A Multi-Scale Deep Learning Framework for Projecting Weather Extremes

Antoine Blanchard
Nishant Parashar
Boyko Dodov
Christian Lessig (now at ECMWF)
Themis Sapsis (MIT)

Large-Scale Deep Learning for the Earth System – 4 September 2023
Preparing for a New World of Climate Extremes
Climate risk is about computing very small probabilities

Climate change is worsening weather extremes

• Megadroughts
• Sea level rise
• Stronger hurricanes
• Extreme rainfall and flooding
• …
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Risk assessment of extremes is challenging
• Worst outcomes have **low probability**
• Weather perils are interconnected

Projected increases in U.S. property losses due to sea level rise and stronger hurricanes (Houser et al., 2015)
Physics-Based GCM + Observations = ML opportunity

Low-resolution GCM simulation (fast but biased)
Physics-Based GCM + Observations = ML opportunity

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Step 1: Bias correction

Reanalysis data
Physics-Based GCM + Observations = ML opportunity

- Low-resolution GCM simulation (fast but biased)
- Step 1: Bias correction
- Low-resolution debiased simulation

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Low-resolution debiased simulation

Step 2: Downscaling

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Step 2: Downscaling

Low-resolution GCM simulation (fast but biased)

High-resolution debiased simulation

Reanalysis data
Atmosphere Dynamics Involve Many Spatial Scales
Compact representation of atmospheric processes is needed

Discrete spherical wavelet frame is used to represent phenomena on a hierarchy of levels

- reduces dimensionality
- allows training of local models
Multi-Scale Deep Learning for Weather Extremes

Bias-correction

Coarse-scale biased GCM simulation → Wavelet transform → Coarse-scale biased wavelet coefficients → LSTM-based Neural Networks → Coarse-scale debiased wavelet coefficients → Inverse wavelet transform → Coarse-scale debiased simulation
Multi-Scale Deep Learning for Weather Extremes

Bias-correction
- Coarse-scale biased GCM simulation
- Wavelet transform
- Coarse-scale biased wavelet coefficients
- LSTM-based Neural Networks
- Coarse-scale debiased wavelet coefficients
- Inverse wavelet transform
- Coarse-scale debiased simulation

Downscaling
- Coarse-scale reanalysis
- Wavelet transform
- Coarse-scale wavelet coefficients
- TCN-based Neural Networks
- Fine-scale wavelet coefficients
- Inverse wavelet transform
- Fine-scale reanalysis
Multi-Scale Deep Learning for Weather Extremes

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Downscaling

- Coarse-scale reanalysis
- Wavelet transform
- Coarse-scale wavelet coefficients
- TCN-based Neural Networks
- Fine-scale wavelet coefficients
- Inverse wavelet transform
- Full-scale debiased simulation with realistic statistics
Statistical Loss Functions
How to make ML predictions statistically consistent with observations
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ML output

Reanalysis
Statistical Loss Functions
How to make ML predictions statistically consistent with observations

Quantile loss

heavy tails and extremes

\[ \mathcal{L}(y, y^*) = \text{MSE}(Q_y, Q_{y^*}) \]
Statistical Loss Functions
How to make ML predictions statistically consistent with observations

Quantile loss
heavy tails and extremes

Cross-spectrum loss
space-time coherency

$\mathcal{L}(y, y^*) = \text{MSE}(Q_y, Q_{y^*})$

$\mathcal{L}(y, y^*) = \text{MSE}(\text{Re}[\Gamma_{y,y_n}], \text{Re}[\Gamma_{y^*,y_n}])$
$+ \text{MSE}(\text{Im}[\Gamma_{y,y_n}], \text{Im}[\Gamma_{y^*,y_n}])$
Statistical Loss Functions
How to make ML predictions statistically consistent with observations

Quantile loss
- heavy tails and extremes

Cross-spectrum loss
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Debiased, High-Resolution Simulation over Europe

- Training protocol described in NeurIPS paper (arXiv:2210.12137)
- Fronts and waves present in the full-scale ML simulation
- Statistics and correlations consistent with reanalysis

Vorticity close to ocean surface
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![Graphs showing vorticity distribution in Zurich and Athens](image-url)
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Conclusions
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Key ingredients:

- compact, multi-scale representation of atmospheric processes
- statistical loss functions for extremes and space-time coherency
- divide-and-conquer strategy for efficient training of regional models
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Current thrusts:
• incorporate more physics and perils
• benchmark different seq-to-seq/generative models
• upgrade GCM from SPEEDY to CAM (NCAR)