MAX-PLANCK-INSTITUT
FÜR METEOROLOGIE

Deep learning based super-resolution for ICON-O

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DKRZ DEUTSCHES KLIMARECHENZENTRUM

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Gefördert vom Bundesministerium für Bildung und Forschung (BMBF) unter Förderkennzeichen 16ME0679K. Supported by the European Union - NextGenerationEU

Introduction

- **Climate models are comprised of two important components:**
  - dynamical core and subgrid models
  - Dynamical core:
    - Grid resolving features
  - Subgrid Model:
    - Parametrization of unresolved features ((Sub)Mesoscale Parametrization, Ice)

- **Physically, the ocean complex dynamics allows for the energy to be transferred for different scales**
  - Then this subgrid parametrization will play a higher role

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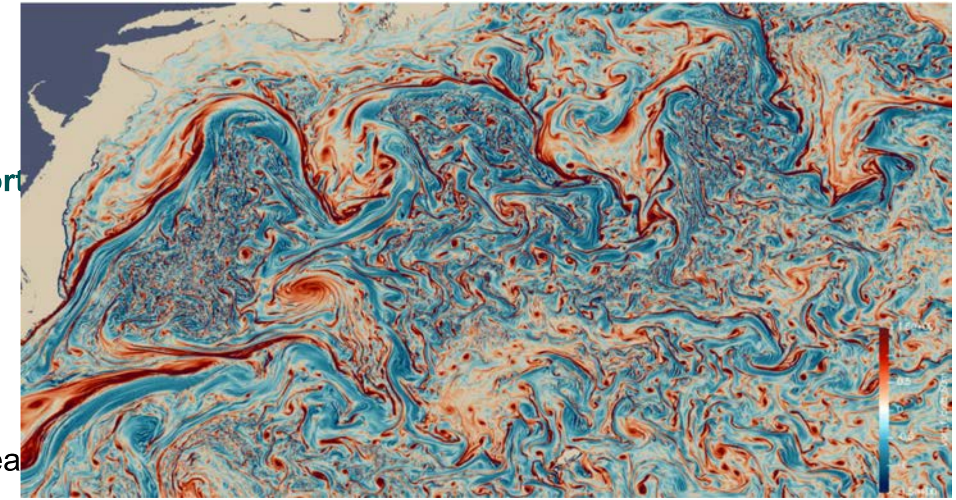

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Introduction

- **In order to improve accuracy of climate projections, finer mesh resolution is required**
  - This in turn greatly increases computational cost
- **Machine Learning has now been rapidly increasing and being investigated and being used in many climate areas**
  - Parametrization (Previous talk Ernout N.)
  - PINN solve free surface (Previous talk Gorenstein I.)
  - **Super-resolution** (image, video processing)
    - This methodology uses Convolutional Neural, Generative Adversarial Network or Diffusion models
    - Super-resolution has been also successfully applied in climate science as image inpainting

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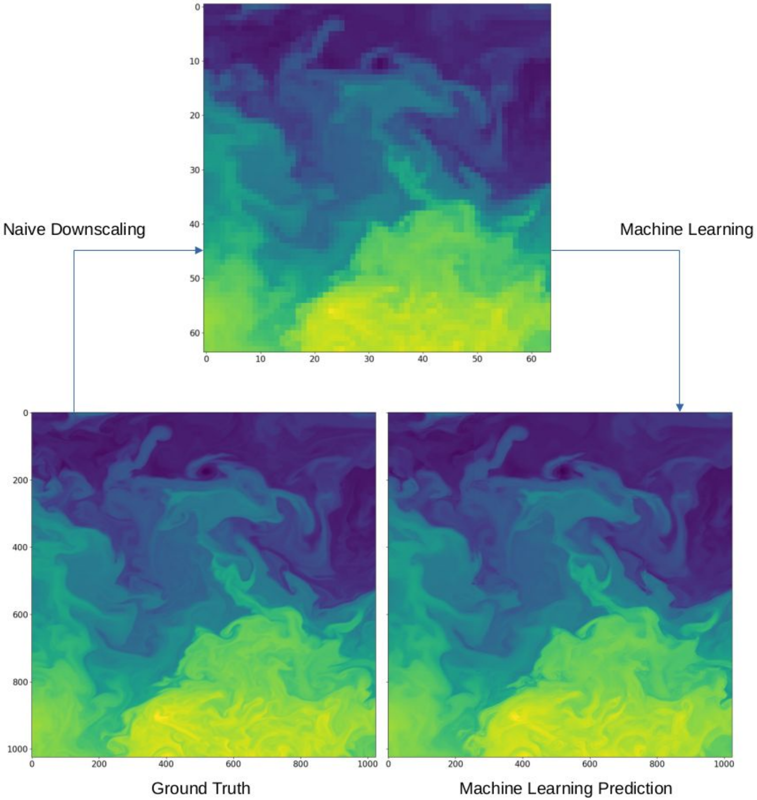

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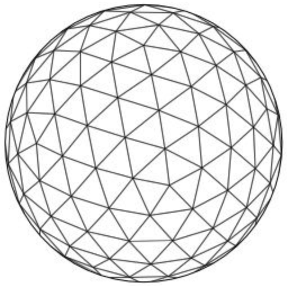
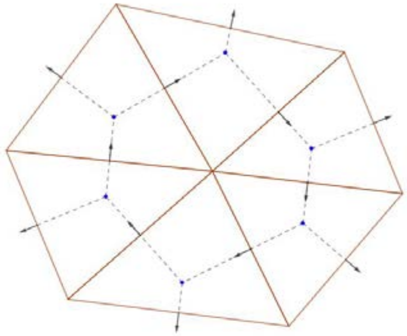
Introduction

- **Can we train a Machine Learning to help numerical models estimate a high resolution output from a low resolution output?**

- **Objective:**
    - Run a shallow water global simulation (in ICON-O) in a coarse mesh while also correcting it with a ML-model trained with high resolution data

Methodology



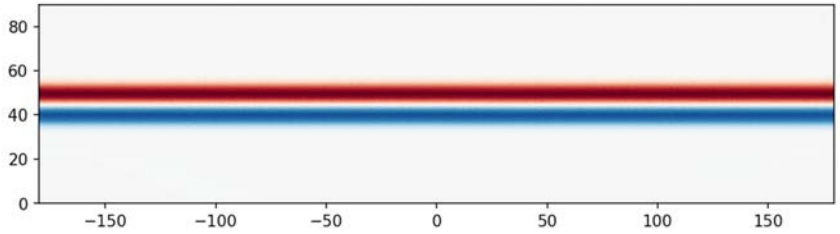


- **ICON-O:**
  - Dynamical Core:
    - Spherical Grid
    - Finite Volume (C-grid)
      - **Based on Admissible Reconstructions (minimizes noise in triangular grids)**
    - Triangular grid (icosahedral based)
    - Solves the invariant form equation

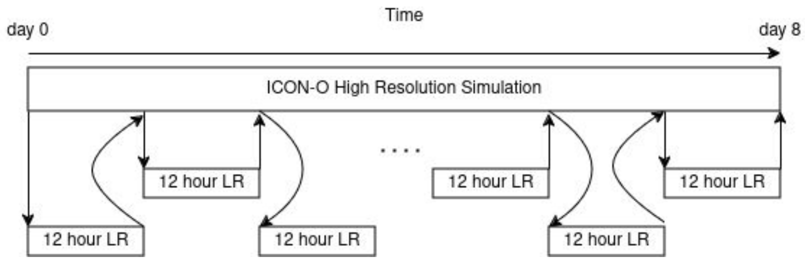
$$\underbrace{\frac{\partial \mathbf{v}}{\partial t} + \nabla \cdot (\mathbf{v} \otimes \mathbf{v}) + g\nabla(b+\eta)}_{\text{Advective form}} = \underbrace{\frac{\partial \mathbf{v}}{\partial t} + \omega \mathbf{v} + \nabla \frac{|\mathbf{v}|^2}{2} + g\nabla(b+\eta)}_{\text{Vector invariant form}} = 0$$

Methodology

- **Initial condition (Galewsky et al. 2014):**
  - Geostrophic jet at the north hemisphere;
  - With an additional perturbation
  - Barotropic Instability
  - Maximum velocity 80 ms-1
    - Atmospheric initial condition, but the overall dynamics is present in the ocean



Methodology



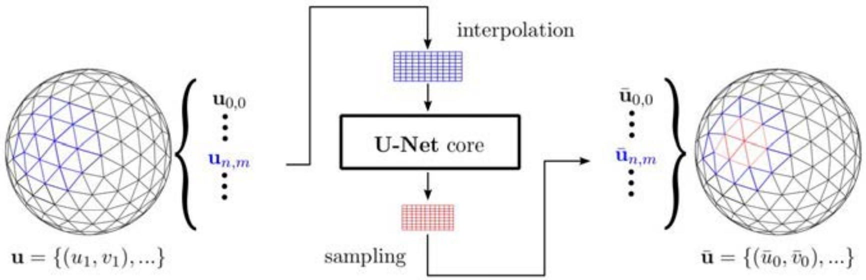
- **Initial condition (Galewsky et al. 2014):**
  - The training data (velocity fields):
    - Pair of 2.5km and 20km (with 12 hour integrated comparison output)
      - **Velocity fields substituted HR -> LR**
    - 10 days integration with 12 hour output
    - Jet location core at ~42 N +/- 5
    - 8 different perturbation location
    - Total: 23 different conditions with 12 hour output=383 snapshots
  - Coupled Run (Traditional Barotropic Instability):
    - At each 12 hours, the LR output is delivered to the trained ML for correction.

Methodology

- **Neural Network:**
  - The grid is divided into patches and interpolated into a regular high-resolution grid with 10% overlap between each patch;
  - Each patch is set inside a U-Net structure (without biases)

$$\mathcal{L} = \mathcal{L}_{\text{abs}} + \gamma \mathcal{L}_{\text{rel}} \quad \mathcal{L}_{\text{abs}} = \frac{1}{N}\sum_{i}^{N} \left(|\bar{u}_i - u_i'|\right)^2 + \left(|\bar{v}_i - v_i'|\right)^2 \quad \mathcal{L}_{\text{rel}} = \frac{1}{N}\sum_{i}^{N} \left(\min\left[1, \frac{|\bar{u}_i - u_i'|}{u_i' + \epsilon}\right] + \min\left[1, \frac{|\bar{v}_i - v_i'|}{v_i' + \epsilon}\right] \right)$$

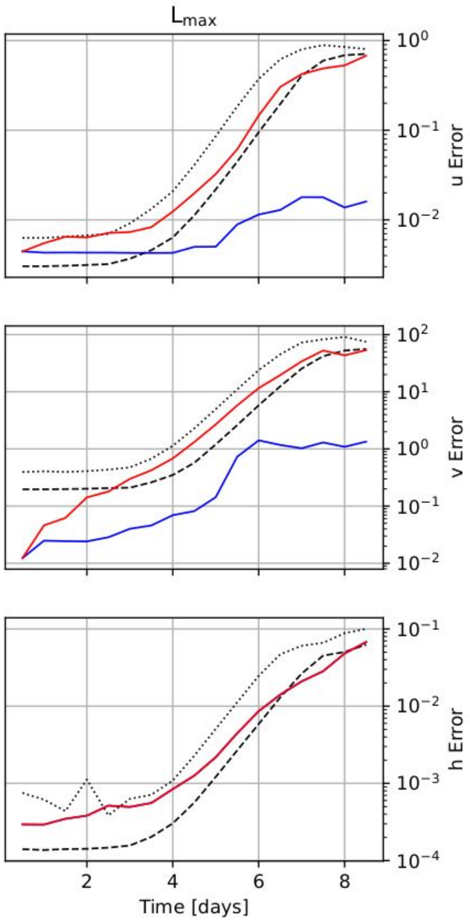
$$\min_{\theta} \mathcal{L}\left(\Theta(\mathbf{u}(t+\tau)), \mathbf{u}'_{\text{hr}}(t+\tau)\right)$$



Results

$$L_{\max} = \frac{\max_j \left| f_j^{[n]} - f_j^{[r]} \right|}{\max_j \left| f_j^{[r]} \right|}$$

- **Result (10day integration):**
    - Maximum Norm error
        - The coupled run initially loses accuracy in the early time
        - As the instability grows the accuracy is improved
        - The same is observed in the height field (which was not corrected by ML)
        - Overall we achieve 10km in our run (2 times fold)
        - As the optimal (blue line) result indicates, there's still room for improvement in the run



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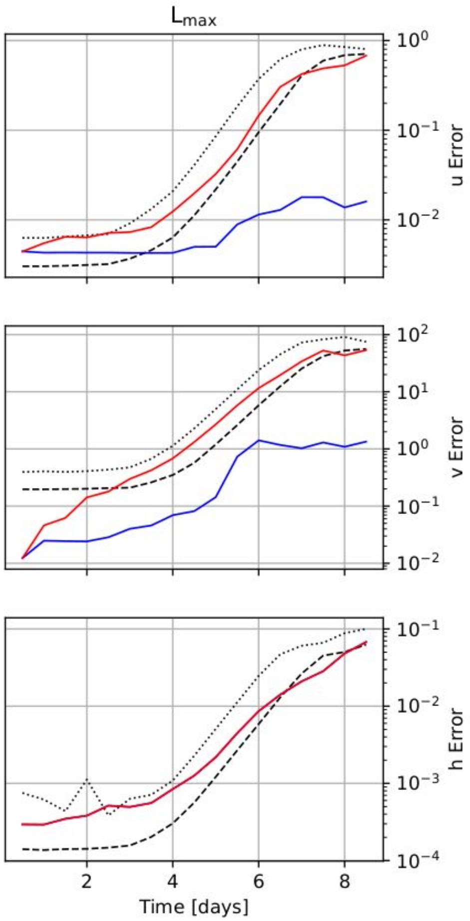
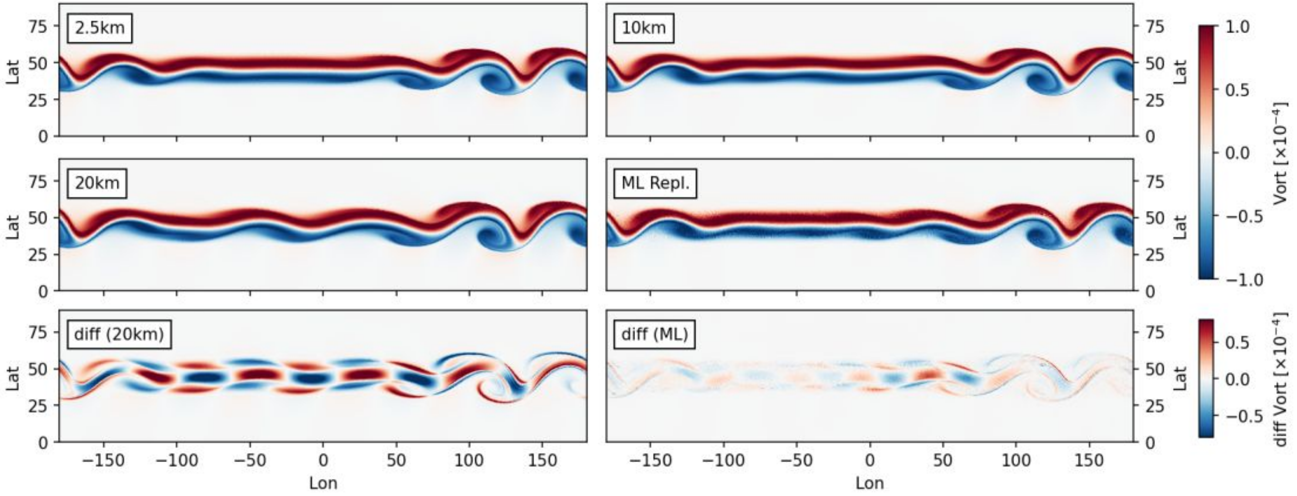
10 km	$\mathrm{ML}_{\mathrm{coupled}}$	20 km
63 s	55 s	31 s



Results

- **Vorticity (instability day 7):**
    - The low resolution triggers the instability earlier due to unstructured grid error, show faster meanderings
    - The coupled run delays this instability with a lower meandering equivalent to the 10km run



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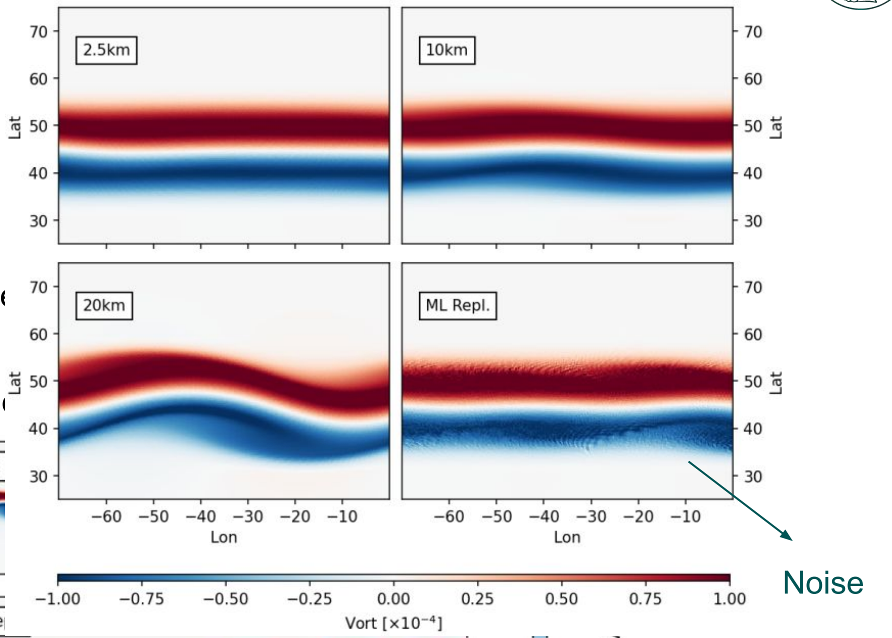
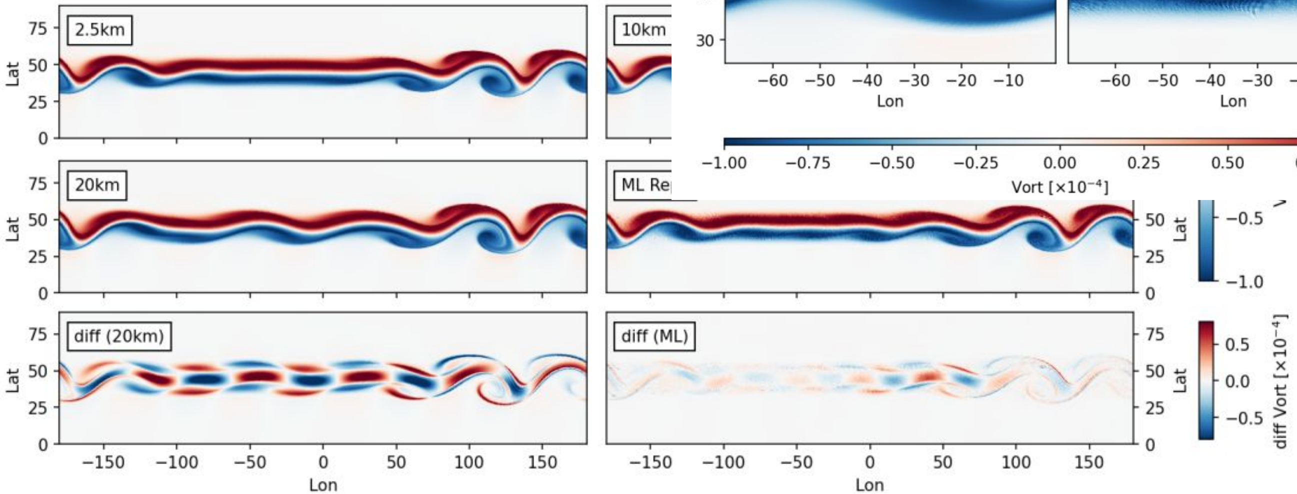
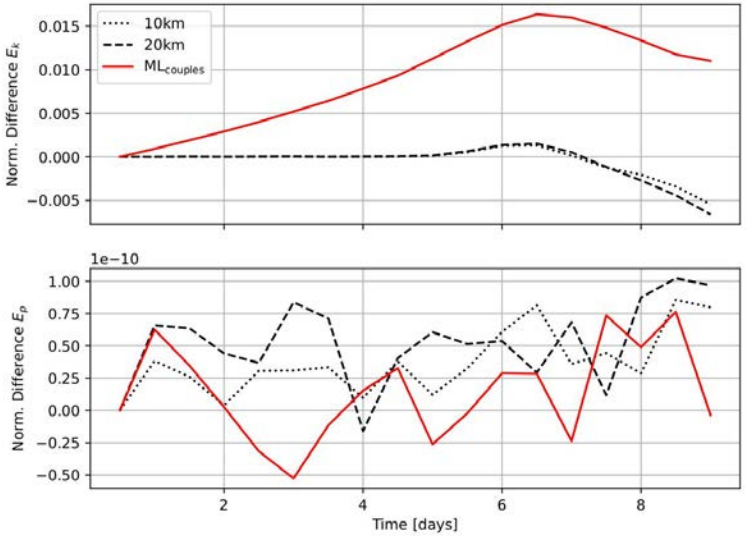




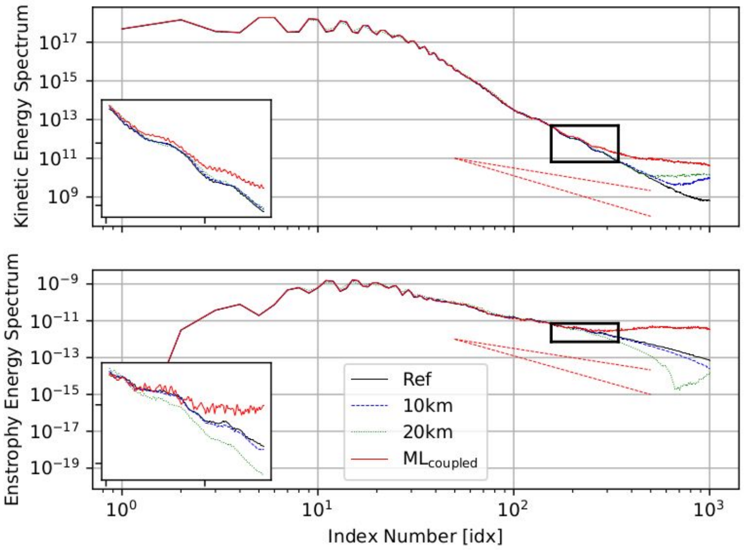
Results

- **Energy conservation**
  - Our choice of assimilation with ML inputs energy into the system;
    - The growth does not seem constant as it decreases after day 6
    - The noise present in the vorticity is possibly being an added energy in the system
  - Potential energy conservation is not violated with our methodology (given that the height is not changed)



Results

- **Spectral energy**
  - The energy spectrum is violated for lower wavenumbers than the other runs
    - The observed input of energy observed is mostly concerned in the smallest scales
    - It does not seem to leak into the largest scales of the grid
  - The Enstrophy is not significantly improved, but it is not damaged by the assimilation
  - Non-dissipative simulation
    - In a more real dissipative simulation, these noises may spuriously contribute to mixing



Summary

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- Summary
  - Our ML methodology for shallow water show potential use for increasing the accuracy of fluid simulations
  - The use CNN (possibly due to its necessity of regular grids) provides spurious noise to the system
    - These can, however, be mitigated by low order pass filters
    - Use ML **Transformers Network**? (ongoing)
  - The assimilation (of substituting variables) may also be improved by diminishing this noise and increase the accuracy (4Dnet, nudging, etc.)
  - **Future Work:**
    - Investigate improvements in data-assimilation technique for the ML coupled runs (preliminary)
    - Investigate different frequencies of assimilation (ongoing)
    - Apply results in a real 3D ocean

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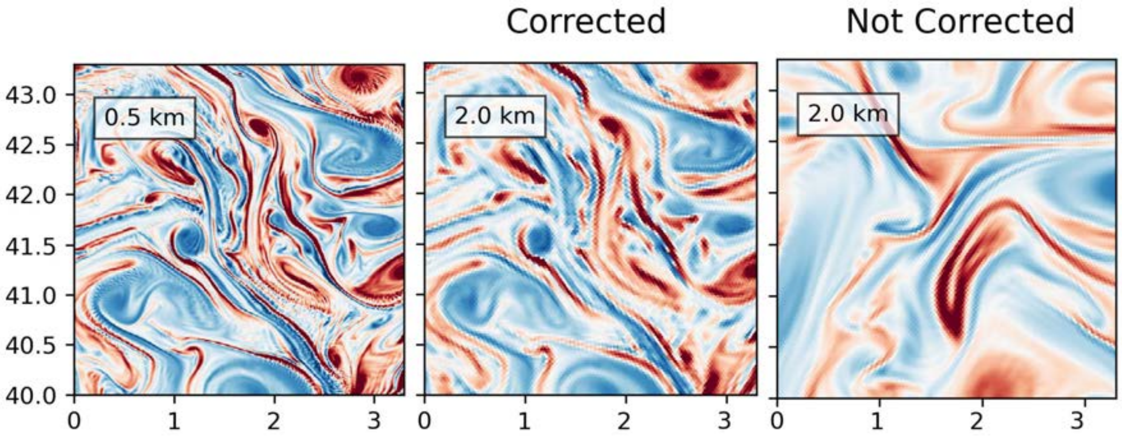

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