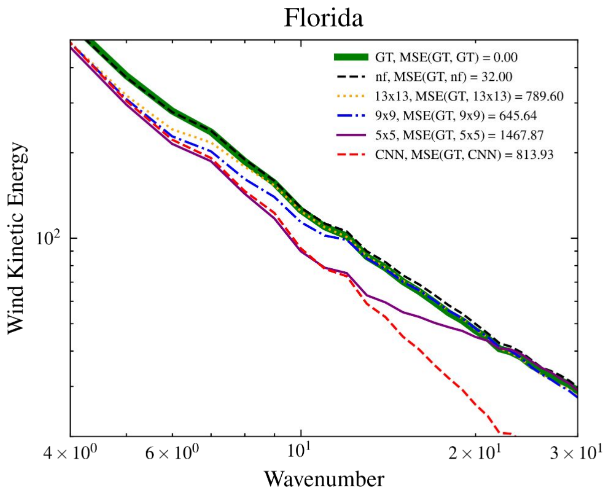


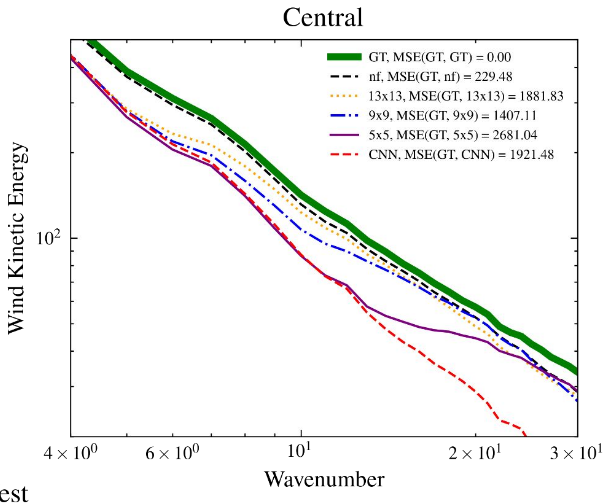


Radial profile of 2D Fourier transform in phase space, then averaged radially

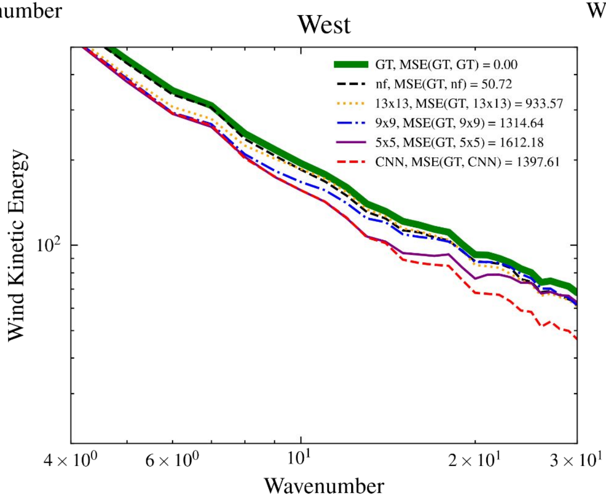


Kinetic Energy Spectrum





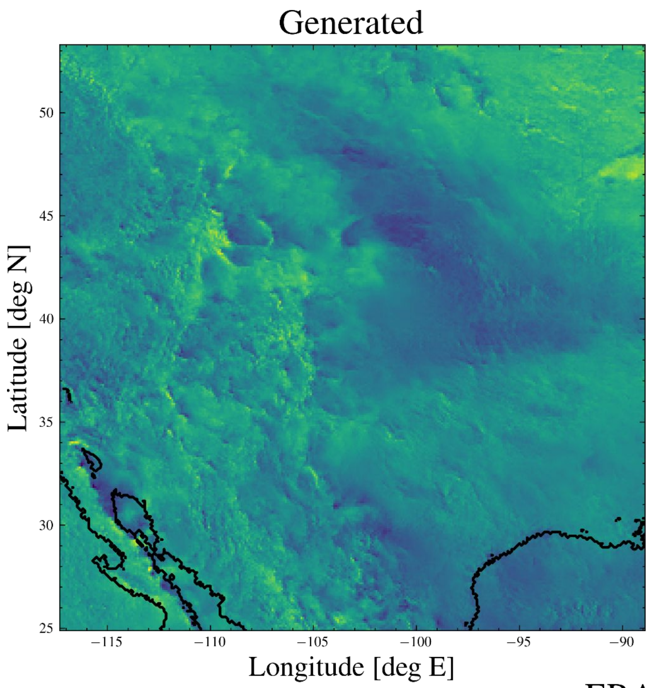
Radial profile of 2D Fourier transform in phase space, then averaged radially

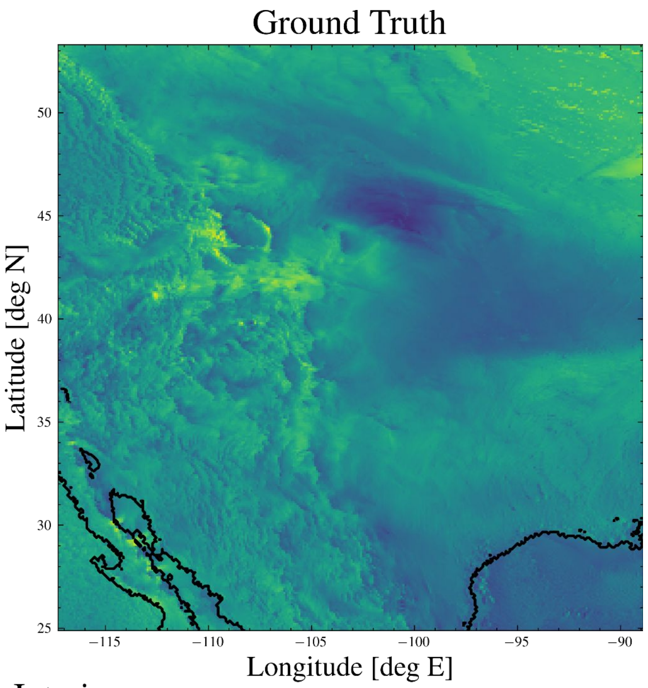


Main Conclusions

1. GANs perform nicely for non-idealized coarse and fine resolution fields
2. GANs **introduce** realistic **fine scale spatial variability** not present in the coarse fields
3. Wasserstein GAN with gradient penalty is **very stable** even with substantially altered loss functions, and many covariates
4. Frequency separation did not yield improved convergence, but reveals the following:
    a. Rigid metrics like MAE, MSE do not necessarily capture quality in extreme SR
    b. Physics informed analyses **can help**

Image: J. Poggie 2016, Purdue University



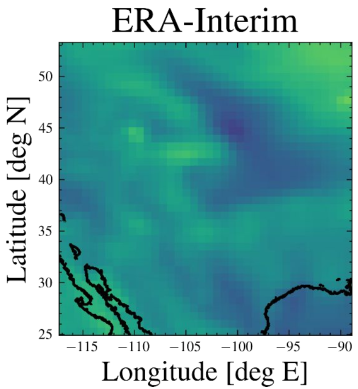


GPUs have memory limit.

Large regions possible
by a single 40GB GPU at Narval

Memory constraints impacts three things:

1. Batch size while training
2. Size of the domain
3. Excessive covariate usage



Future work

1. Exploit available fixed high-resolution fields as covariate (topography/land-sea mask and surface roughness)
   a. Investigate importance of covariates in model in a robust way
   b. This may help build a spatially generalized model
2. Incorporate stochasticity into the model!
   a. Can add additional noisy covariates while training -- non-deterministic GAN (i.e. Leinonen et al. 2020)
3. Incorporate a large number of predictands and predictors to build a more complete model

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