A Multi-Scale Deep Learning Framework for Projecting Weather Extremes

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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
- …

Source: NOAA

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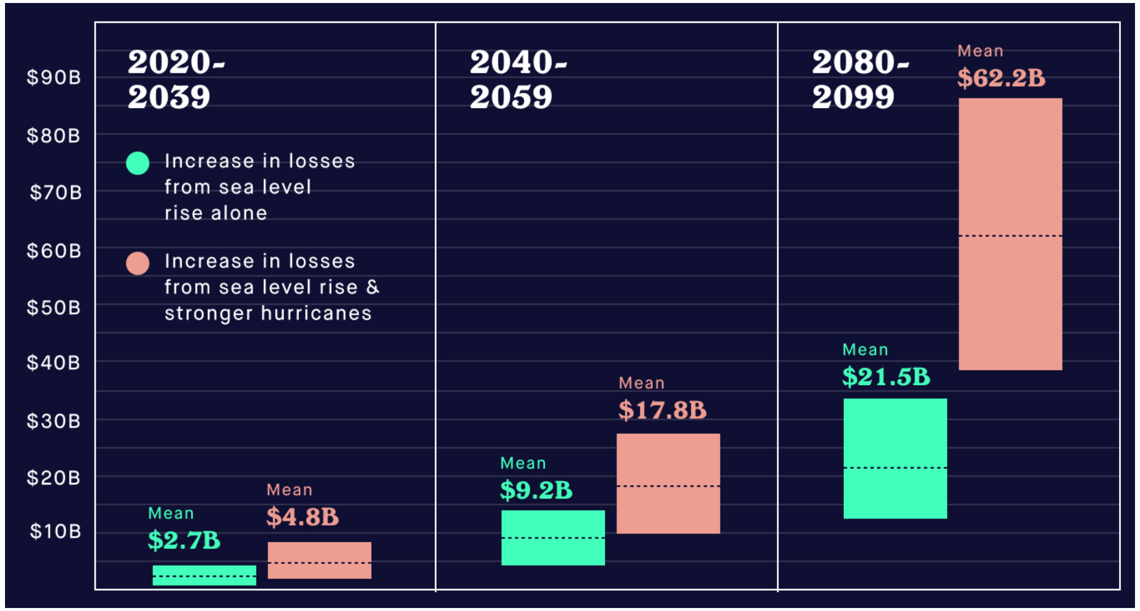
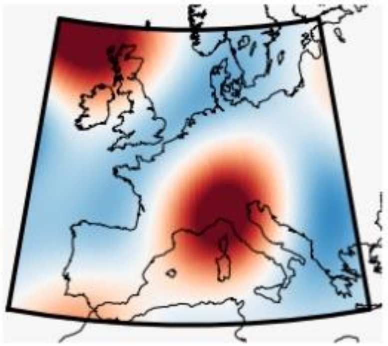
Risk assessment of extremes is challenging

- 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)

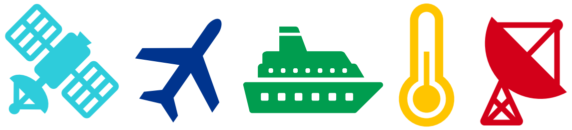
Physics-Based GCM + Observations = ML opportunity

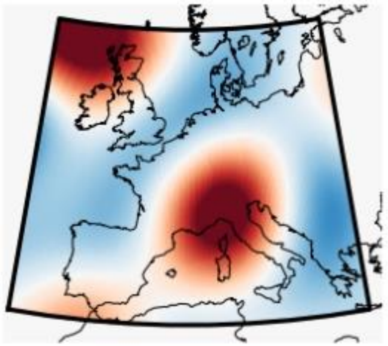


Low-resolution
GCM simulation
(fast but biased)

Physics-Based GCM + Observations = ML opportunity

Reanalysis data





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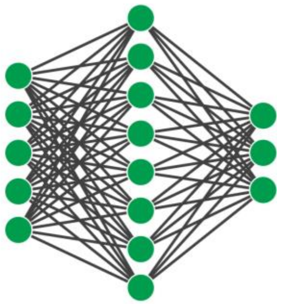

Step 1:
Bias correction

Physics-Based GCM + Observations = ML opportunity

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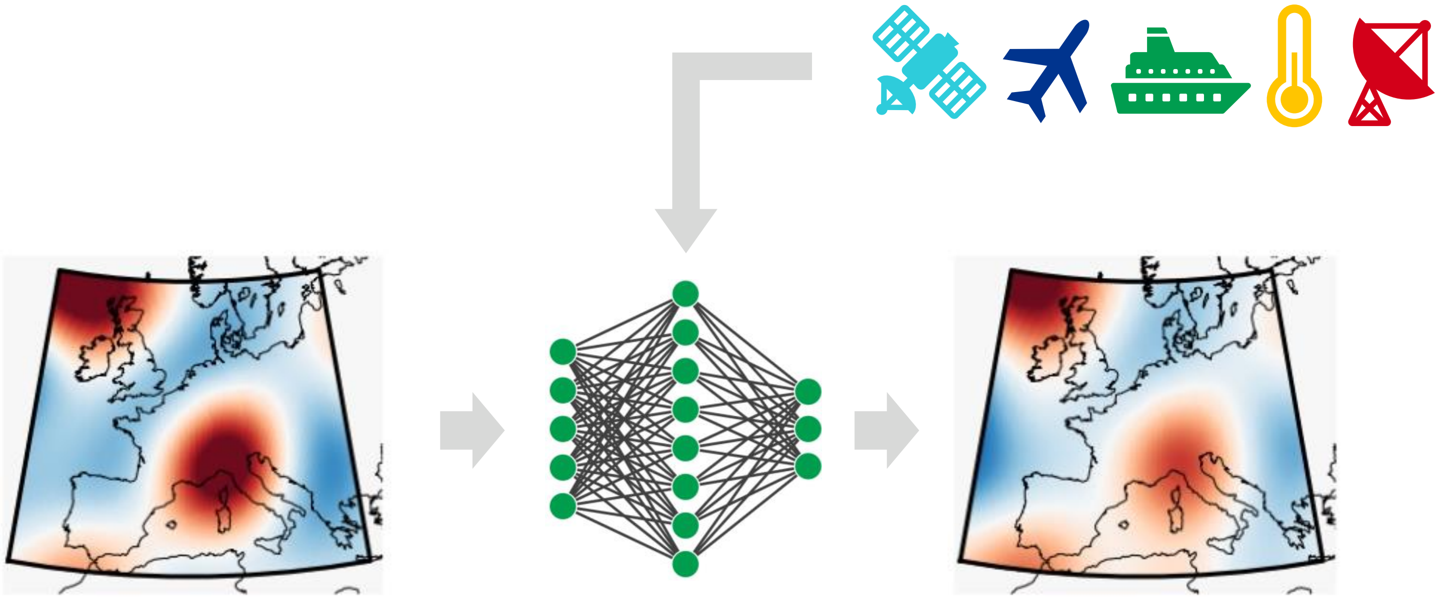

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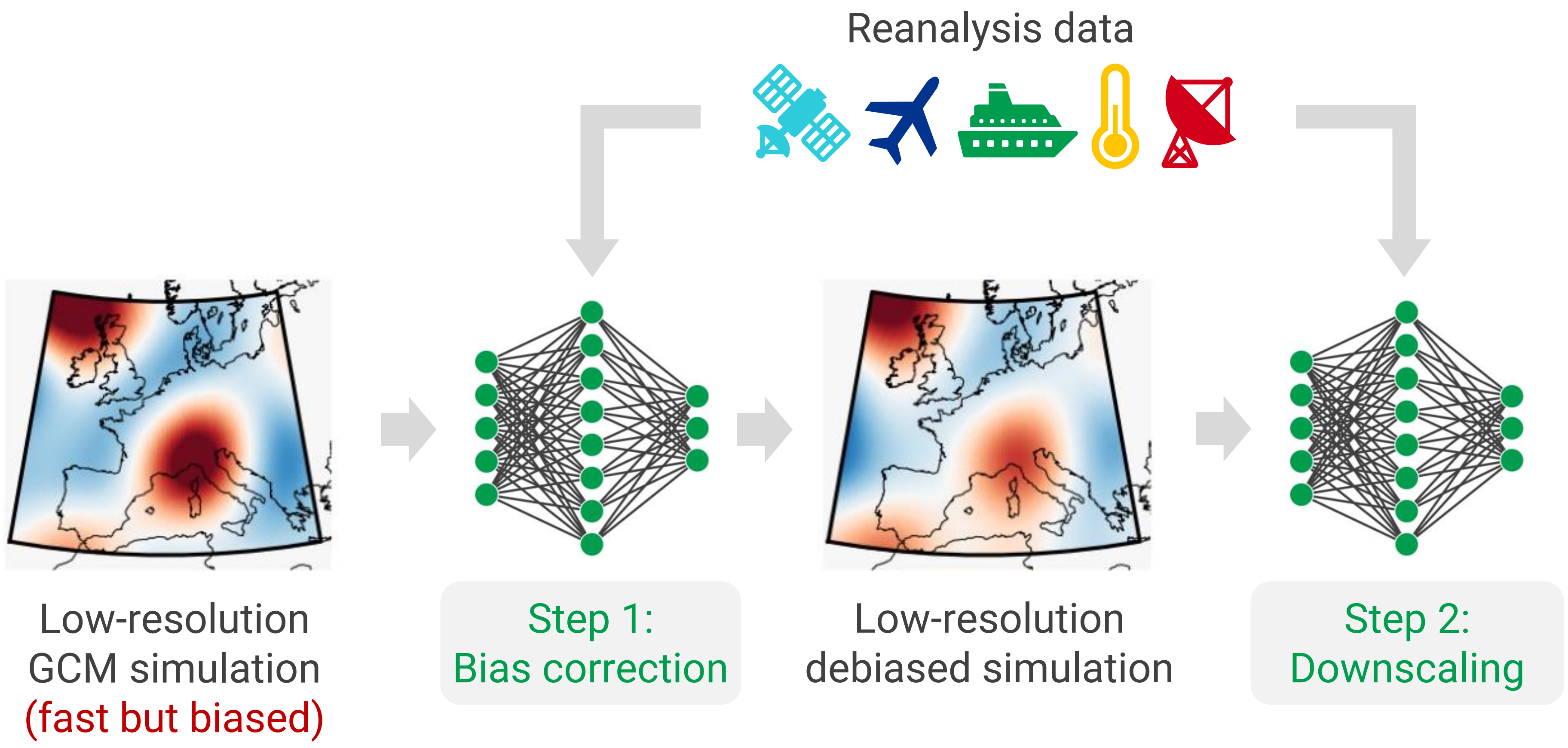

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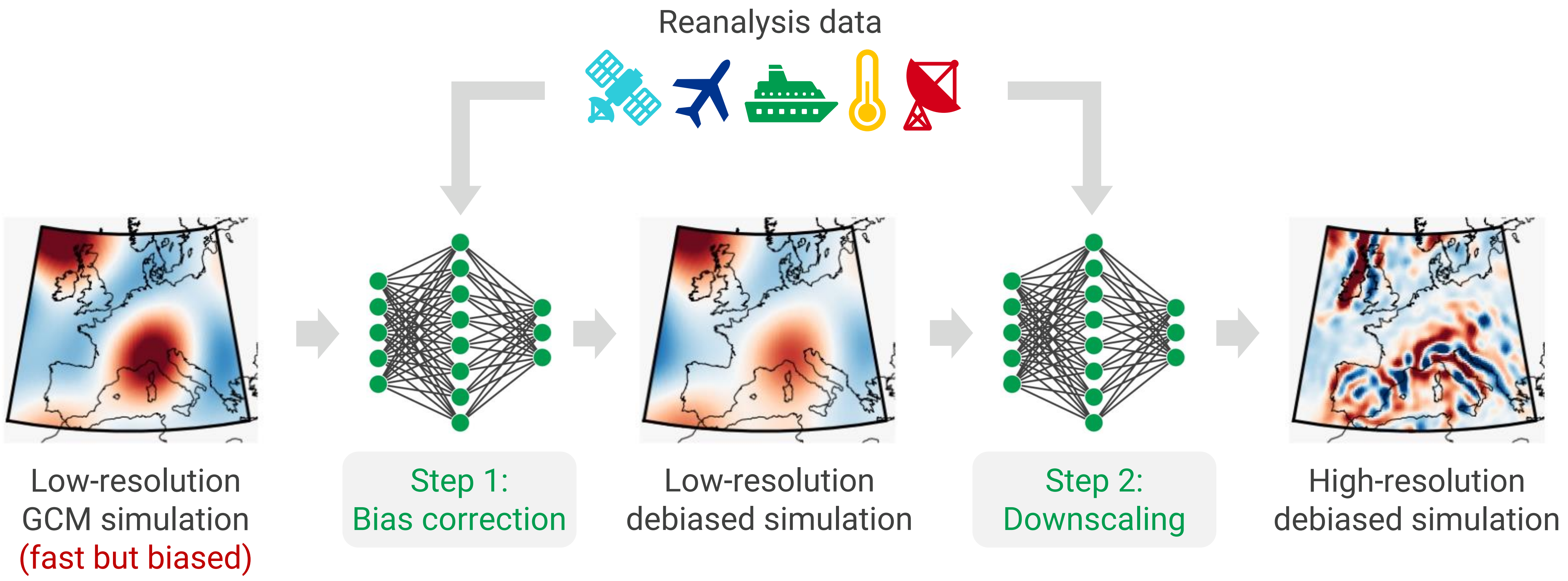
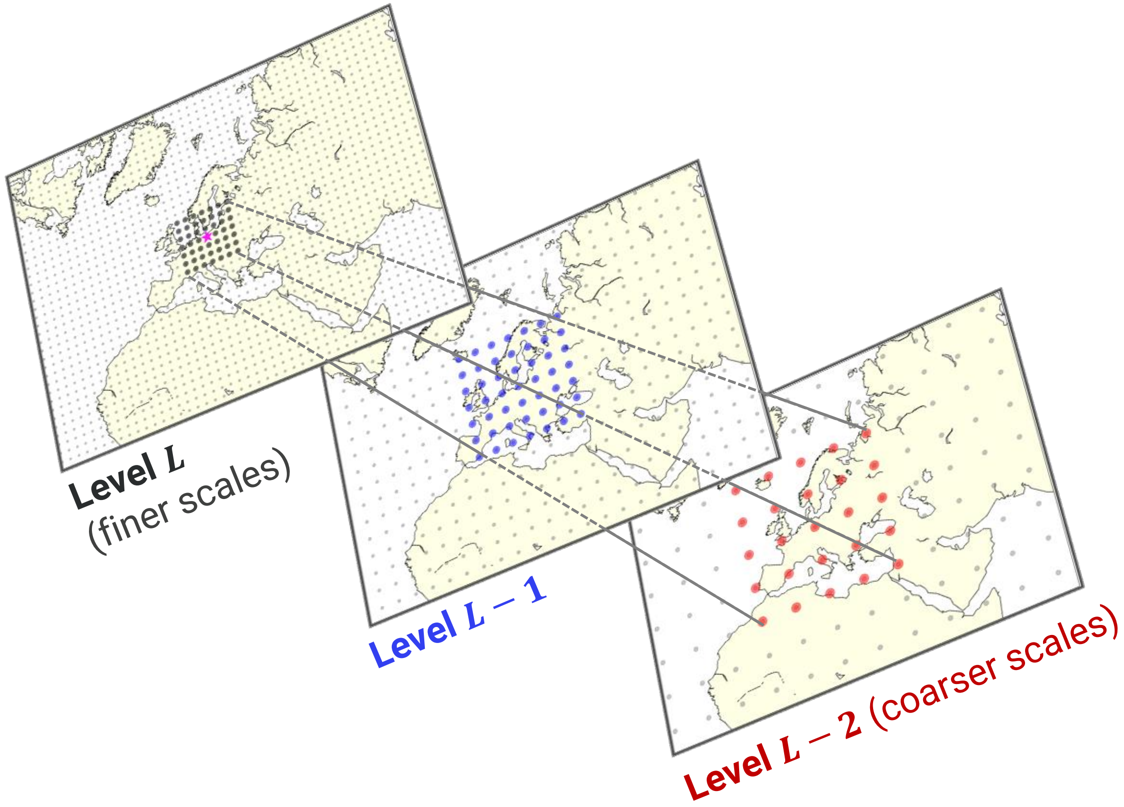


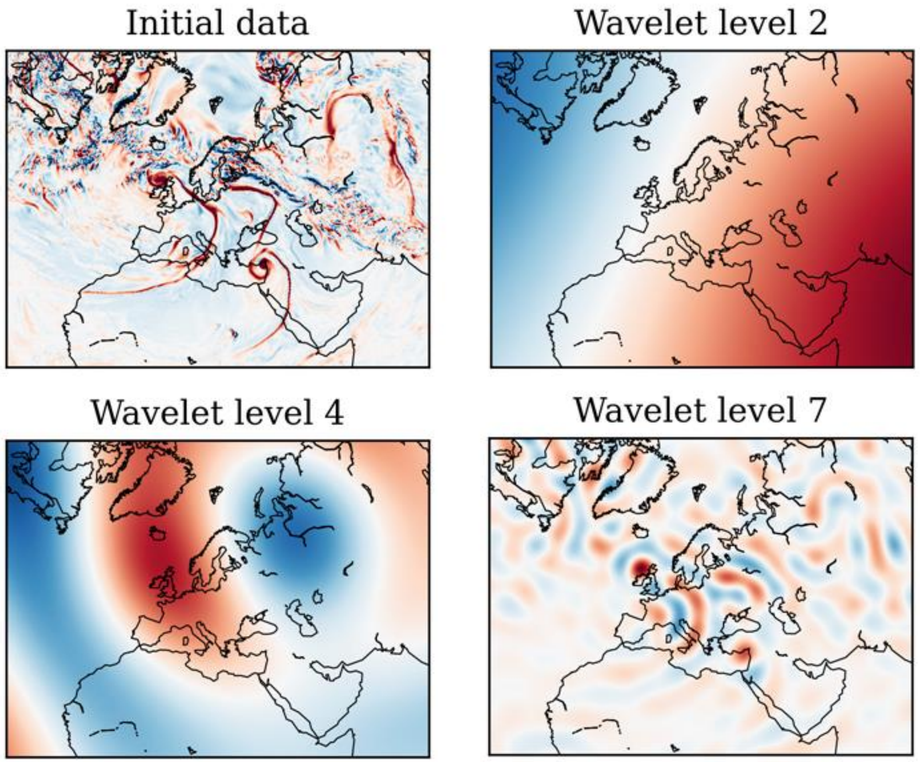
Atmosphere Dynamics Involve Many Spatial Scales

Compact representation of atmospheric processes is needed

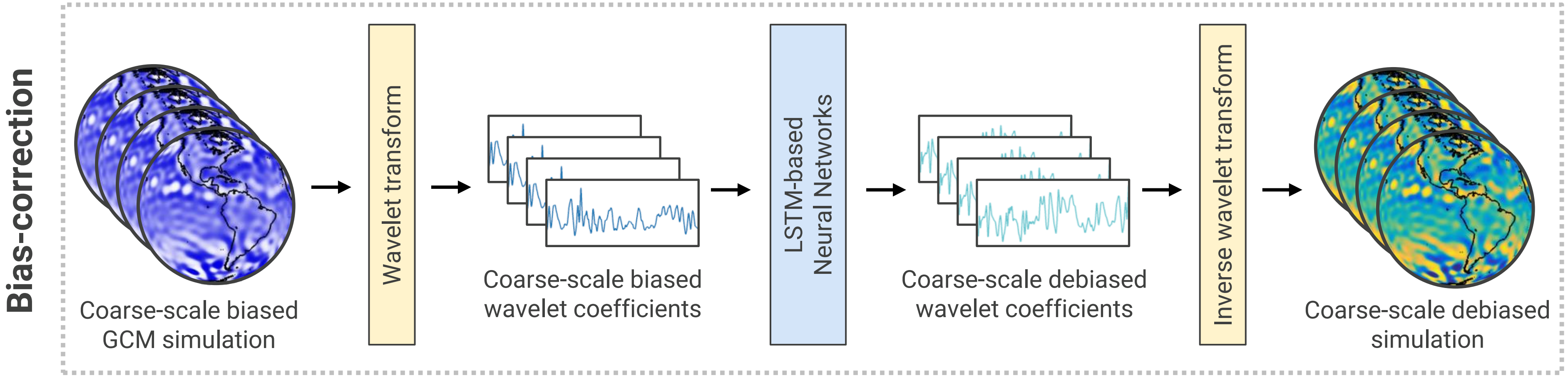
Discrete spherical wavelet frame is used to represent phenomena on a hierarchy of levels

- reduces dimensionality
- allows training of local models





Multi-Scale Deep Learning for Weather Extremes



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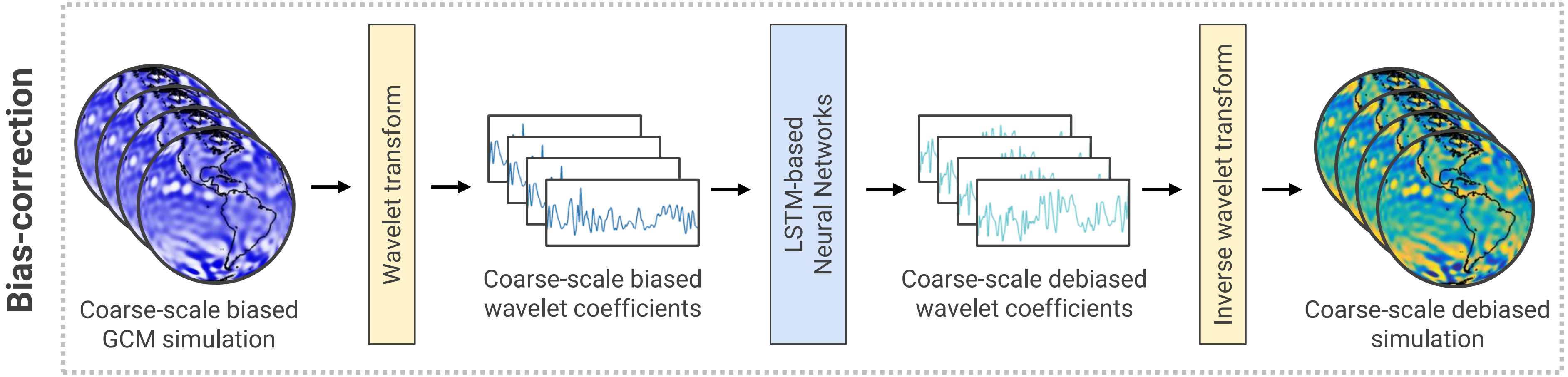

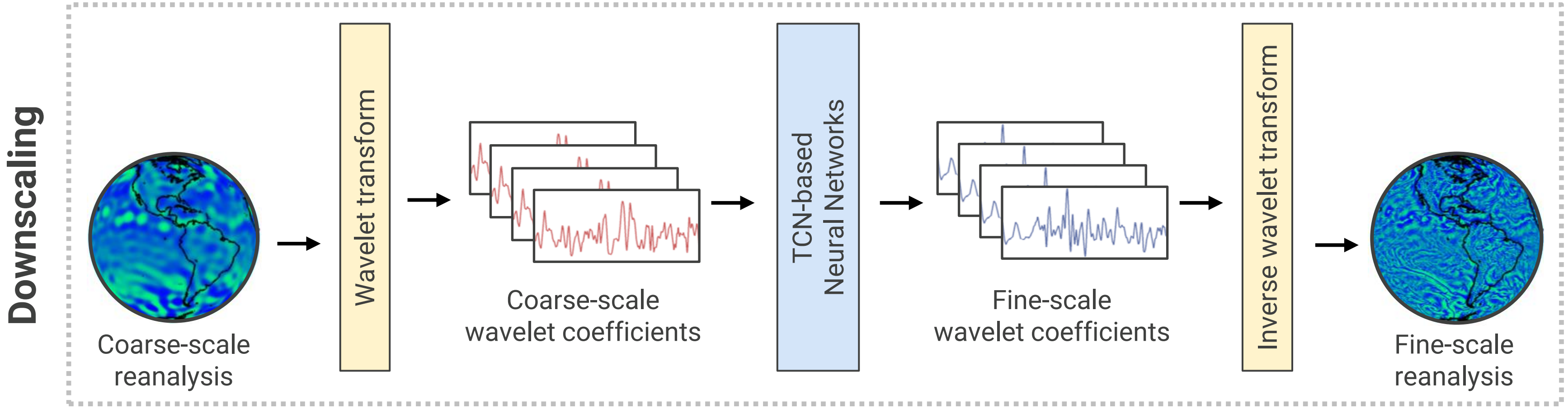

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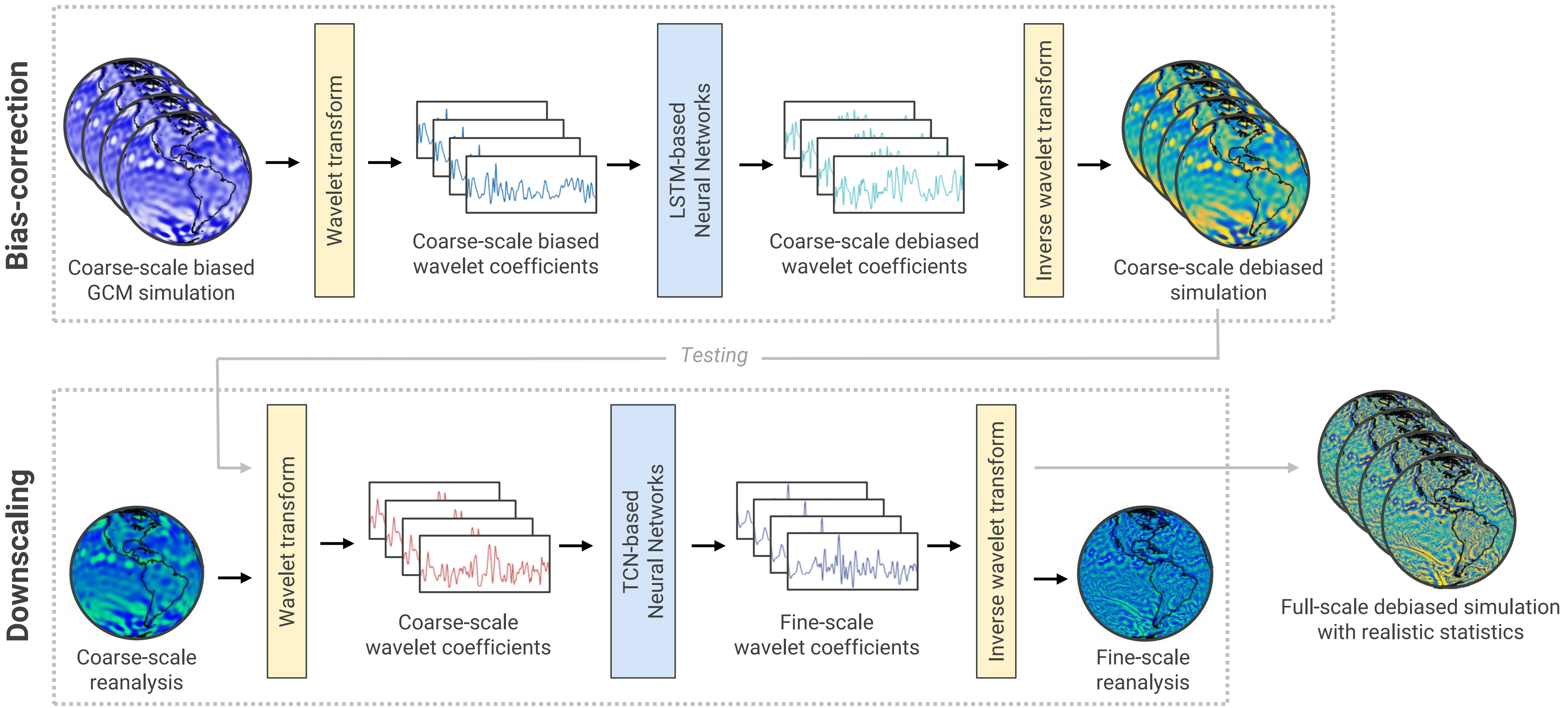
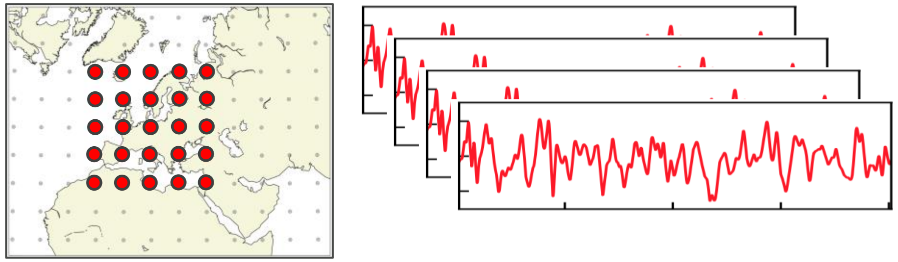


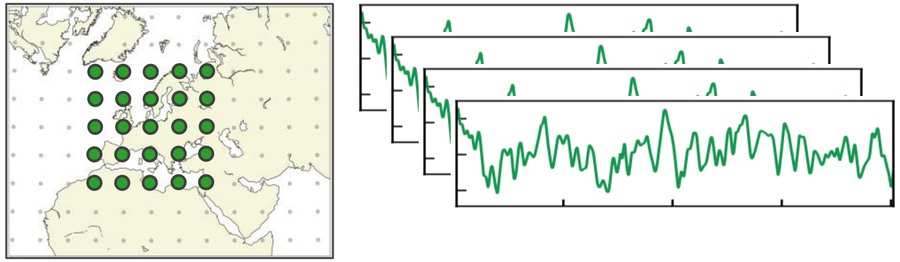
Statistical Loss Functions

How to make ML predictions statistically consistent with observations

ML output



Reanalysis



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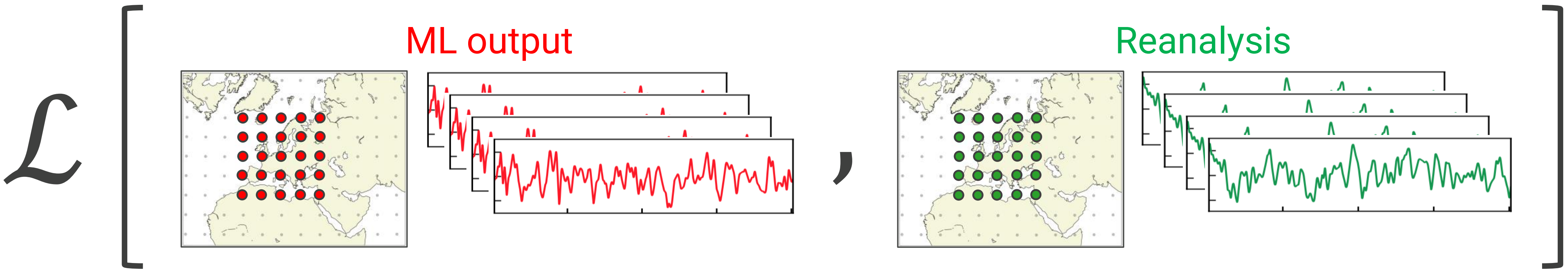

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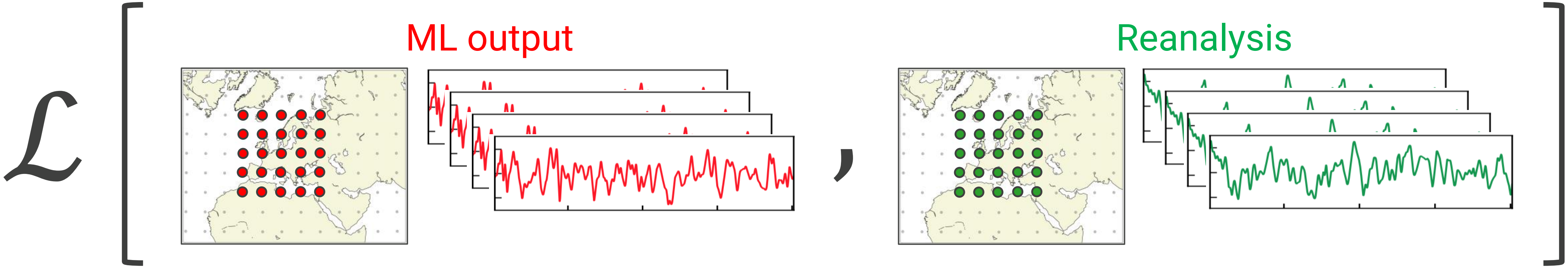

quantiles

Quantile loss heavy tails and extremes $\mathcal{L}(y, y^*) = \mathrm{MSE}(Q_y, Q_{y^*})$

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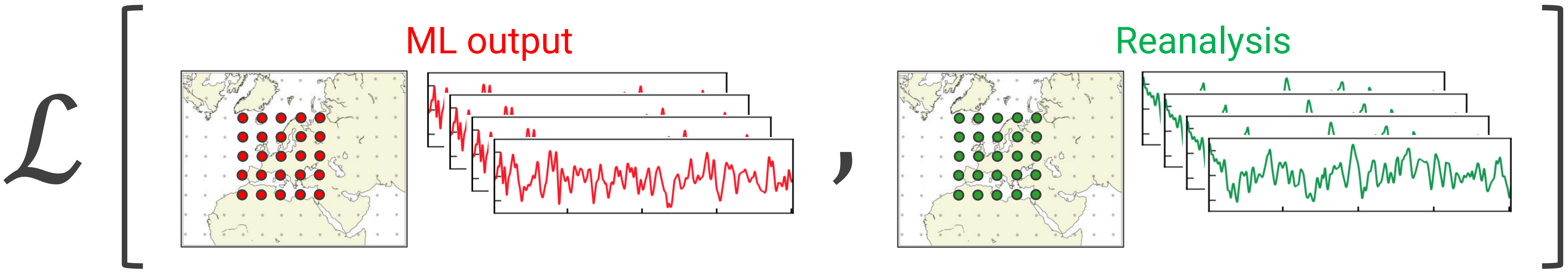

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cross-spectrum

Cross-spectrum loss space-time coherency

$$\mathcal{L}(y, y^*) = \mathrm{MSE}\left(\mathrm{Re}[\Gamma_{y,\mathbf{y}_n}], \mathrm{Re}[\Gamma_{y^*,\mathbf{y}_n^*}]\right) + \mathrm{MSE}\left(\mathrm{Im}[\Gamma_{y,\mathbf{y}_n}], \mathrm{Im}[\Gamma_{y^*,\mathbf{y}_n^*}]\right)$$

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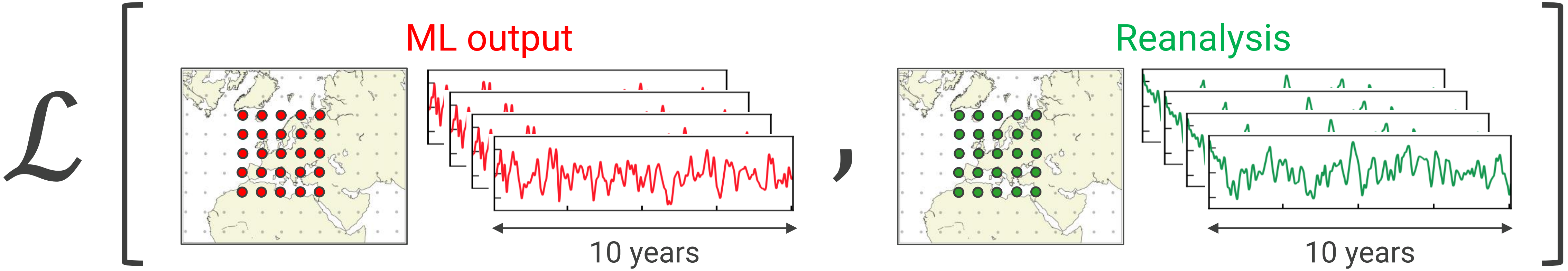

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Debiased, High-Resolution Simulation over Europe

- 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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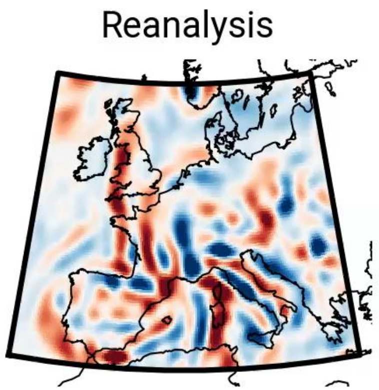

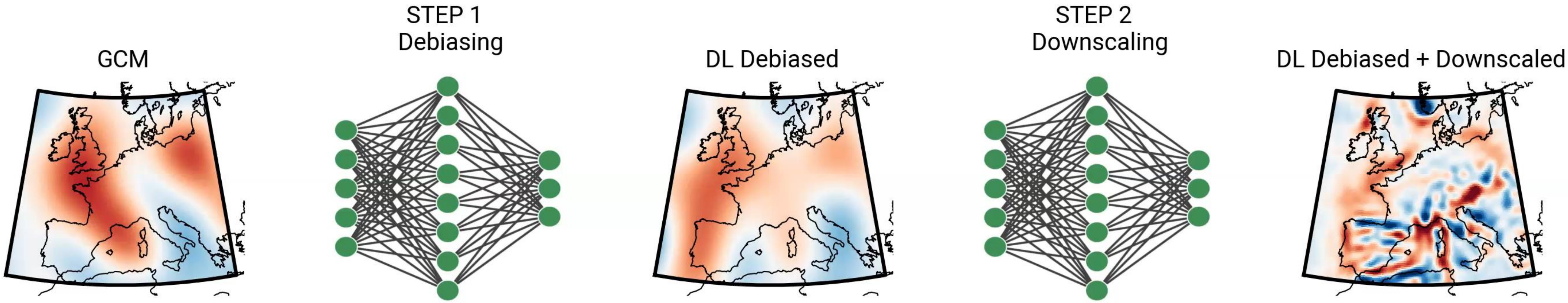

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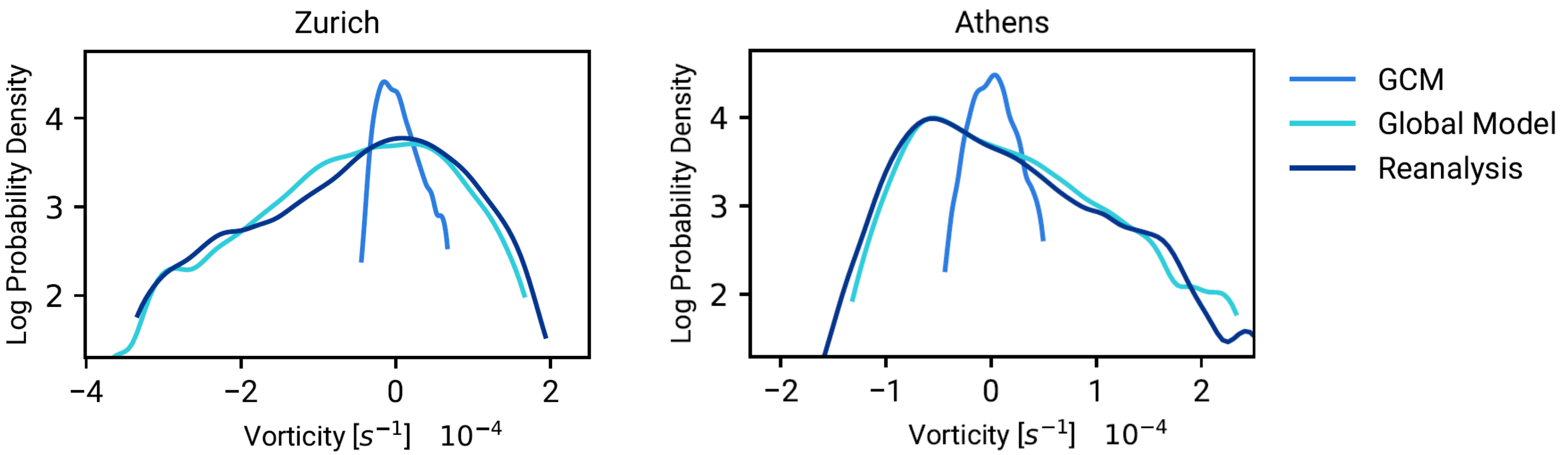

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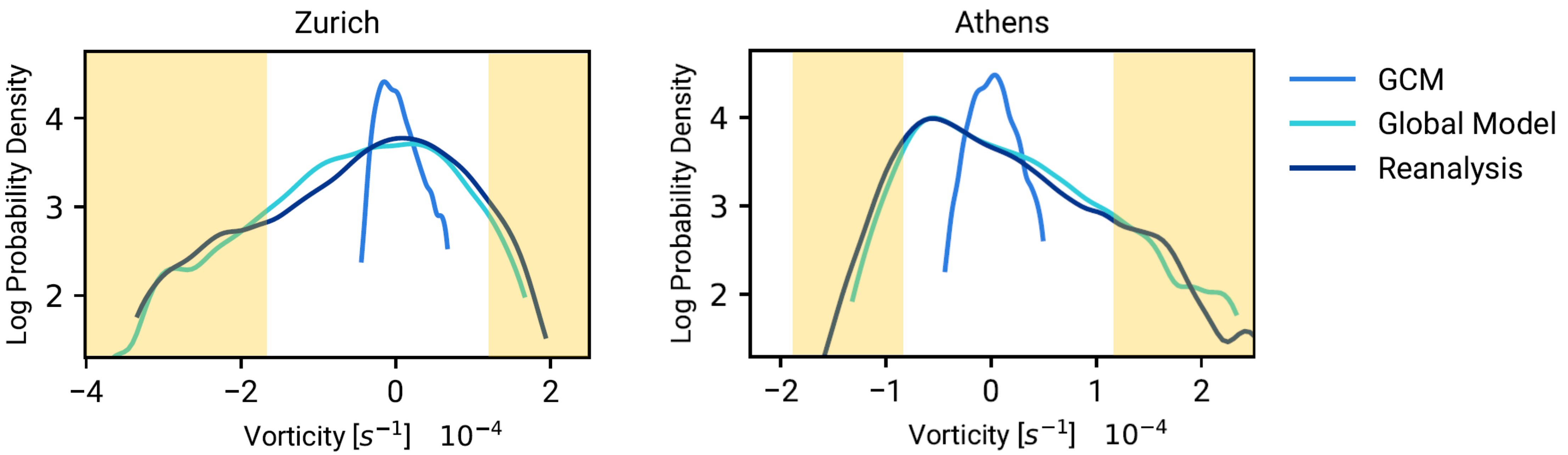

Conclusions

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Key ingredients:

- compact, multi-scale representation of atmospheric processes
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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)