A Multi-Scale Deep Learning Framework for Projecting Weather Extremes

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Tackling Climate Change with Machine Learning @ NeurIPS 2022

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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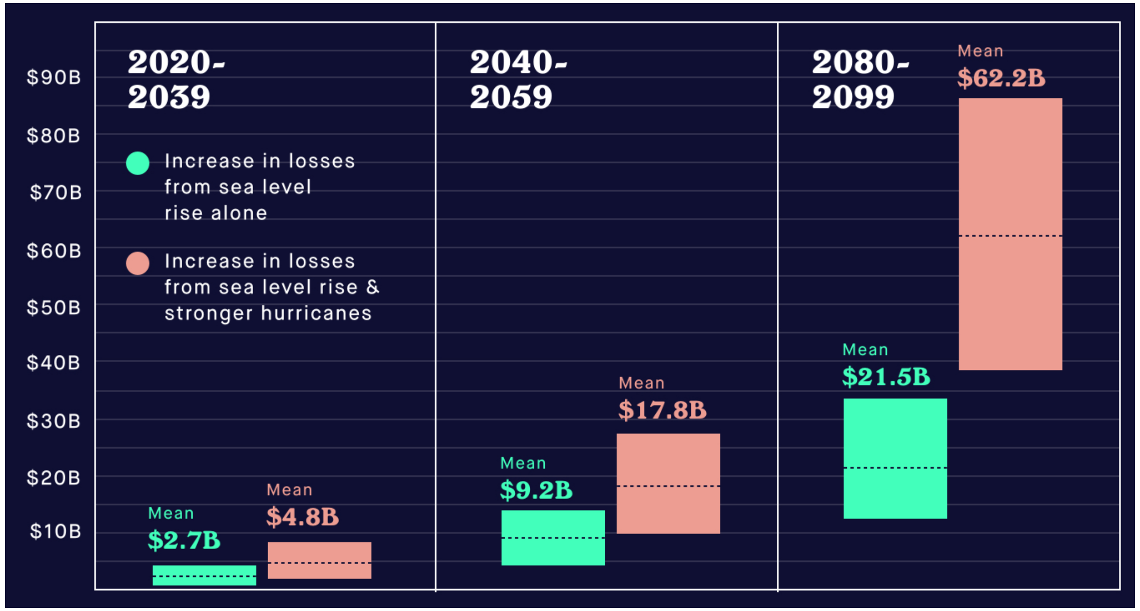
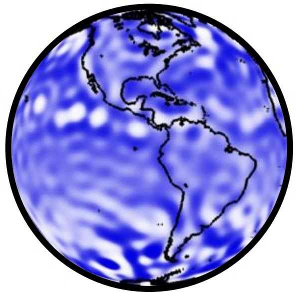
Risk assessment of extremes is challenging

- 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



Simple GCM simulation
(fast but biased)

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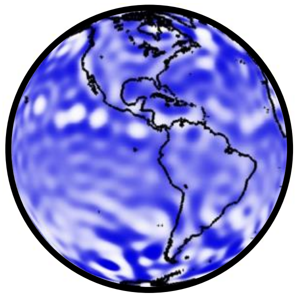

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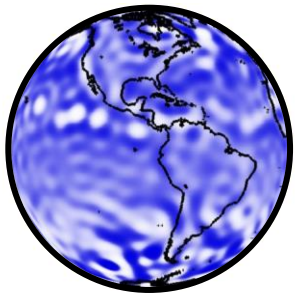

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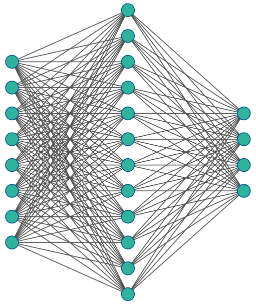

Step 1:
Bias-correction

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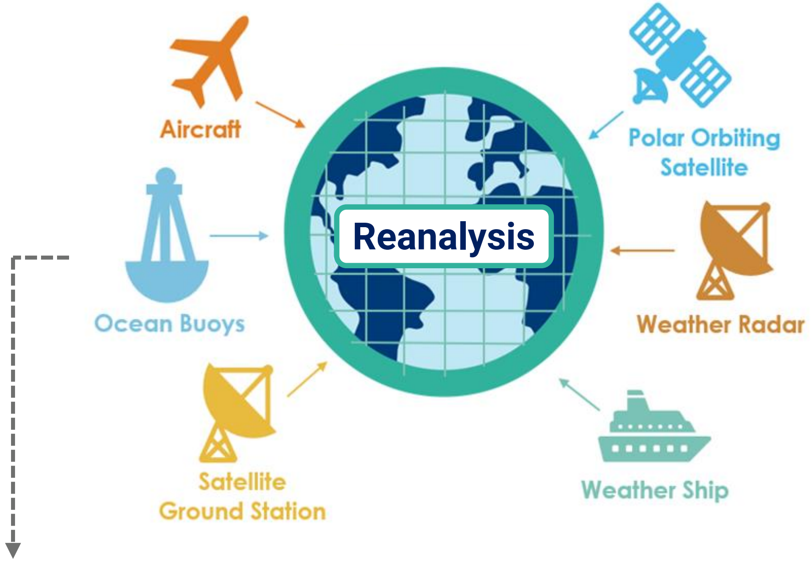

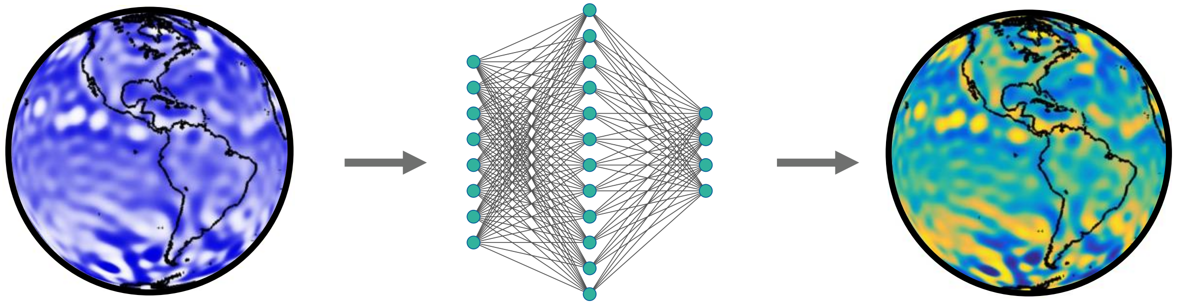

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Step 1:
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Coarse-scale
debiased GCM

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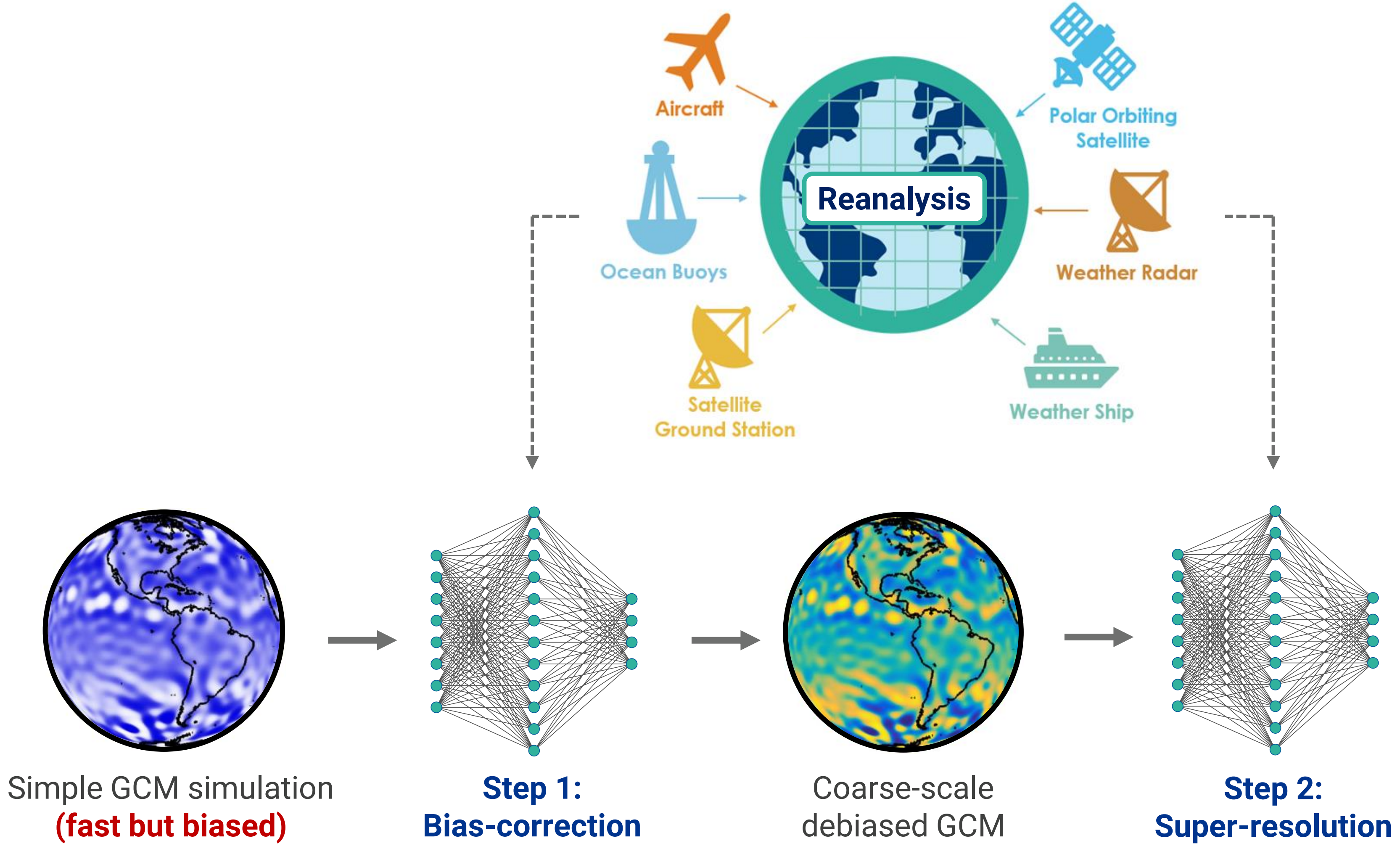

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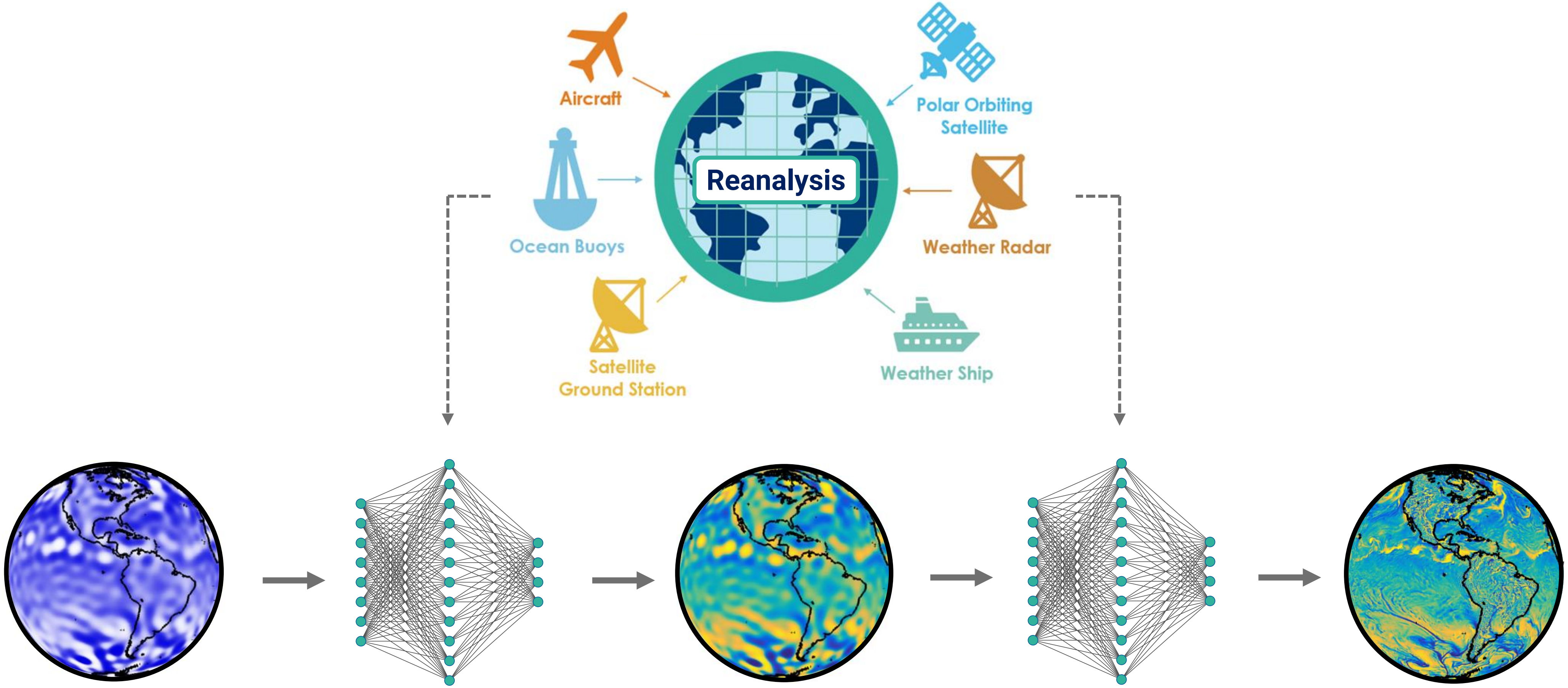

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Step 1: Bias-correction

Coarse-scale debiased GCM

Step 2: Super-resolution

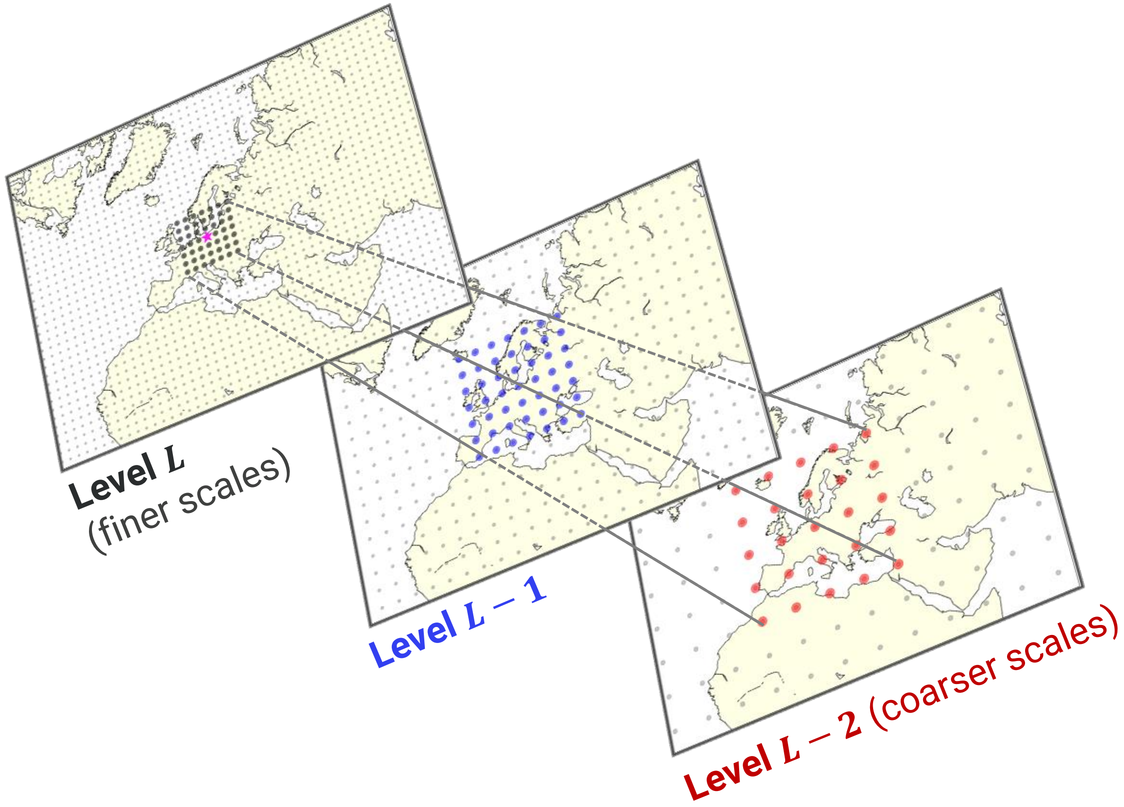
High-resolution debiased simulation

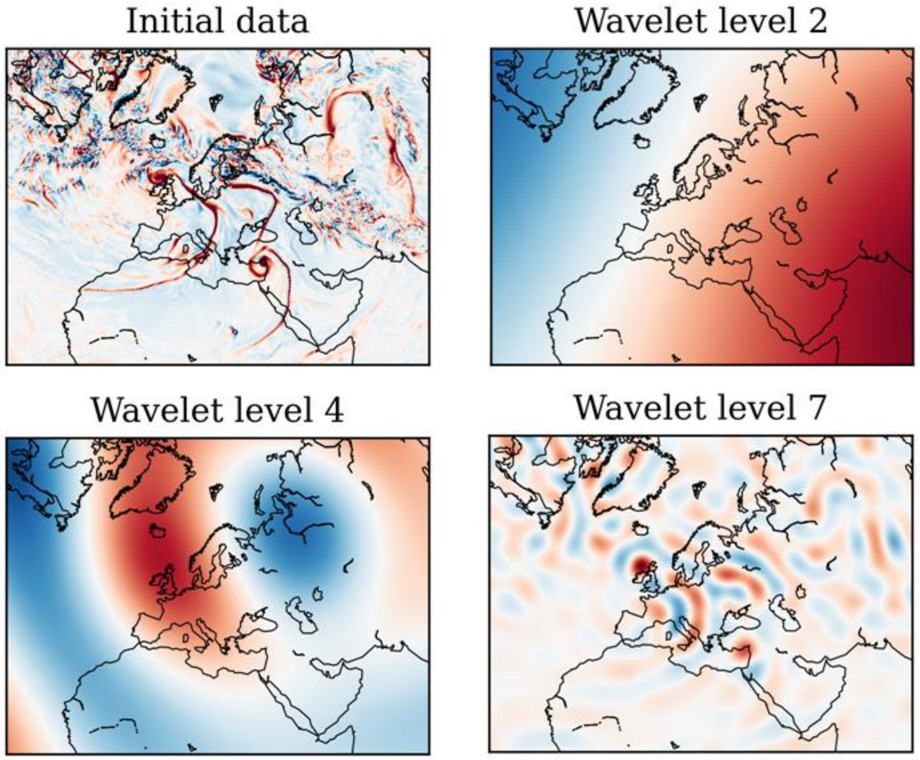
Atmosphere Dynamics Involve Many Spatial Scales

Compact representation of atmospheric processes is needed

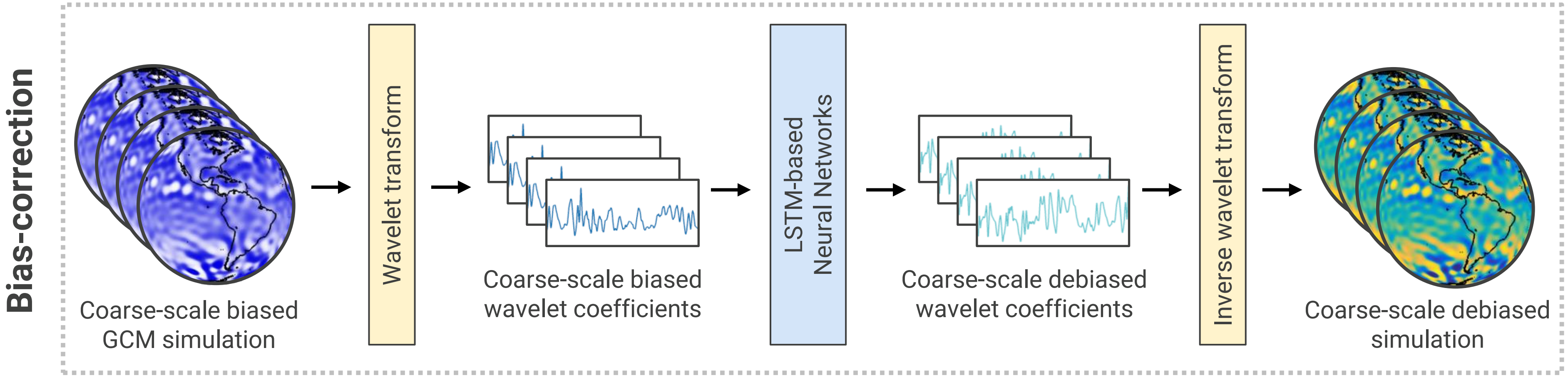
Discrete spherical wavelet frame is used to represent phenomena on a hierarchy of levels

- reduces dimensionality
- allows training of local models





Multi-Scale Deep Learning for Weather Extremes



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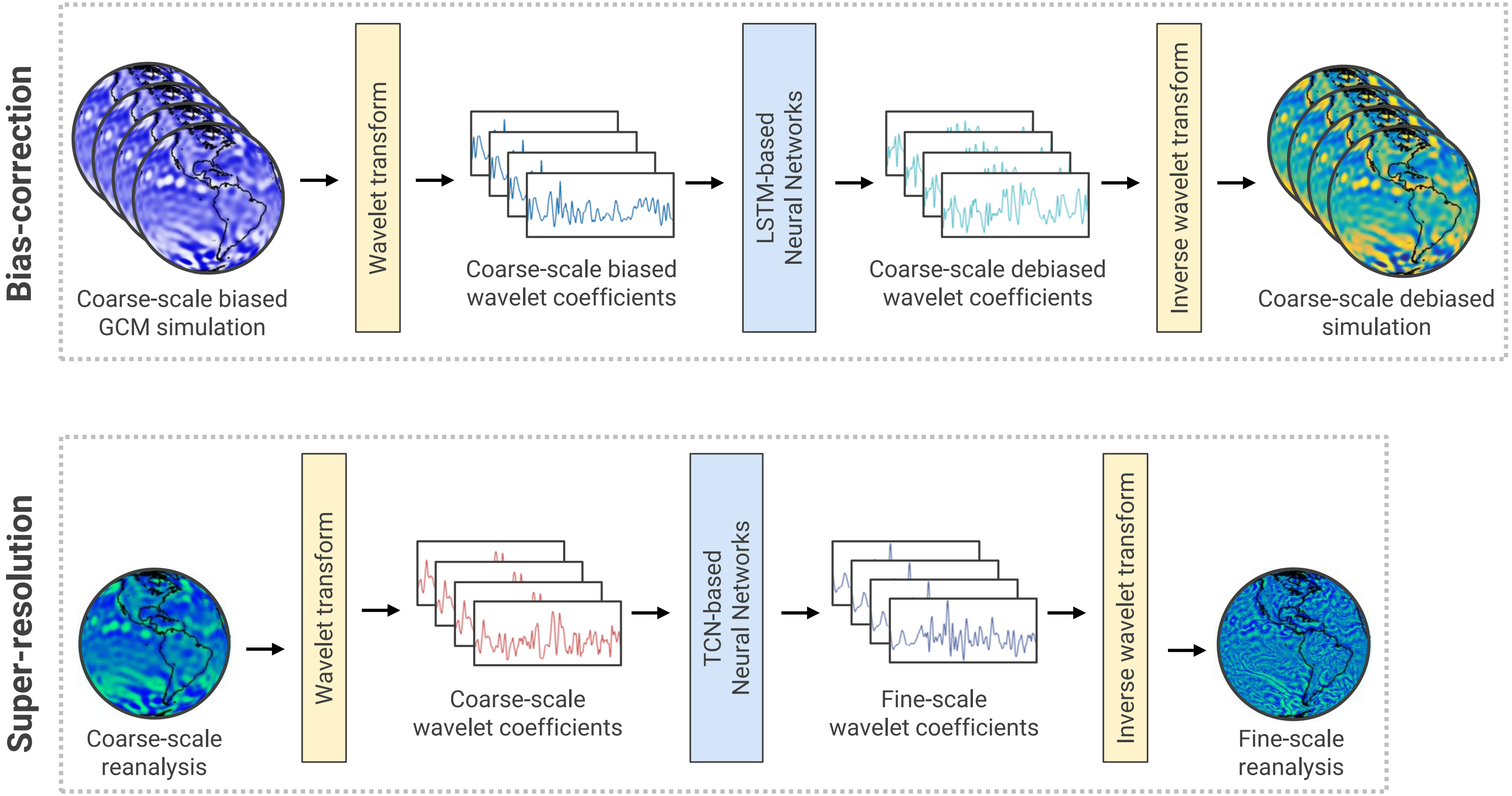

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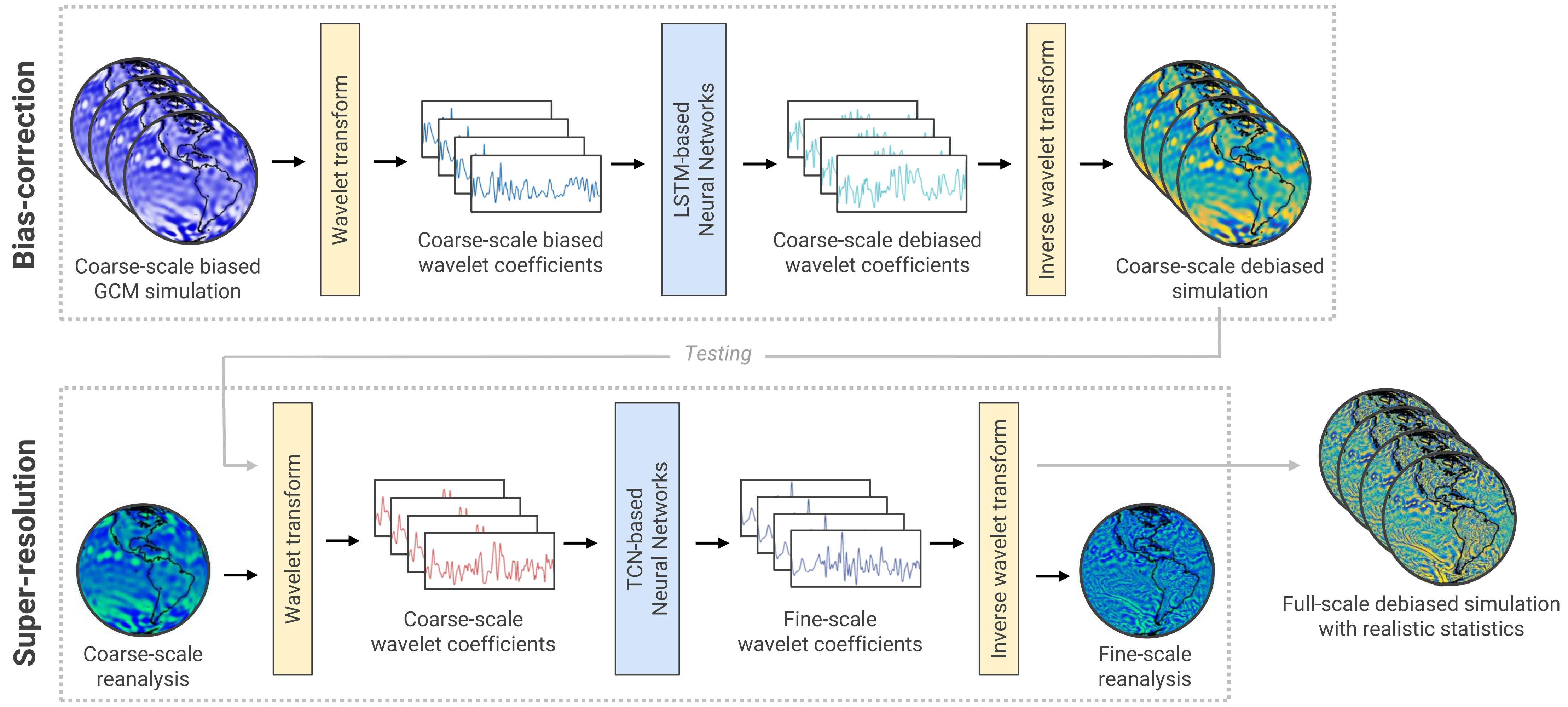
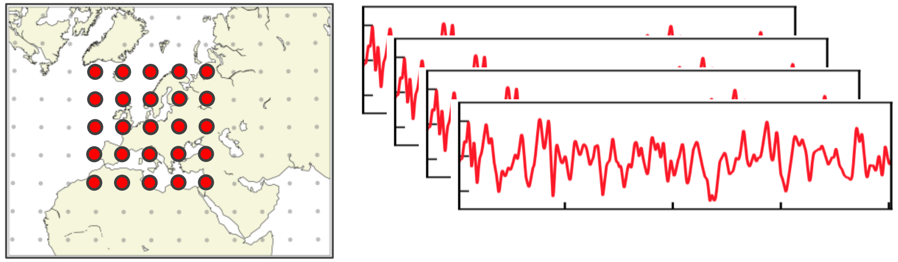


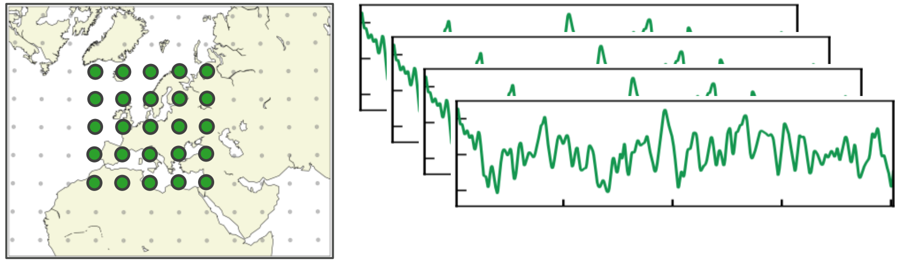
Statistical Loss Functions

How to make ML predictions statistically consistent with observations

ML output



Reanalysis



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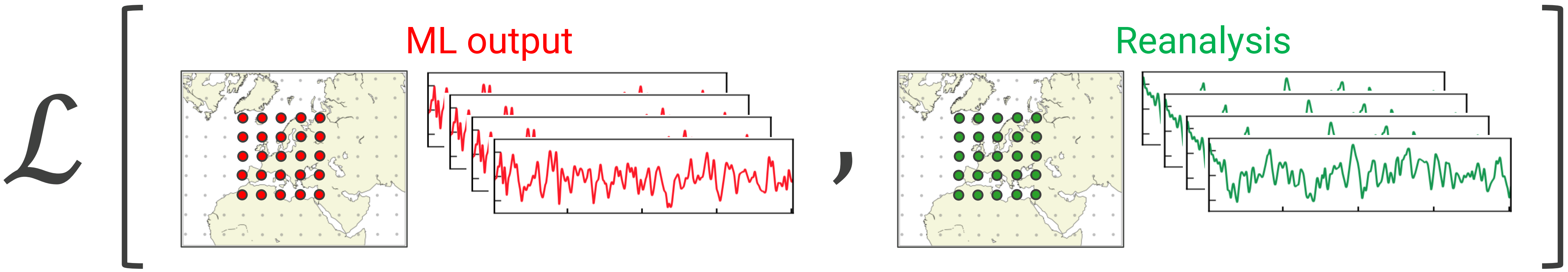

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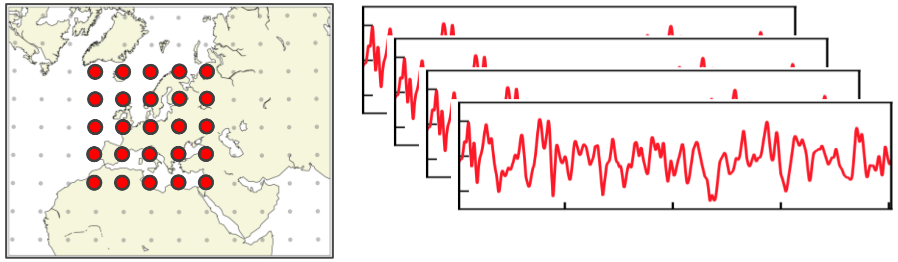

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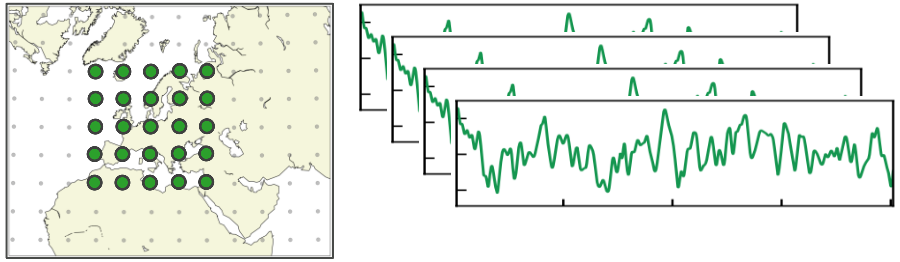

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Quantile loss — heavy tails and extremes

quantiles

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

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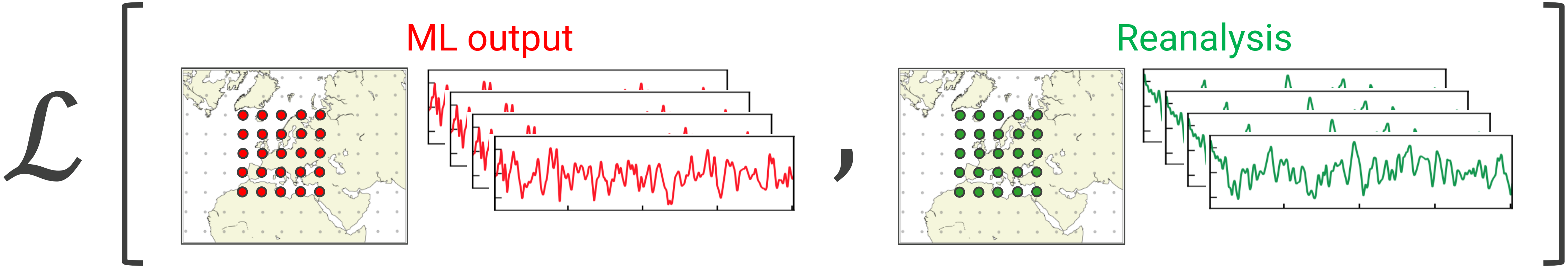

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cross-spectrum

Cross-spectrum loss space-time coherency

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

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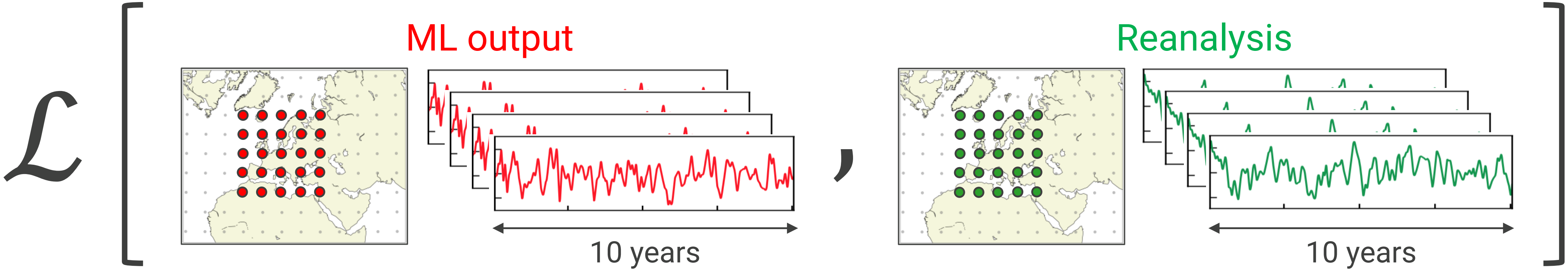

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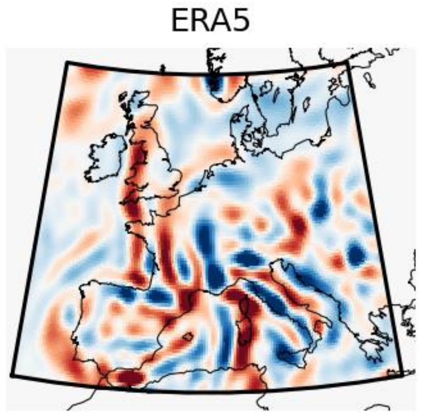
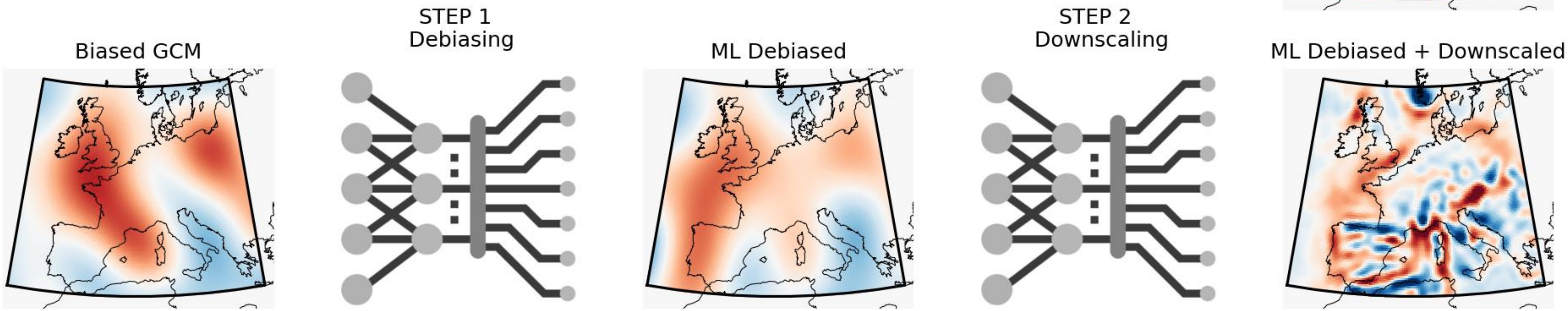
Debiased, High-Resolution Simulation over Europe

- Training protocol described in preprint (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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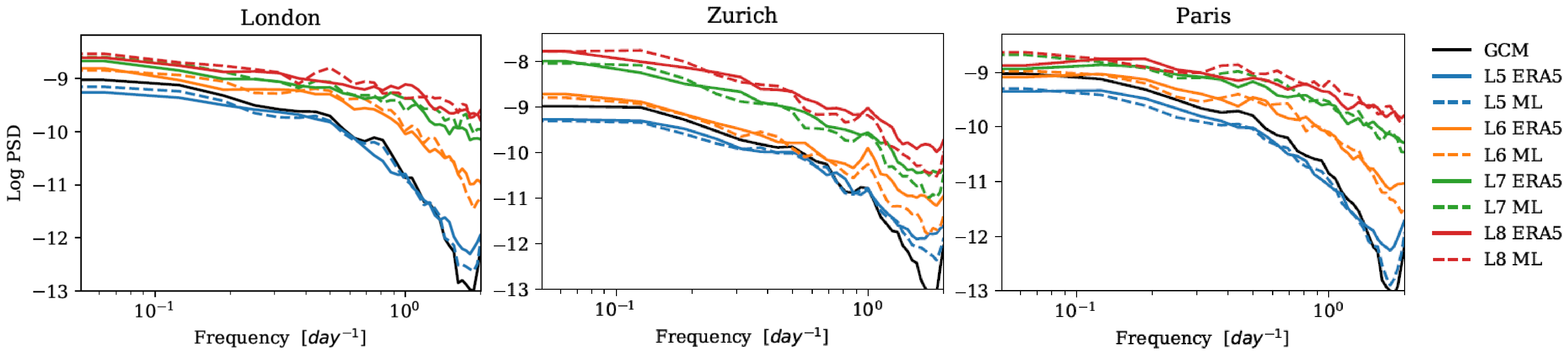

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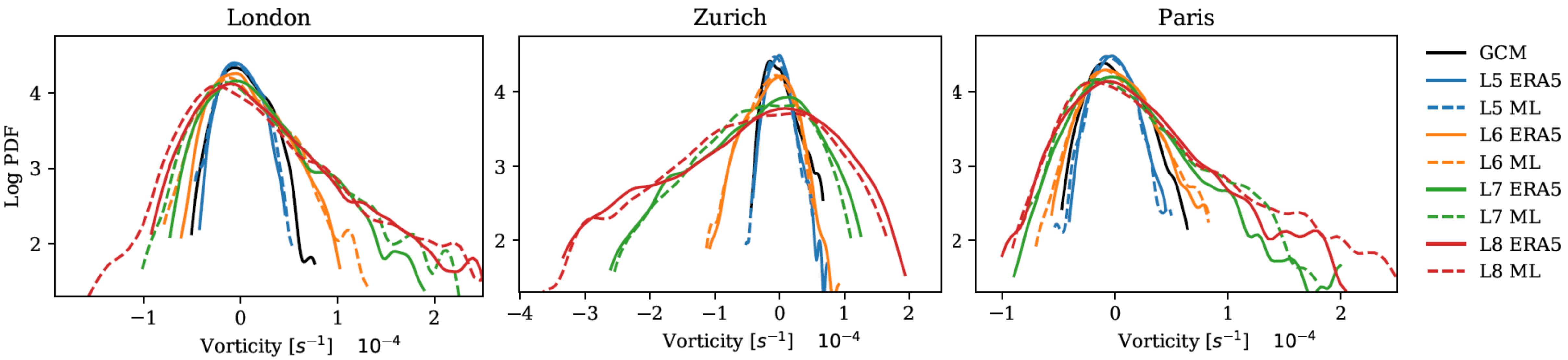

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Conclusions

More details available in our preprint (arXiv:2210.12137)

Key ingredients:

- compact, multi-scale representation of atmospheric processes
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Current thrusts:

- incorporate more physics
- benchmark different seq-to-seq models
- validate with risk-oriented metrics (e.g., storm severity)