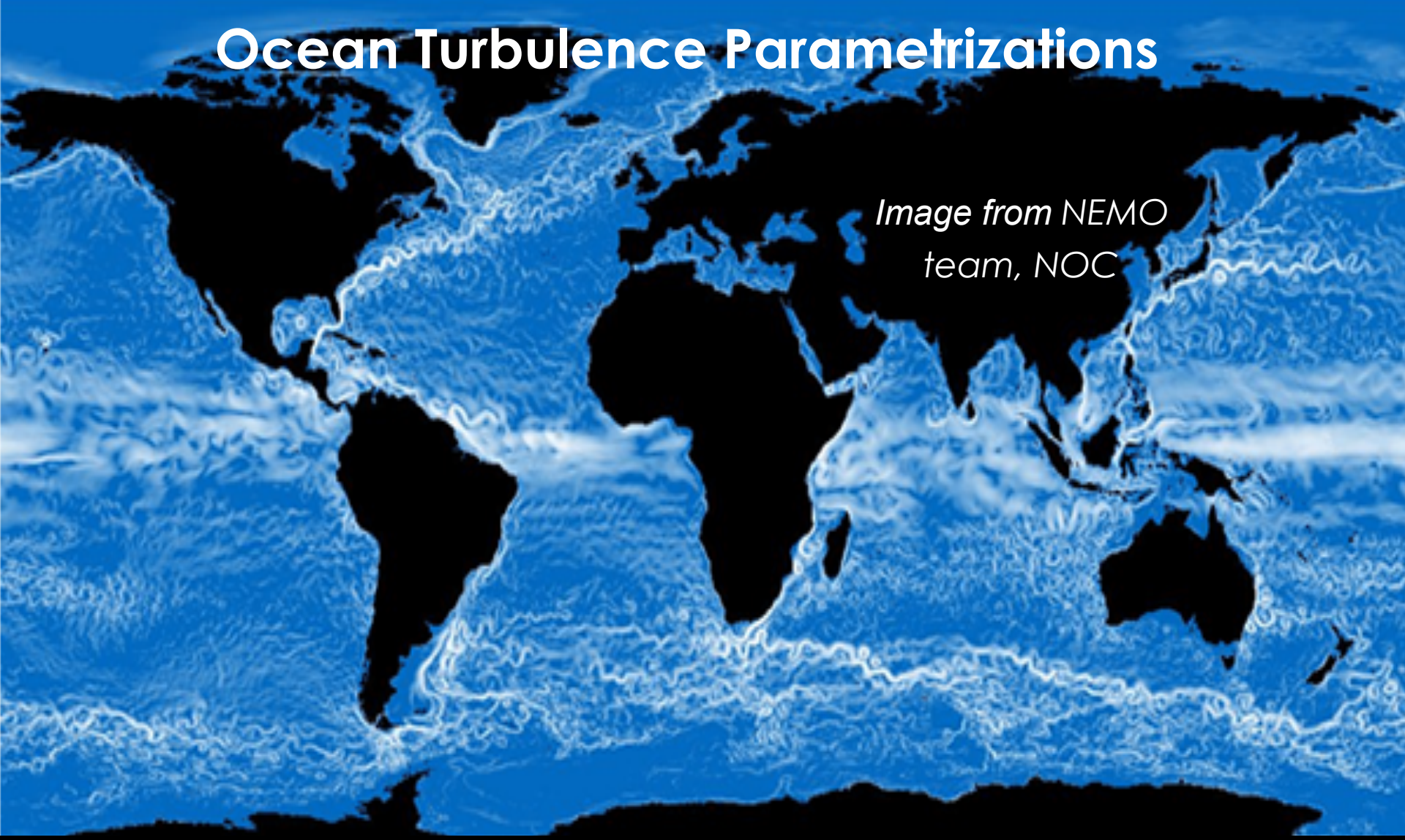
Ocean Turbulence Parametrizations



Laure Zanna

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on sabbatical @ Princeton/GFDL

Outline (with an ocean turbulence focus)

- The sub-grid parametrization problem

- The traditional approach & its caveats

- Our (& others) complementary approach: focus on sub-grid turbulence forcing, rather than one process due to the lack of scale separation

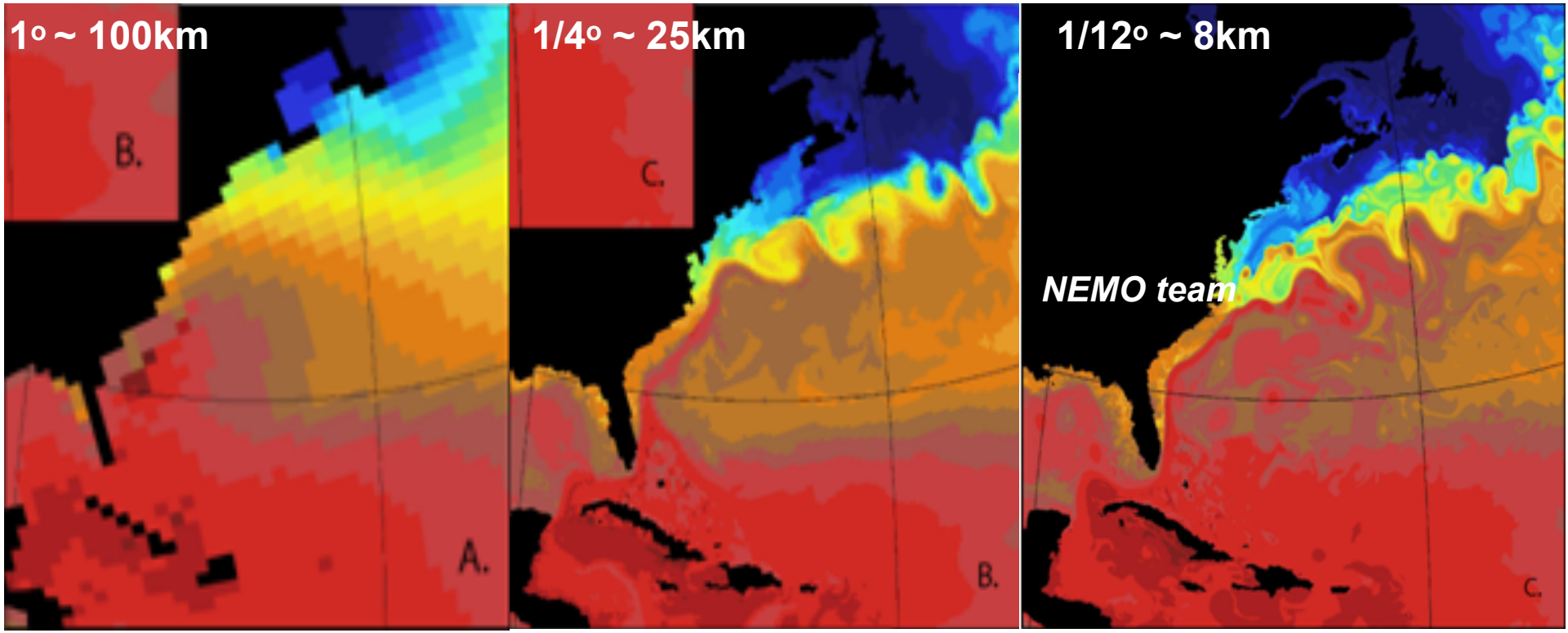
  1) coarse-graining from models + new mathematically- and physically-constrained relationships

  2) imperfect "observations" & machine learning (Neural Networks)

- Some results with implementations, caveats & ways forward

Ocean Models & Resolution

Resolution



Timestep

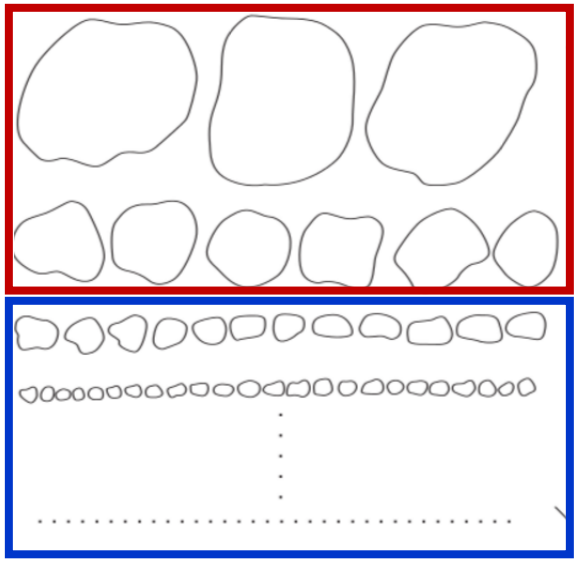
Computational cost

Aim: Turbulence Closure in Numerical Simulations

- Governing Equations, e.g. zonal/x-direction:

$$\frac{\partial u}{\partial t} + \mathrm{u} \cdot \nabla_h u - f v = -\frac{1}{\rho_0}\frac{\partial p}{\partial x} + \frac{F_x}{\rho_0}$$

- Reynolds-Averaged Equation of motions:



($\bar{}$) = slow/large-scale fluctuations
> grid-box size

( )' = fast/small-scale (eddy) fluctuations
< grid-box size

$$\frac{\partial \bar{u}}{\partial t} + \bar{u}\frac{\partial \bar{u}}{\partial x} + \bar{v}\frac{\partial \bar{u}}{\partial y} - f\bar{v} = -\frac{1}{\rho_0}\frac{\partial \bar{p}}{\partial x} + \frac{\bar{F}_x}{\rho_0} - \underbrace{\frac{\partial \overline{u'u'}}{\partial x} - \frac{\partial \overline{u'v'}}{\partial y}}$$

- **Turbulence Closure Problem:** how to mimic the eddy/Reynolds stress which represent the effects of small/fast fluctuations on large-scale

Traditional Approach to Parametrization

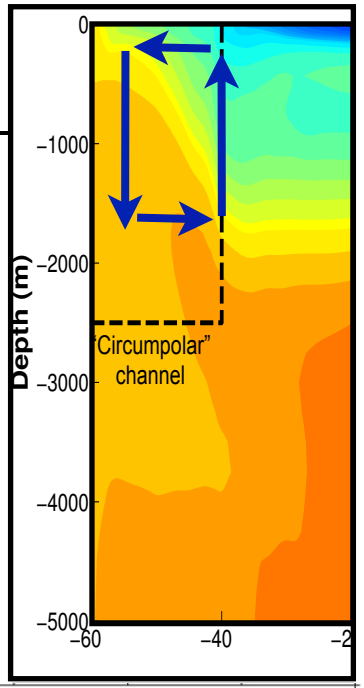
- **One process**: baroclinic mesoscale eddies *(**Gent-McWilliams**, 1990, Gent et al 1995)*

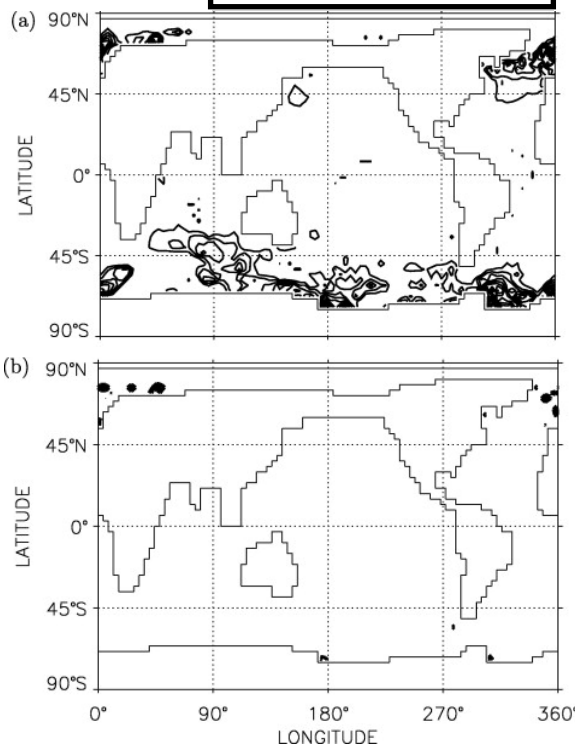
- **One effect** associated with the process: baroclinic instability with conversion of APE into KE & flattening of isopycnal

- **One functional form**: depends on the gradient of buoyancy

- **One parameter** = positive definite & spatially-dependent

➡ *Large improvements to large-scale circulation, especially Southern Ocean & density distribution, stratification, eliminated spurious convection*

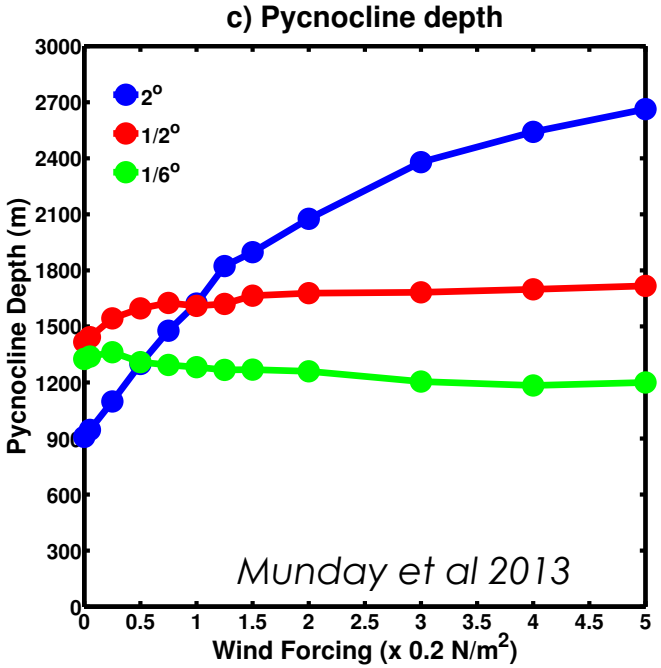


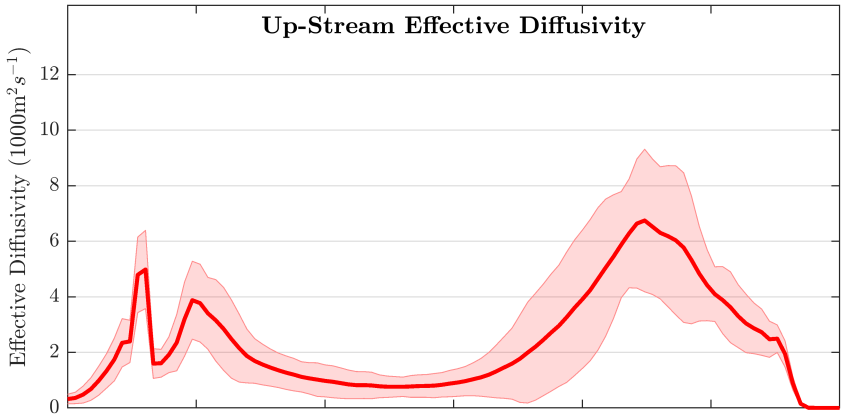


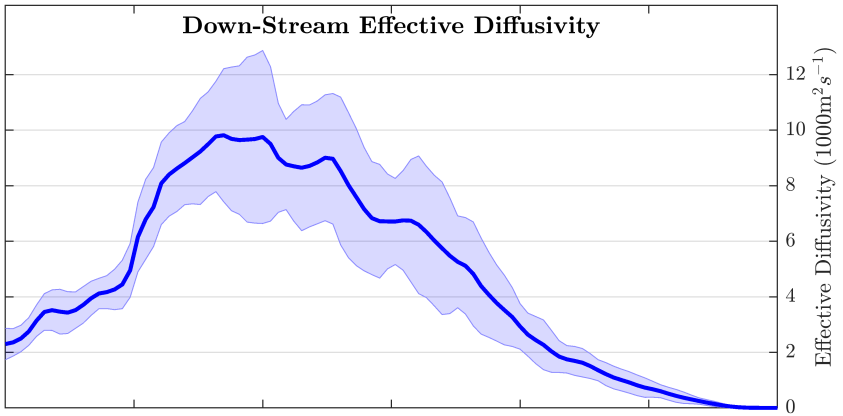
Gent et al, 1995

Caveats: Missing processes & Unknown Parameters

- Imperfect parametrizations b/c:
  - Missing effects (e.g., sensitivity/response to forcing)
  - Unknown parameters which are often not observable (or physical)
  - Missing Interaction with other processes & different scales





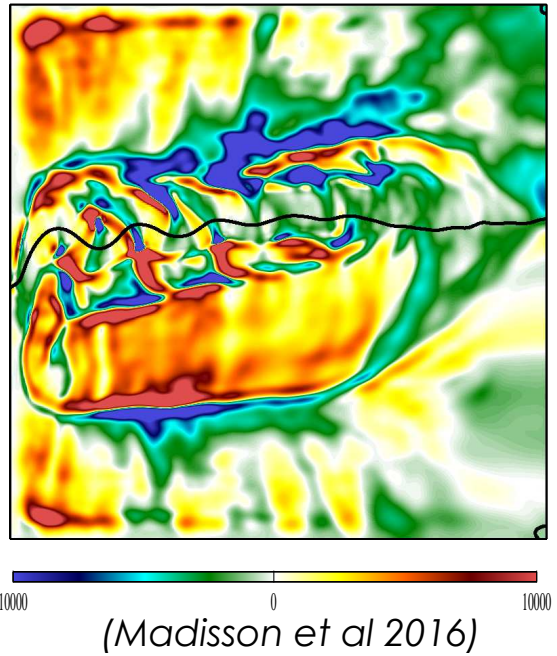


Bolton, Abernathey & Zanna, In Prep

Improving on Current sub-grid parametrizations

- **Constraining parameters**: using observations or model output with data-assimilations; caveat: assumes a perfect parametrization & enough information

- **Additional parametrizations:** to include more effects or to fix problems introduced by other sub-grid scales - e.g., energy backscatter *(Jansen et al 2015)*



(Madisson et al 2016)

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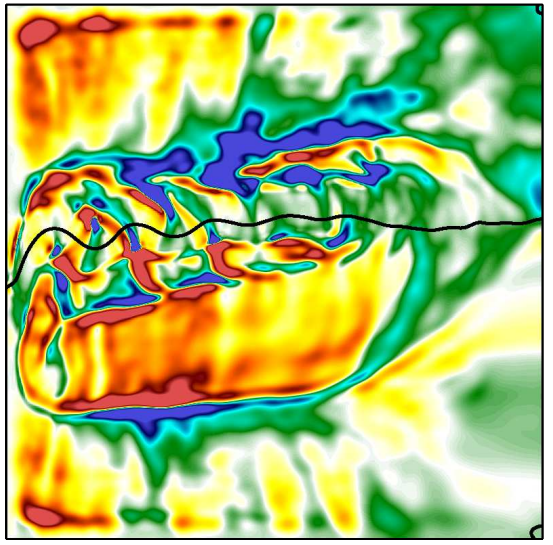

(Madisson et al 2016)

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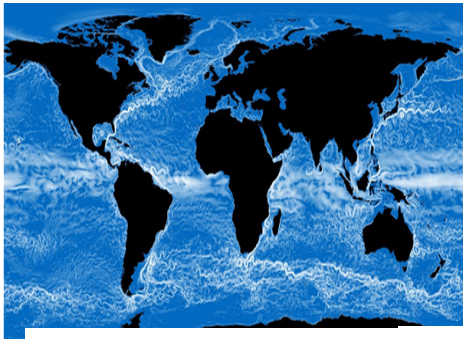
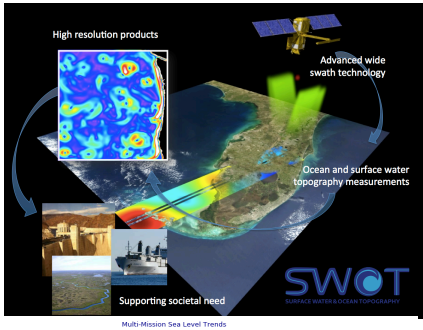
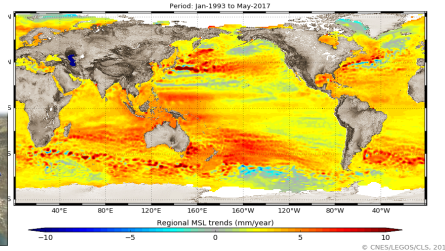
- **Focus on the total sub-grid tendencies**: Extract/diagnose the entire sub-grid tendency & its statistics from models or observations → deduce something about the missing physics & its effect







Using high-resolution simulations & Coarse-Graining

- Coarse-graining + find relationship between terms - deterministic or stochastic - which relate to the resolved physics
- Key aspects missing: quasi-2D turbulence, jet sharpening, enhanced shear
- Diagnostics in an idealized baroclinic 3 layers potential vorticity (PV) model

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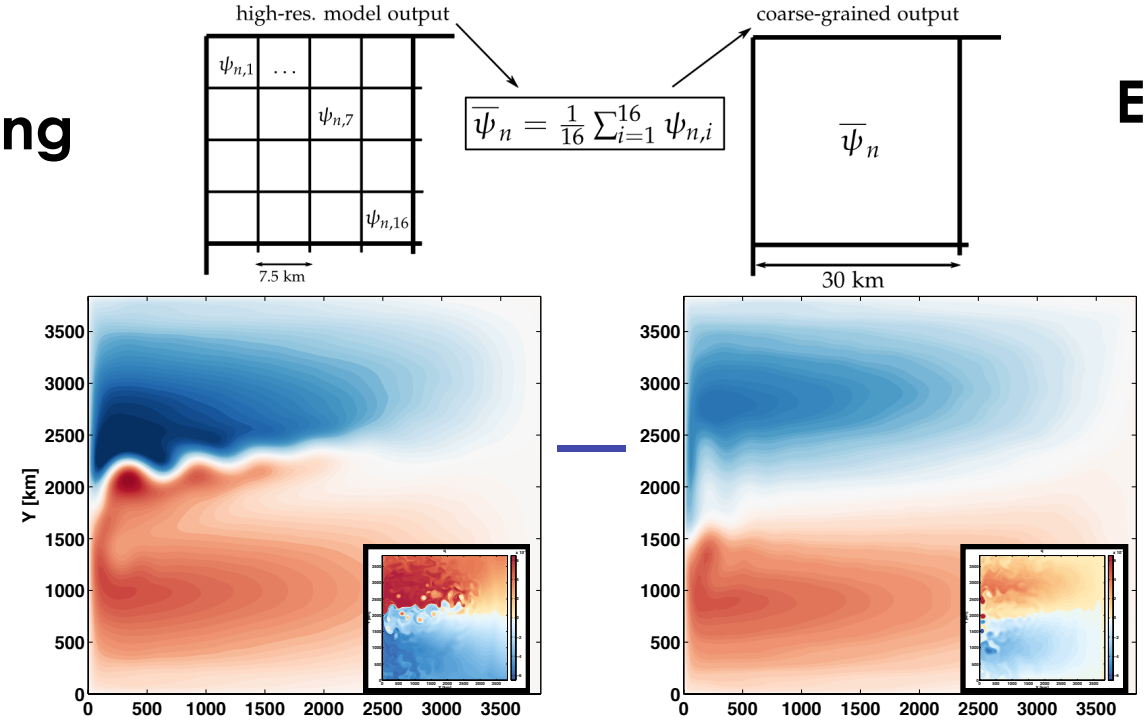
Eddy Resolving (7.5km)



Eddy Permitting (30km)

- Eddy Forcing:

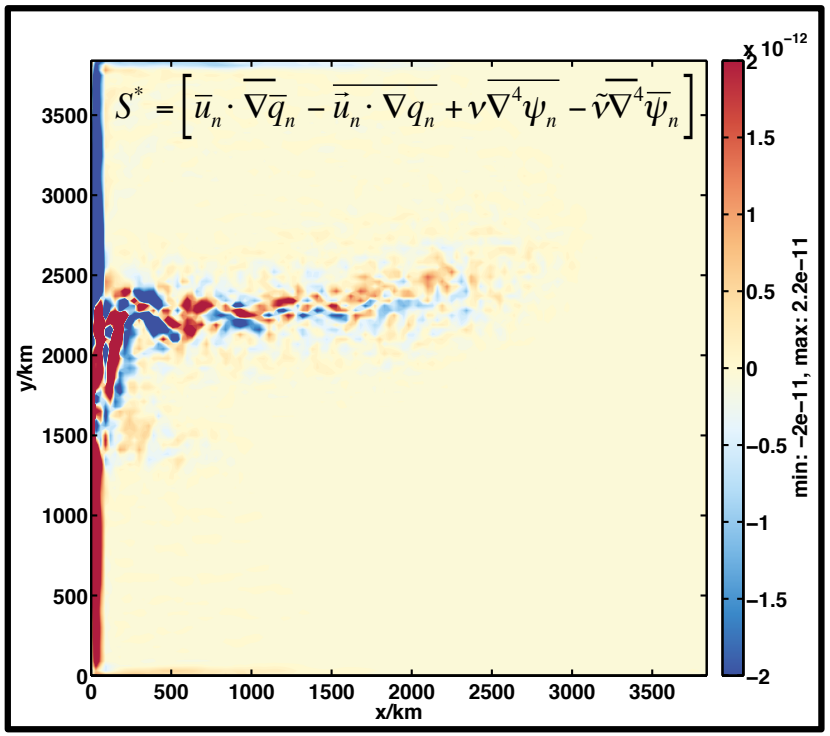
$$S^* = \overline{\nabla \cdot (\bar{\mathbf{u}}\bar{q})} - \overline{\nabla \cdot (\mathbf{u}q)} + \nu\overline{\nabla^4\psi} - \tilde{\nu}\overline{\nabla}^4\overline{\psi}.$$

LowRes — High-Res

Using high-resolution simulations & Educated Guess

- Eddy Forcing = a visco-elastic stress x parameter depending on resolution
- depends on the local rate of shear (with some memory) & the deformation of the parcel
- Conserves PV & momentum
- Holds under a very wide range of Reynolds

Diagnosed Turbulence Forcing from coarse-grained models



Mana & Zanna, 2014

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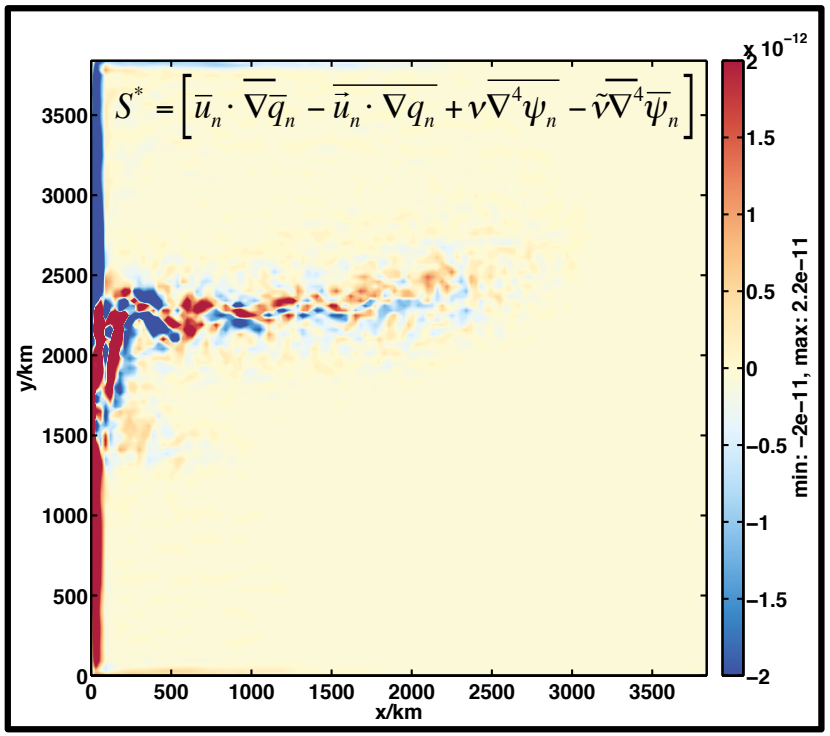
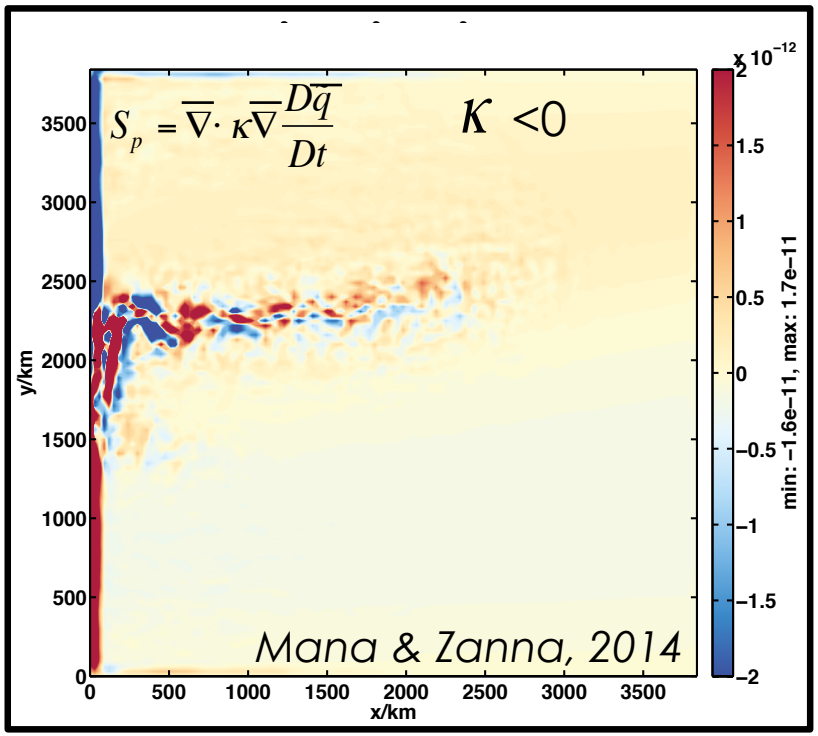
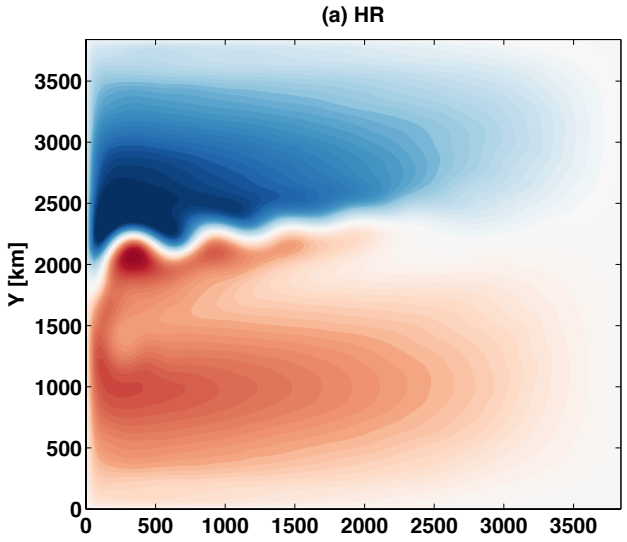


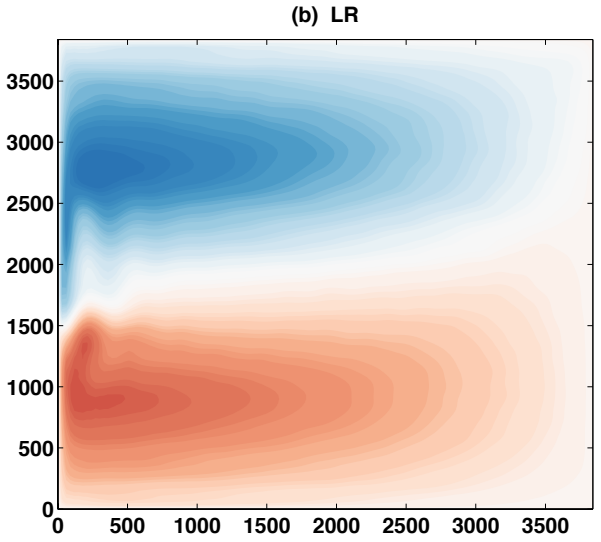
Non-Newtonian Parametrization based on coarse-grained resolved scales



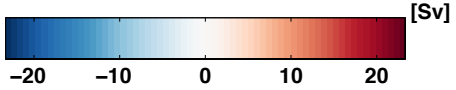
Implementation into QG: Steady-State Streamfunction

7.5 km (truth)

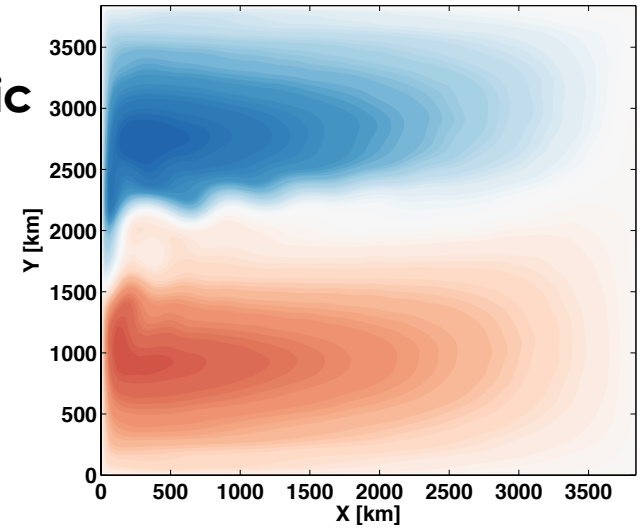




30 km (no param)



30 km + deterministic



- Reduced amplitude of parameter for numerical stability

Zanna, Mana, Anstey, David, Bolton 2017

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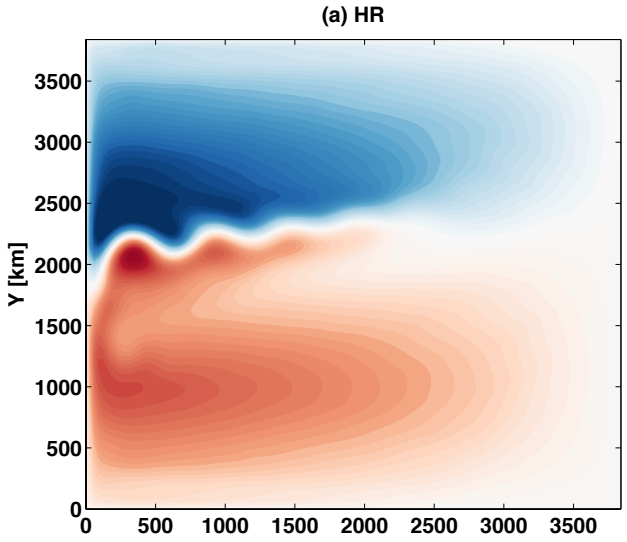

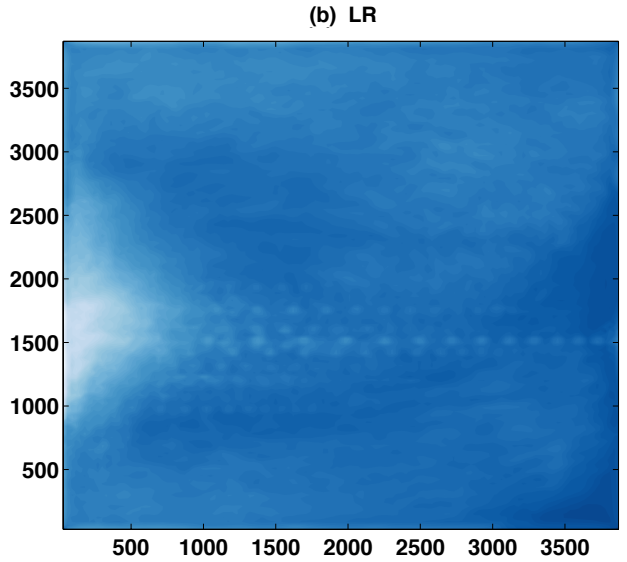

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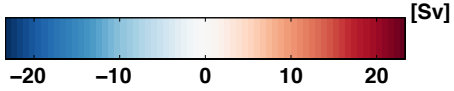

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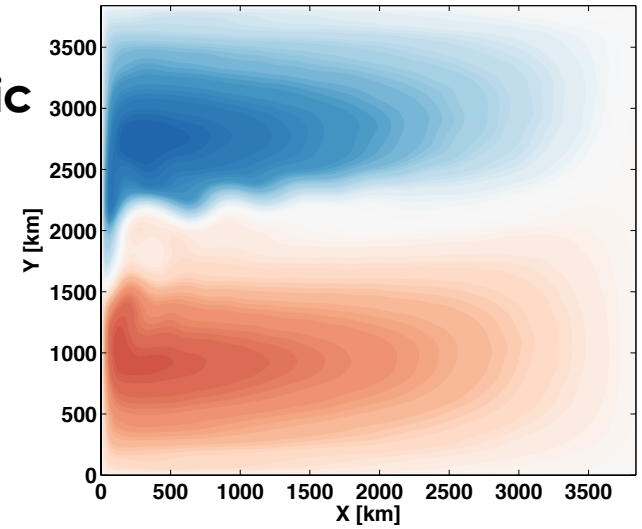
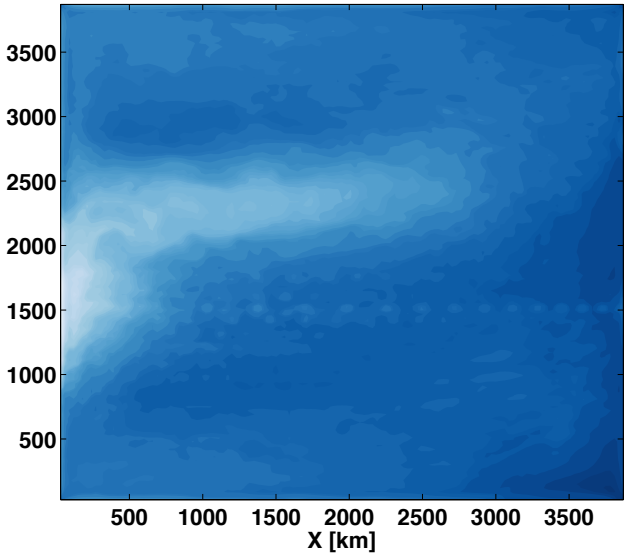
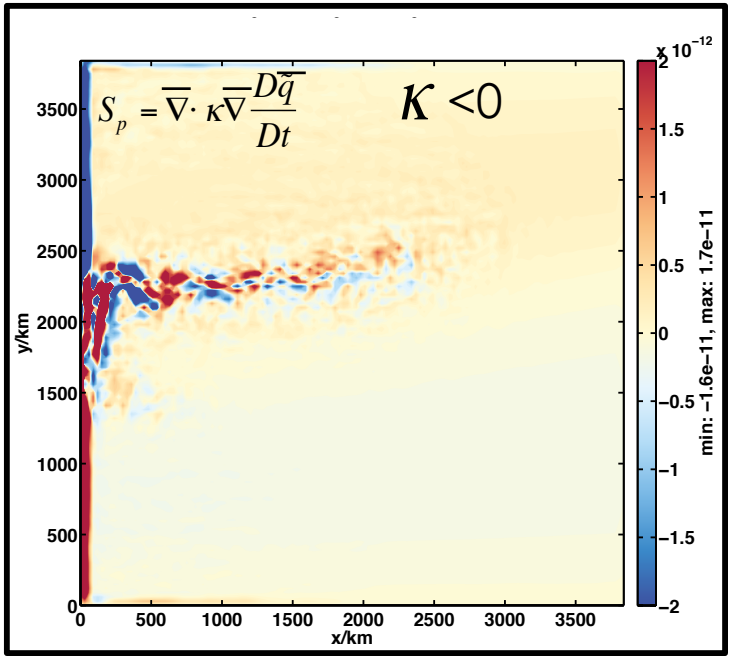




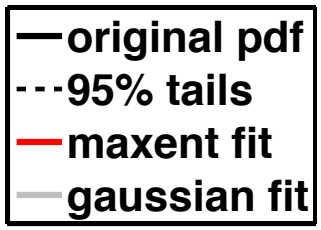
Zanna, Mana, Anstey, David, Bolton 2017

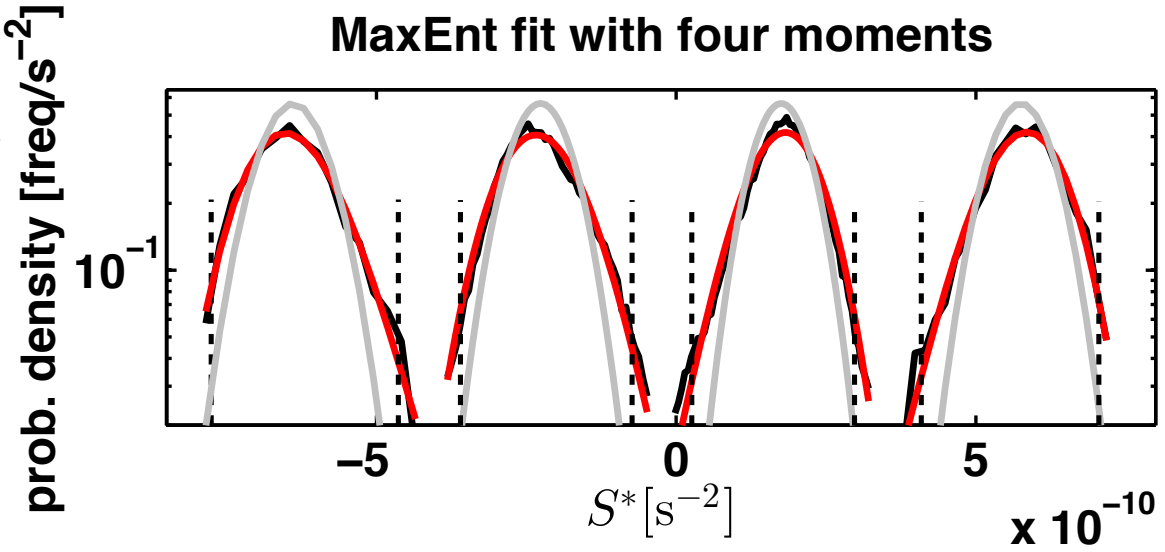
Using high-resolution simulations & Educated Guess



- Turbulence forcing is not fully deterministic
- Moments depends resolution, surface forcing, stratification

Conditional PDFs of eddy forcing on visco-elastic stress





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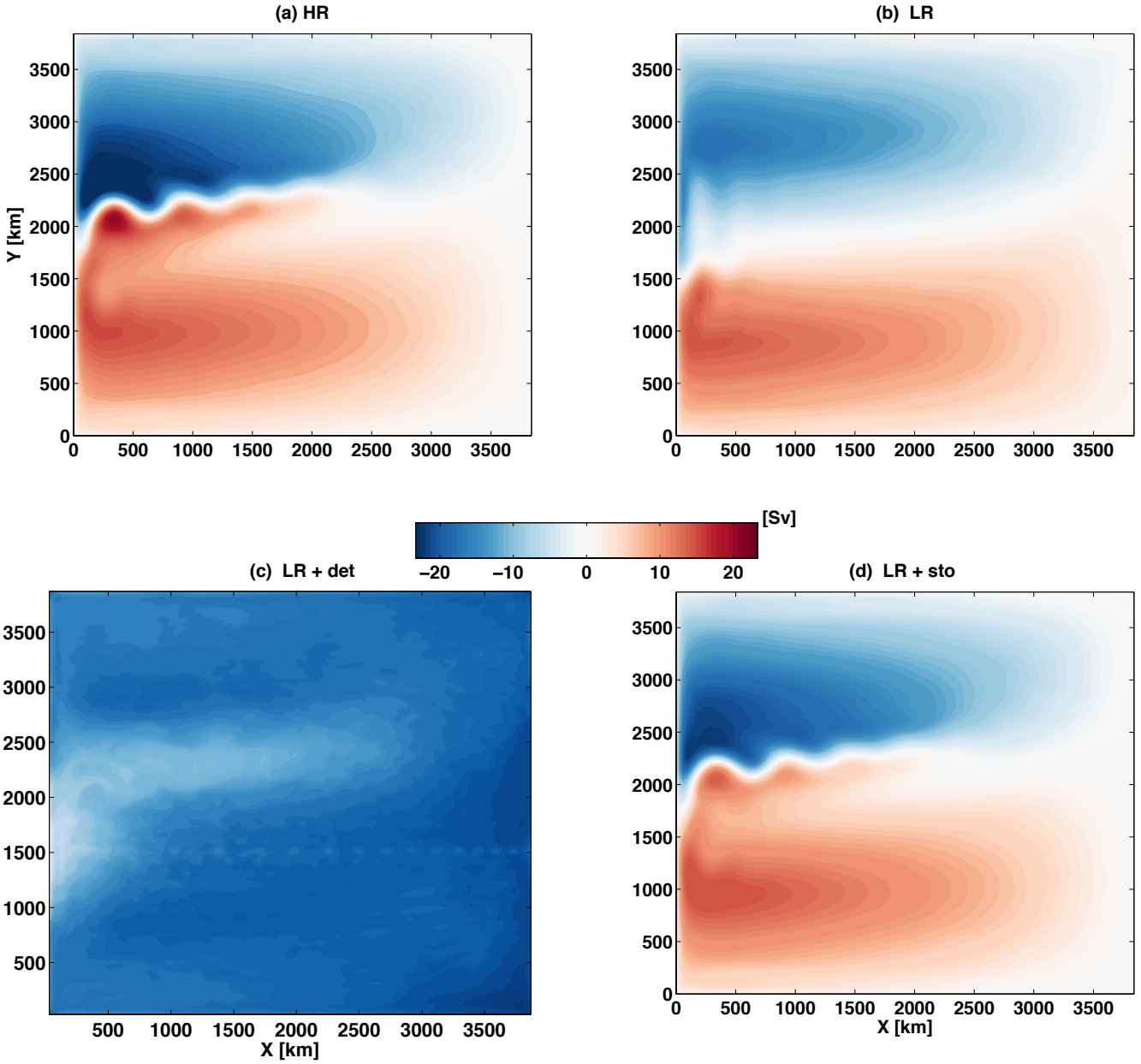


30 km (no param)

30 km + stochastic

Zanna, Mana, Anstey, David, Bolton 2017

Using high-resolution models: Caveats & Ways Forward

- **Difficulties transplanting ideas** from idealised models into complex ocean/climate models

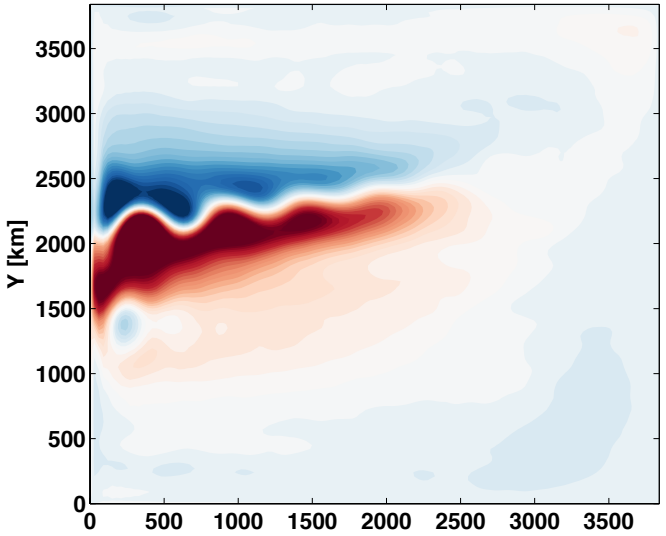
  ongoing implementation:

  with Alistair Adcroft (Princeton, GFDL) in MOM6

  with Scott Bachman (NCAR) in MITgcm

- Assumes the high-res model is the "truth"

MOM6: HR- parametrised run



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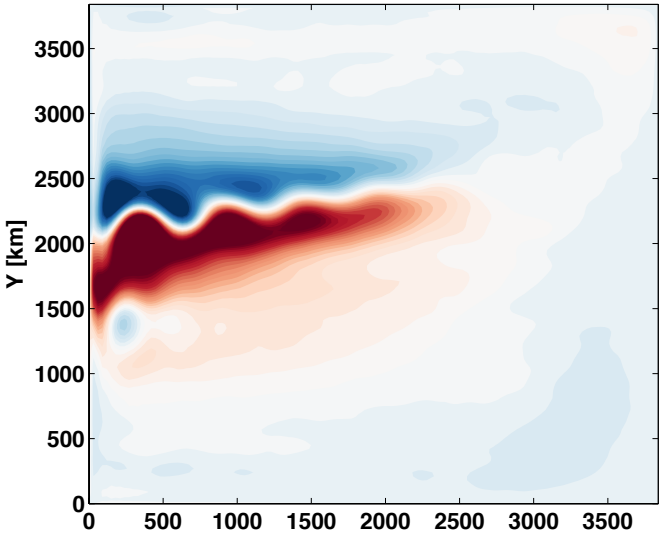

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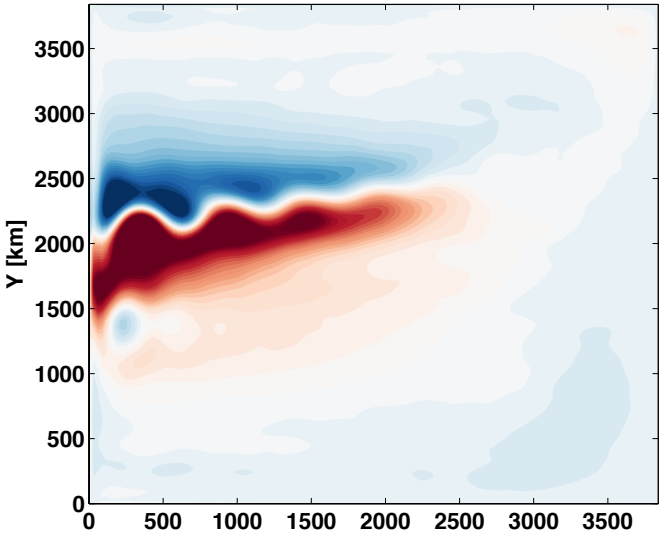

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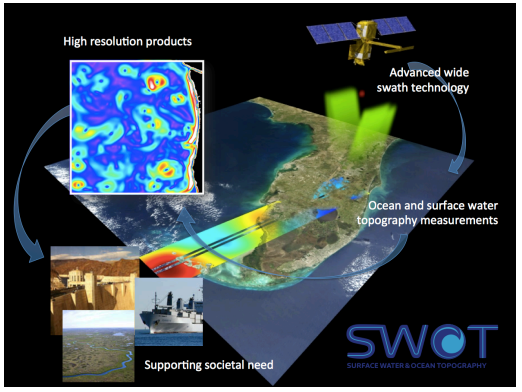
- **Disconnect between diagnostic & implementation**: numerical instabilities, unbounded solutions - impose constraints for numerical stability (e.g., 2nd-order deterministic or stochastic closures)?

Using observations - Learning the Unseen but felt

- Similar idea using imperfect/smoothed//filtered observations
- Tool: same model data, Gaussian filtered
- Goal: Prediction of sub-grid momentum forcing when Neural Network is trained on smooth streamfunction (equivalent to SSH from satellite data)



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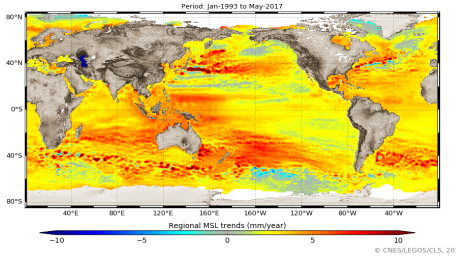

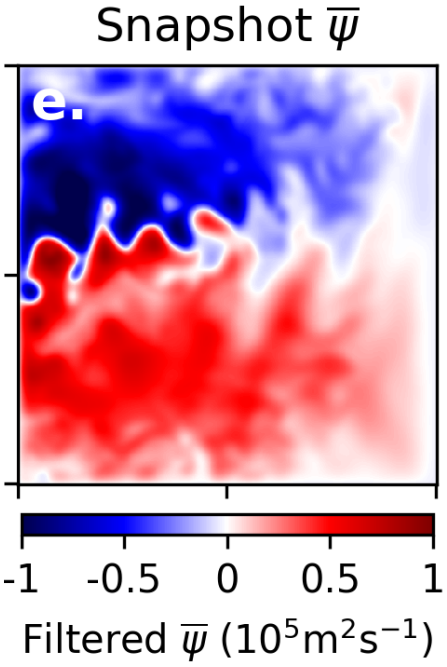

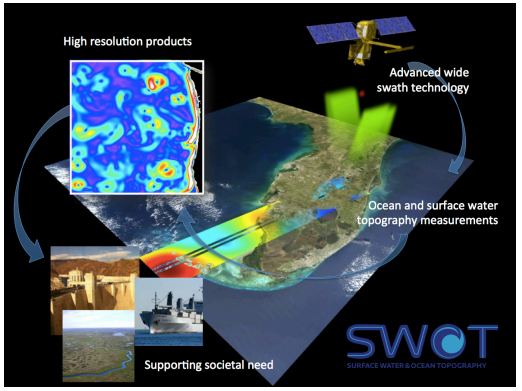

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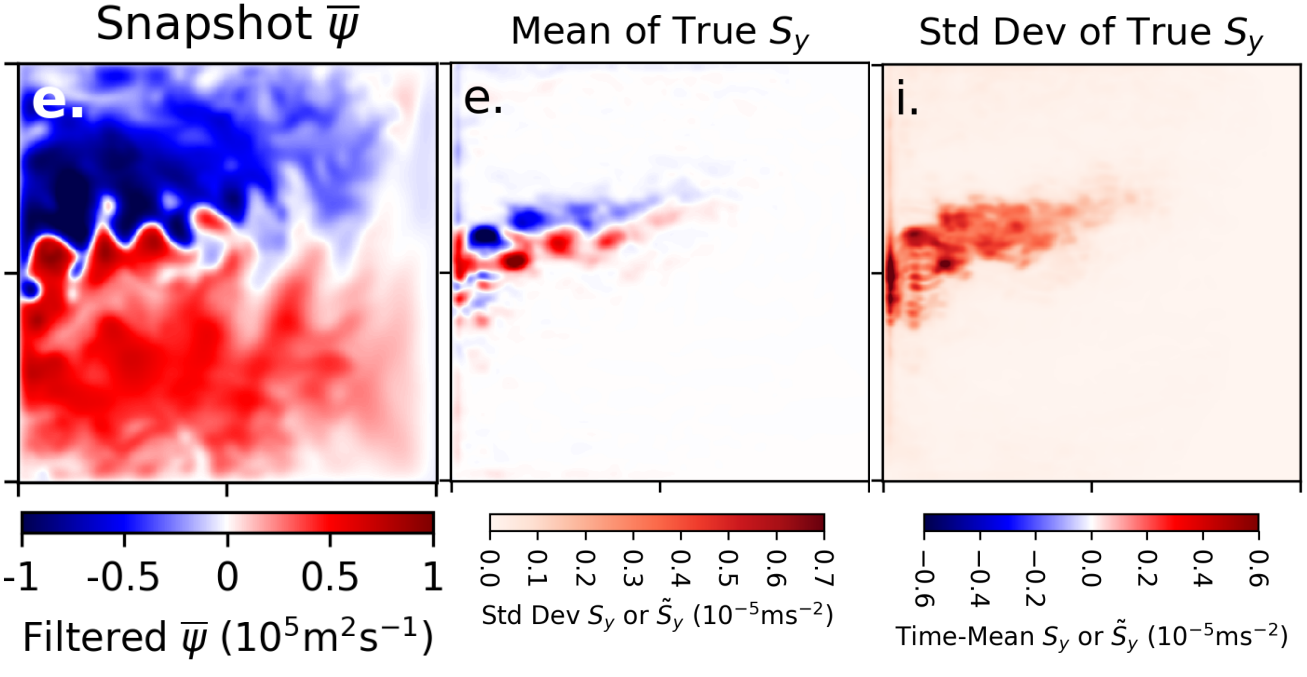

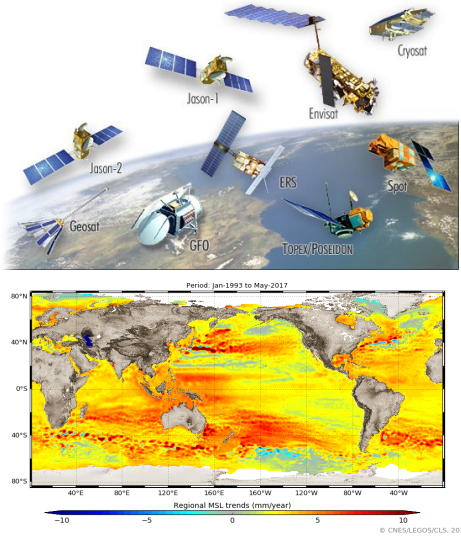

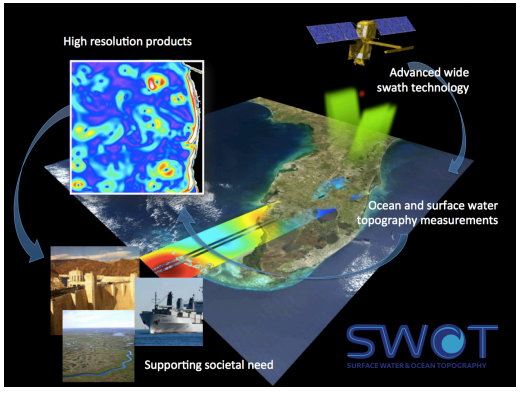

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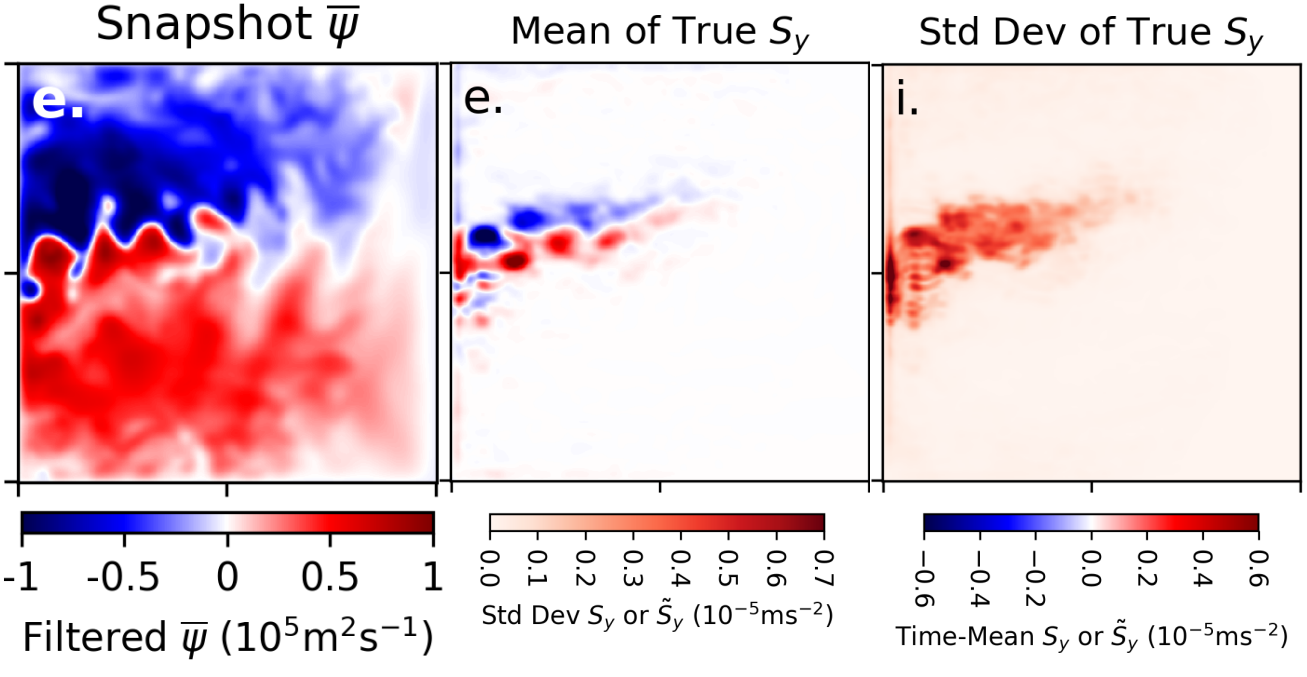
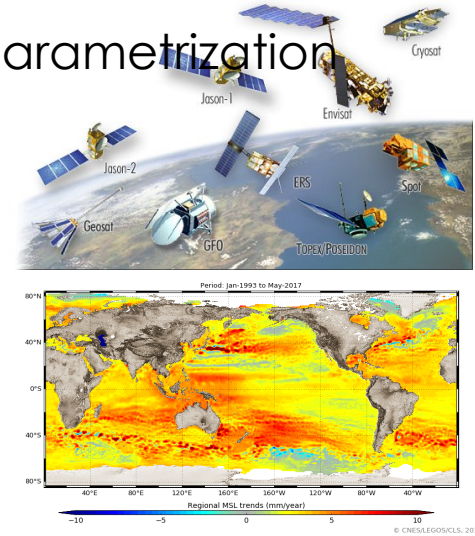
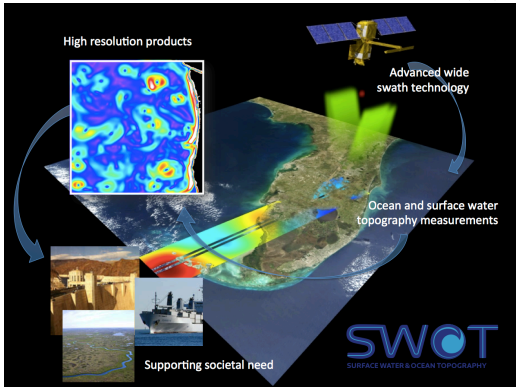
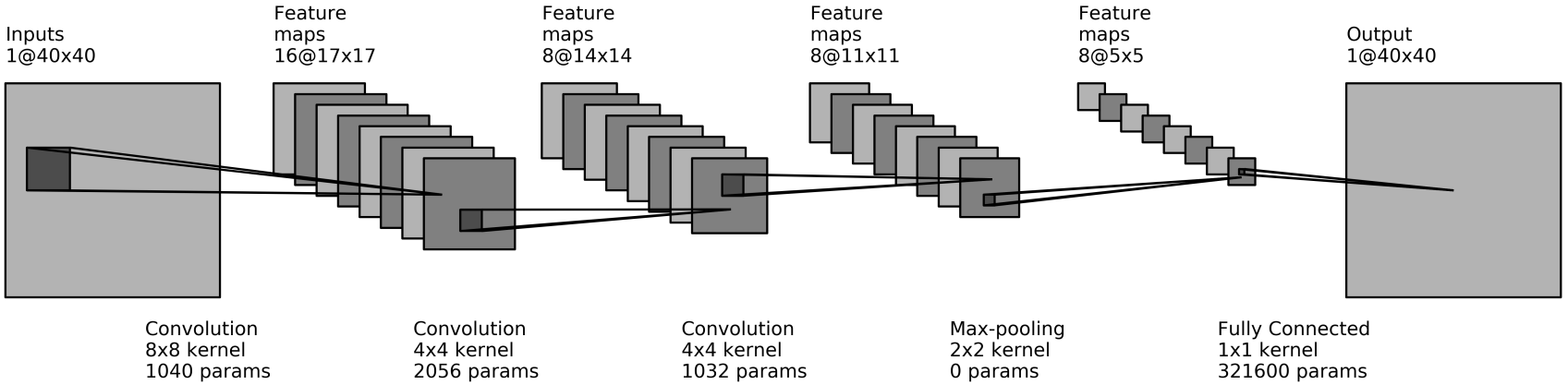
- Similar idea using imperfect/smoothed//filtered observations
- Tool: same model data, Gaussian filtered
- Goal: Prediction of sub-grid momentum forcing when Neural Network is trained on smooth streamfunction (equivalent to SSH from satellite data)
- Next step: use the NN as a way to design & implement a parametrization

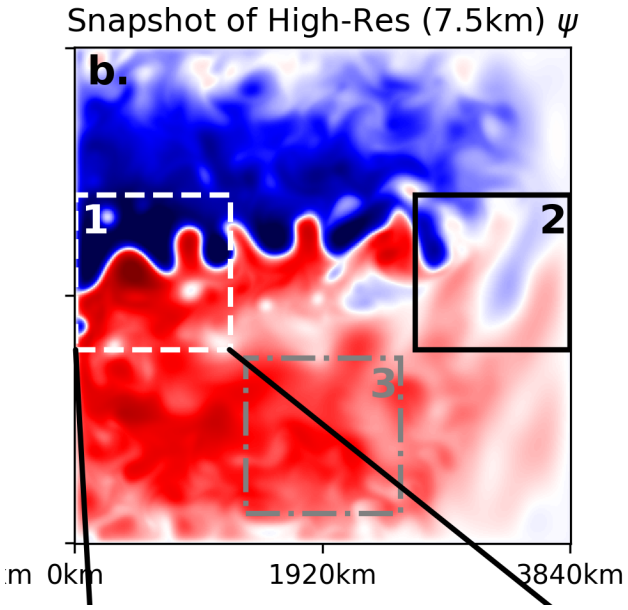






Neural Networks Architecture

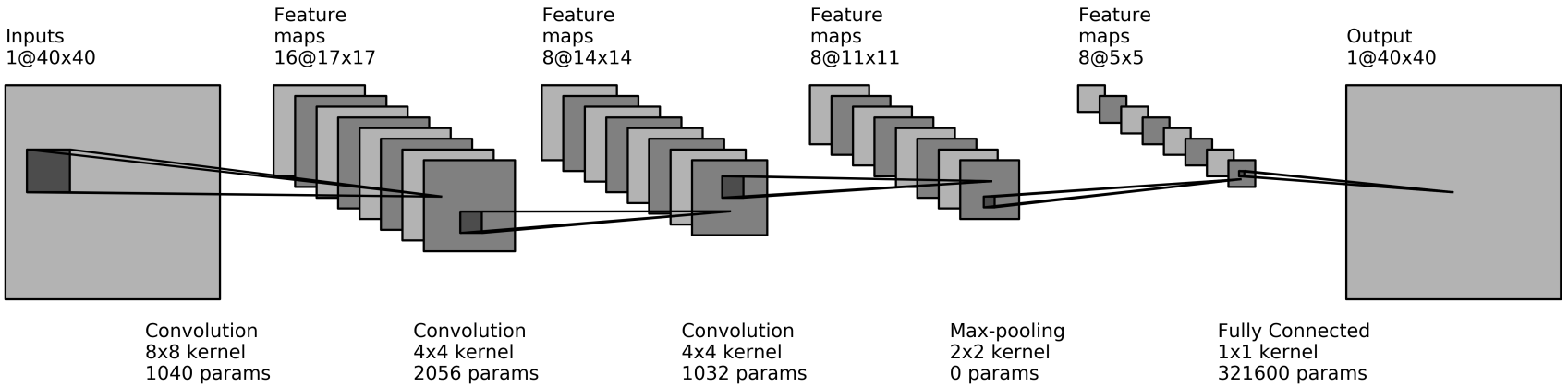


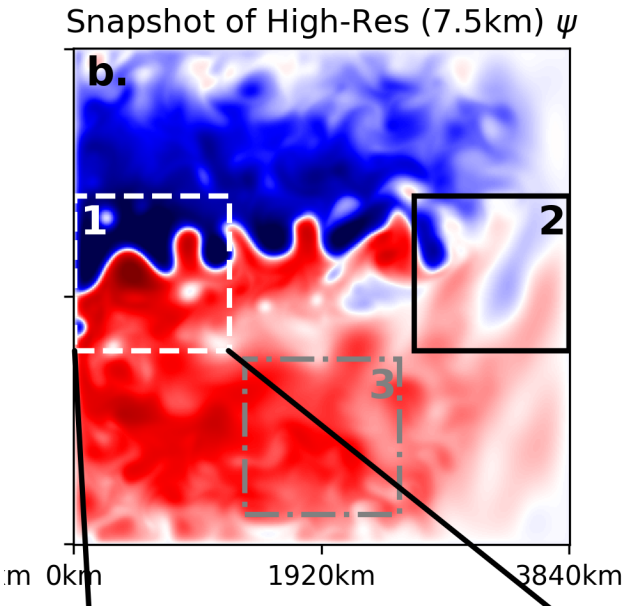


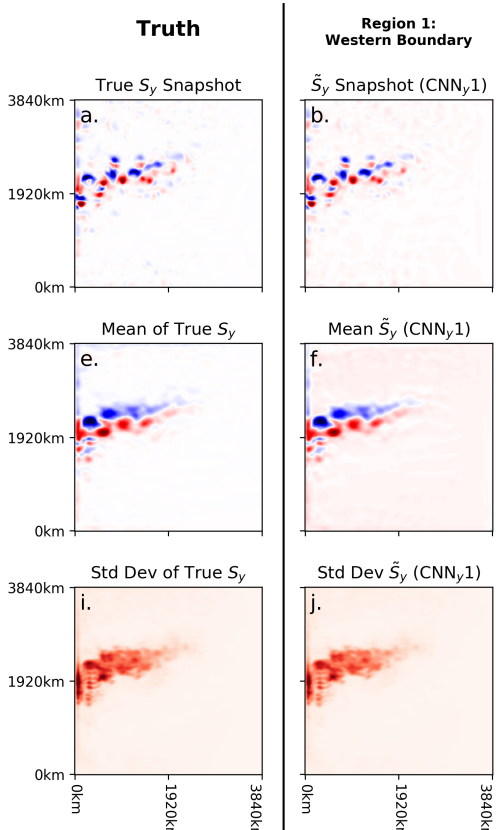
- 9 yrs for training
- 1 yrs for prediction

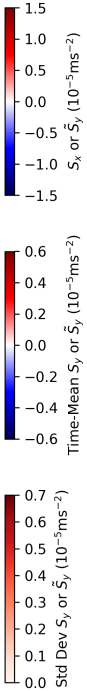
Bolton & Zanna, In Prep

Neural Networks Architecture





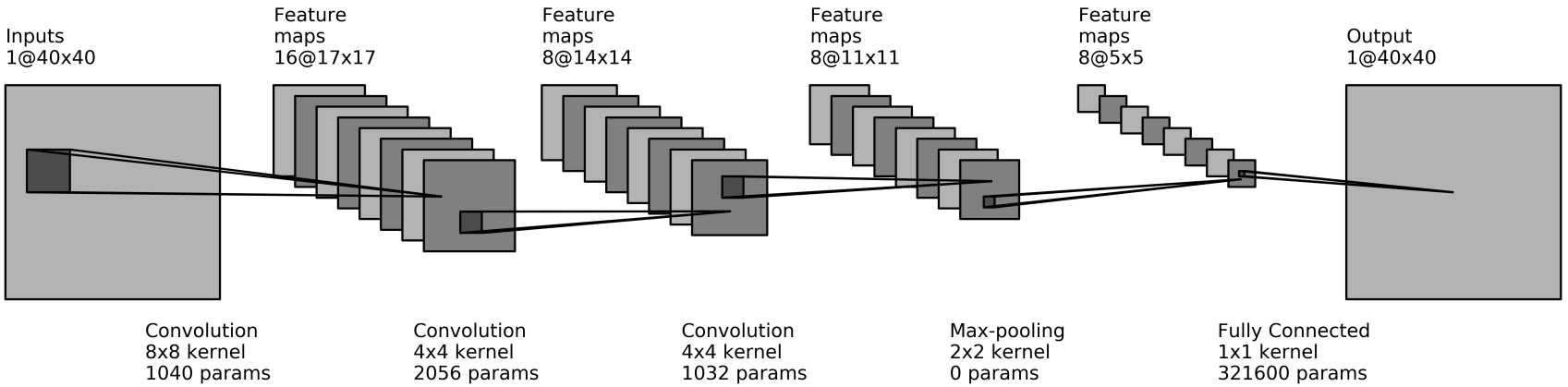


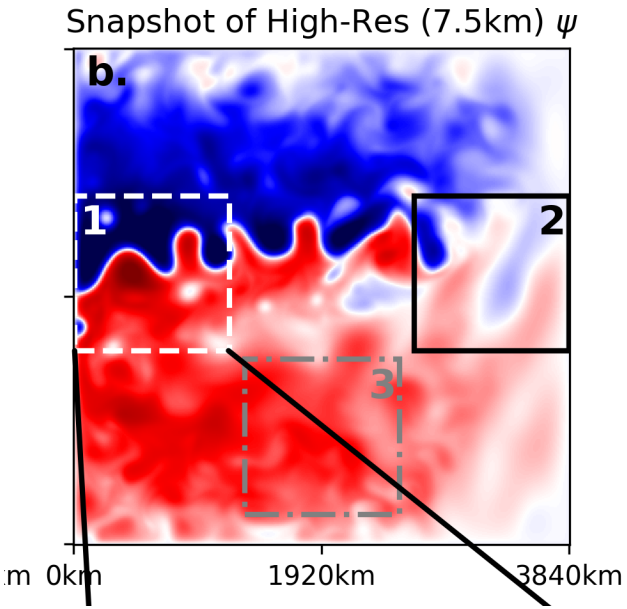


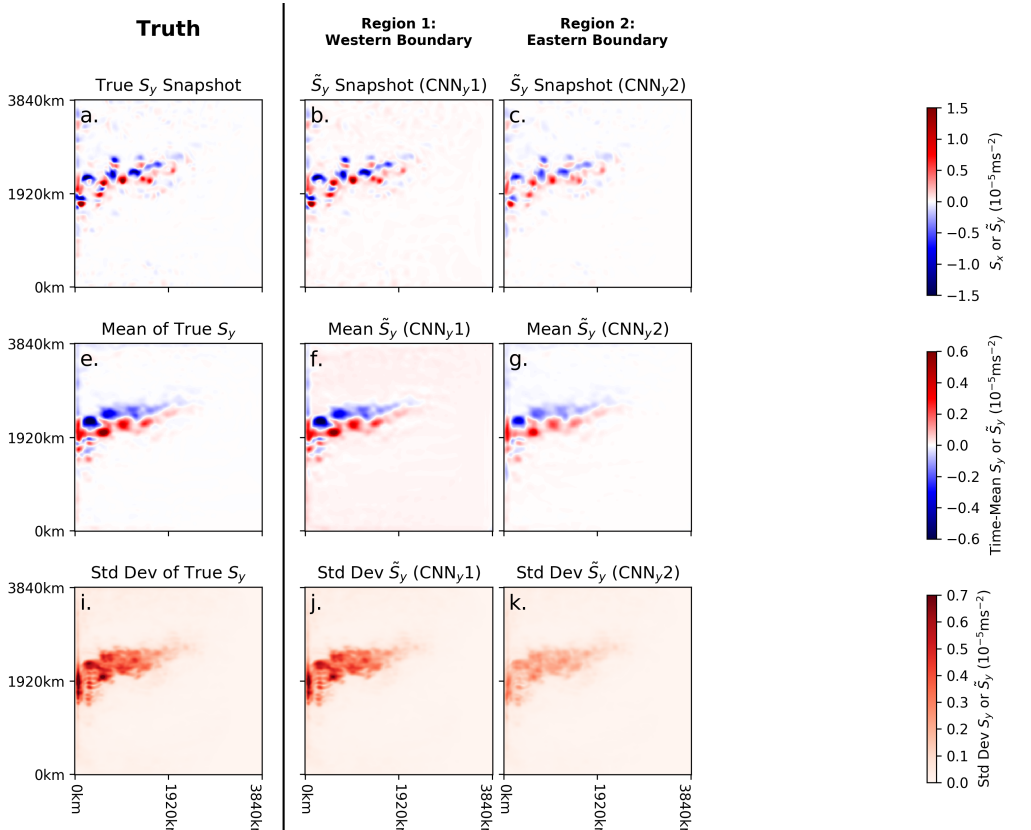
- Performance based on the region used for training

Bolton & Zanna, In Prep

Neural Networks Architecture



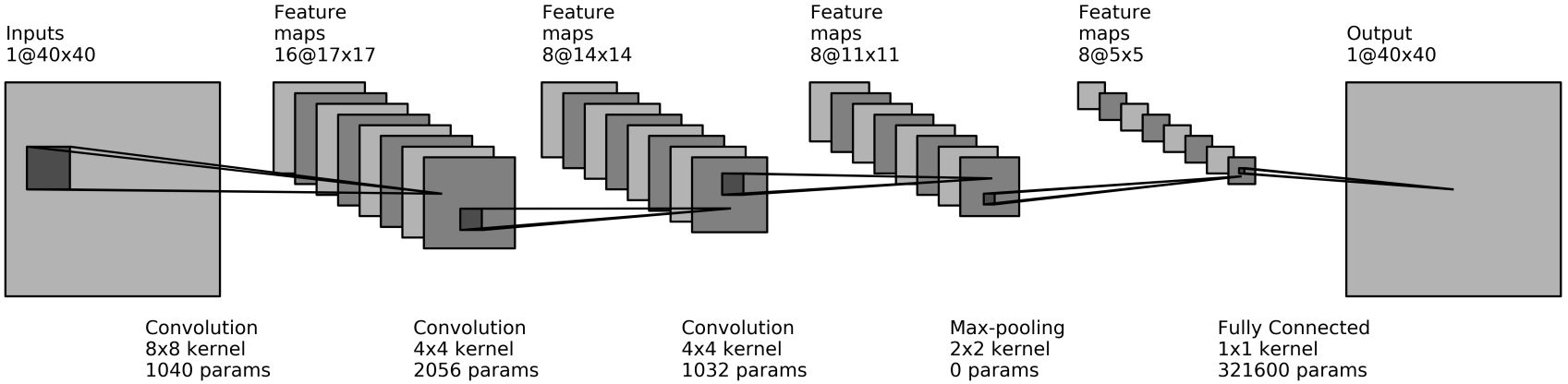


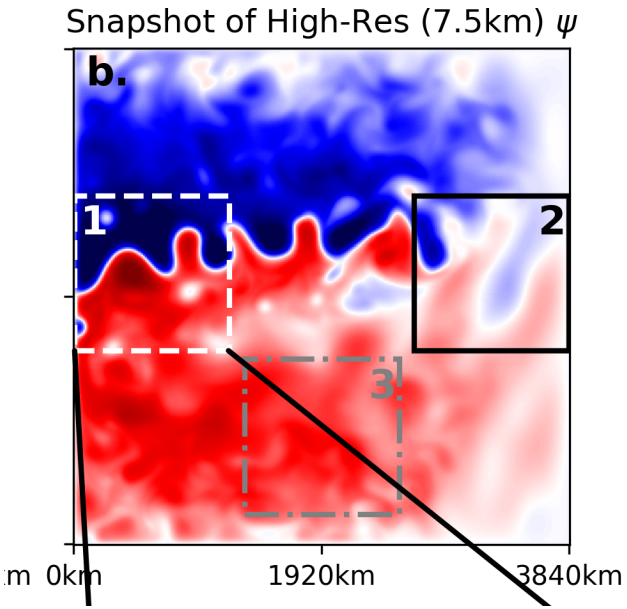


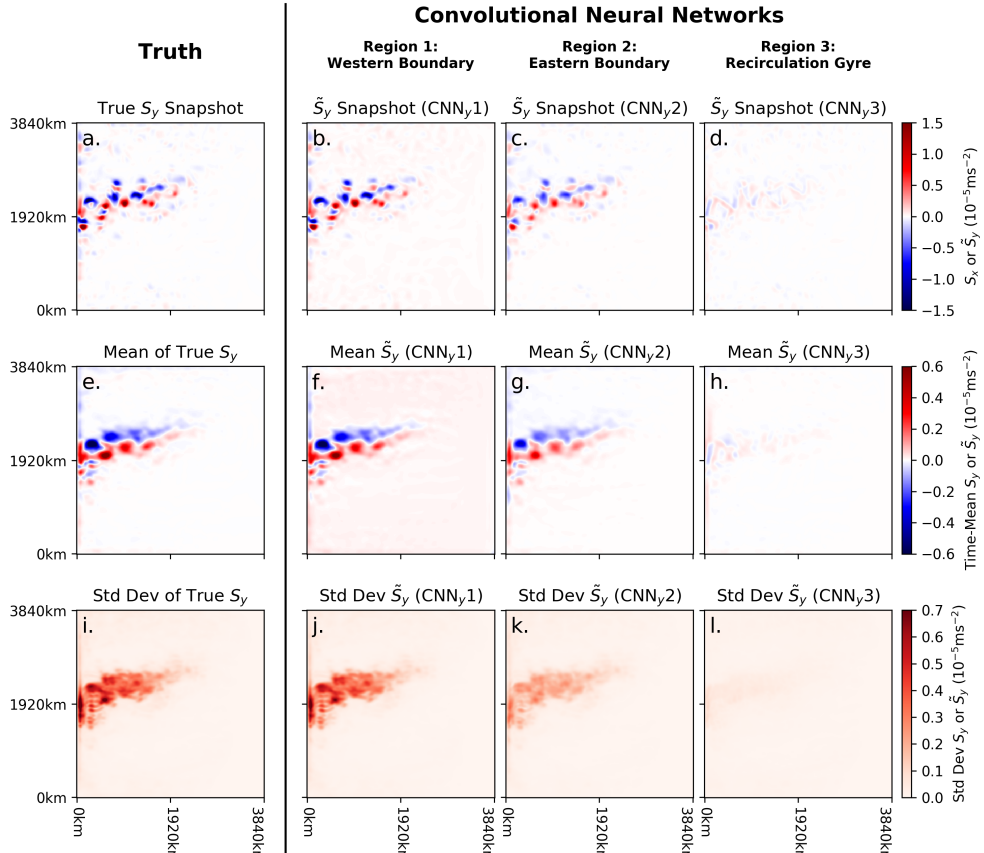
- Performance based on the region used for training

Bolton & Zanna, In Prep

Neural Networks Architecture





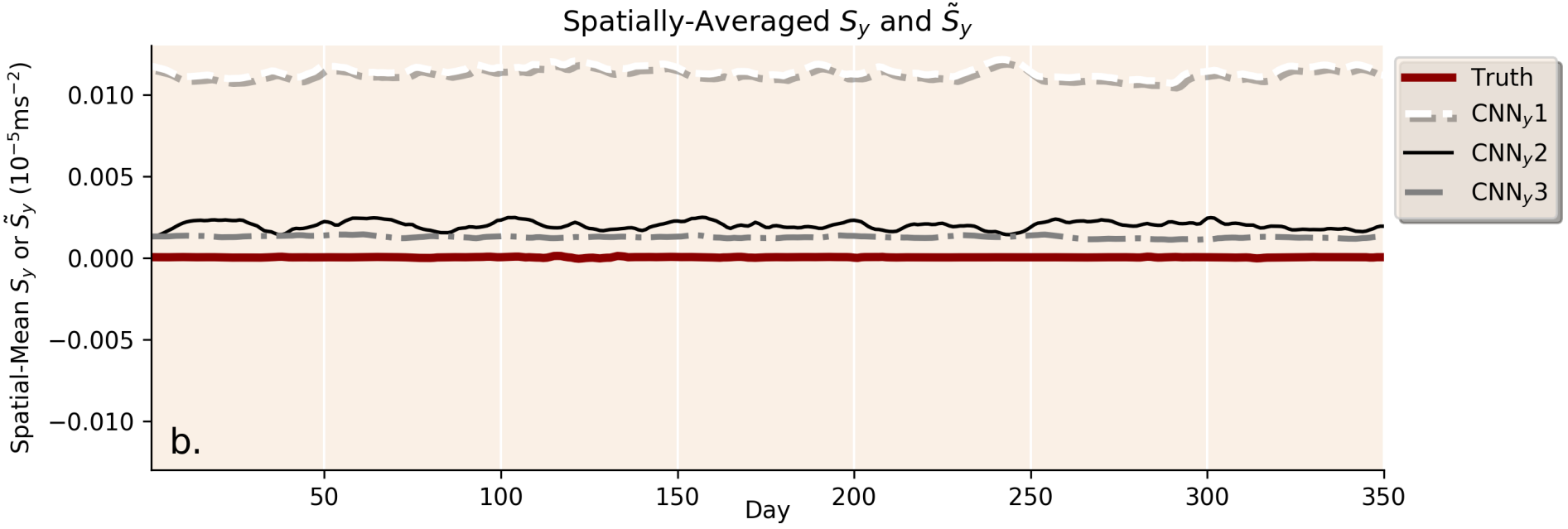


- Performance based on the region used for training

Bolton & Zanna, In Prep

Using observations - Caveats

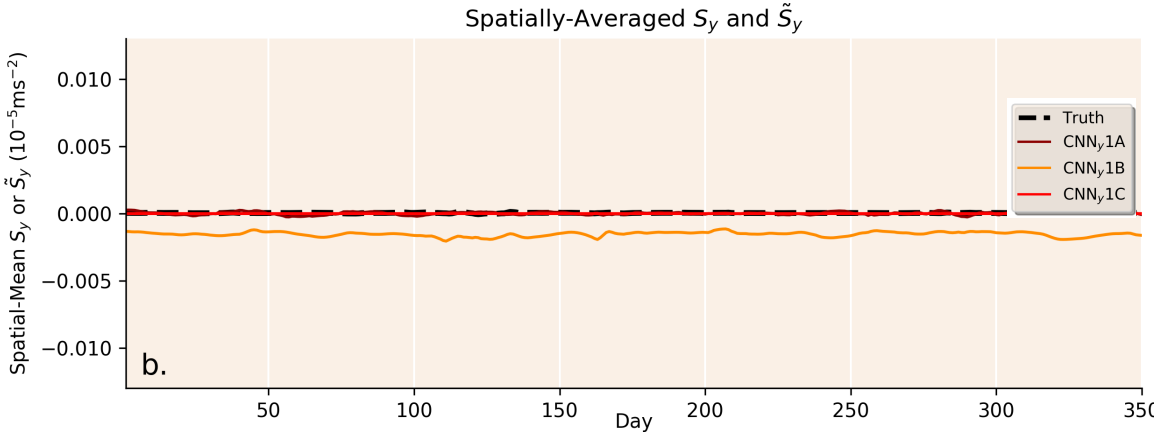
- Quality/relevance of the training + length
- No physics - except for the physics implicit into the input function
- Numerical instabilities generated when implemented into a prognostic model (in progress)



Bolton & Zanna, In Prep

Using Observations - Next Steps

- Minimisation: better targets or constraints (based on the application)



Bolton & Zanna, In Prep

Using Observations - Next Steps

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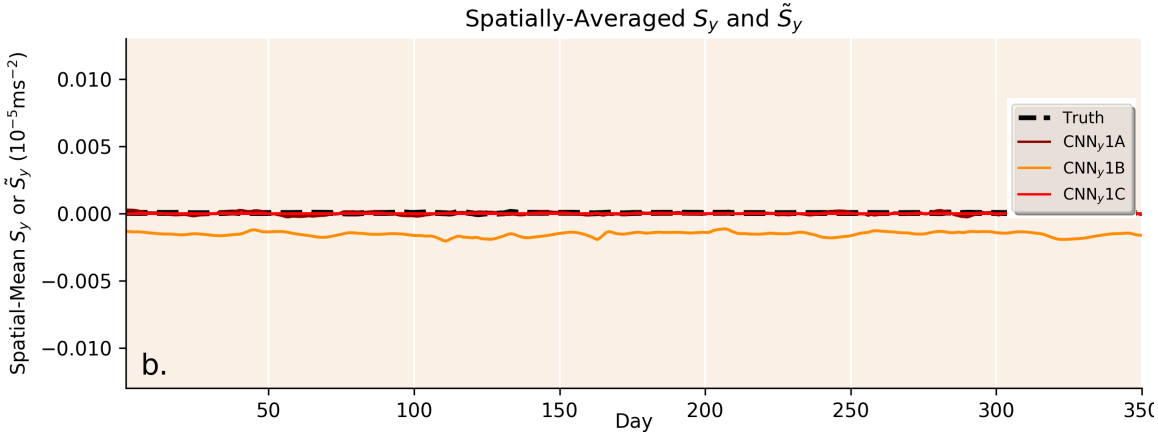
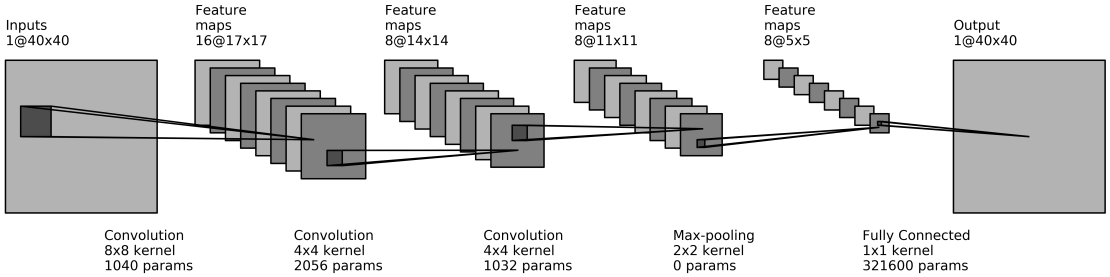
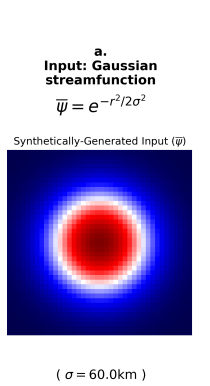
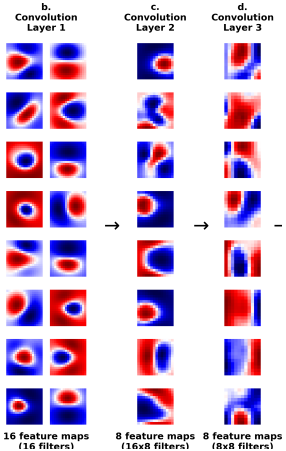
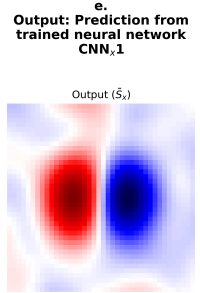


- Learning from the Networks' Architecture





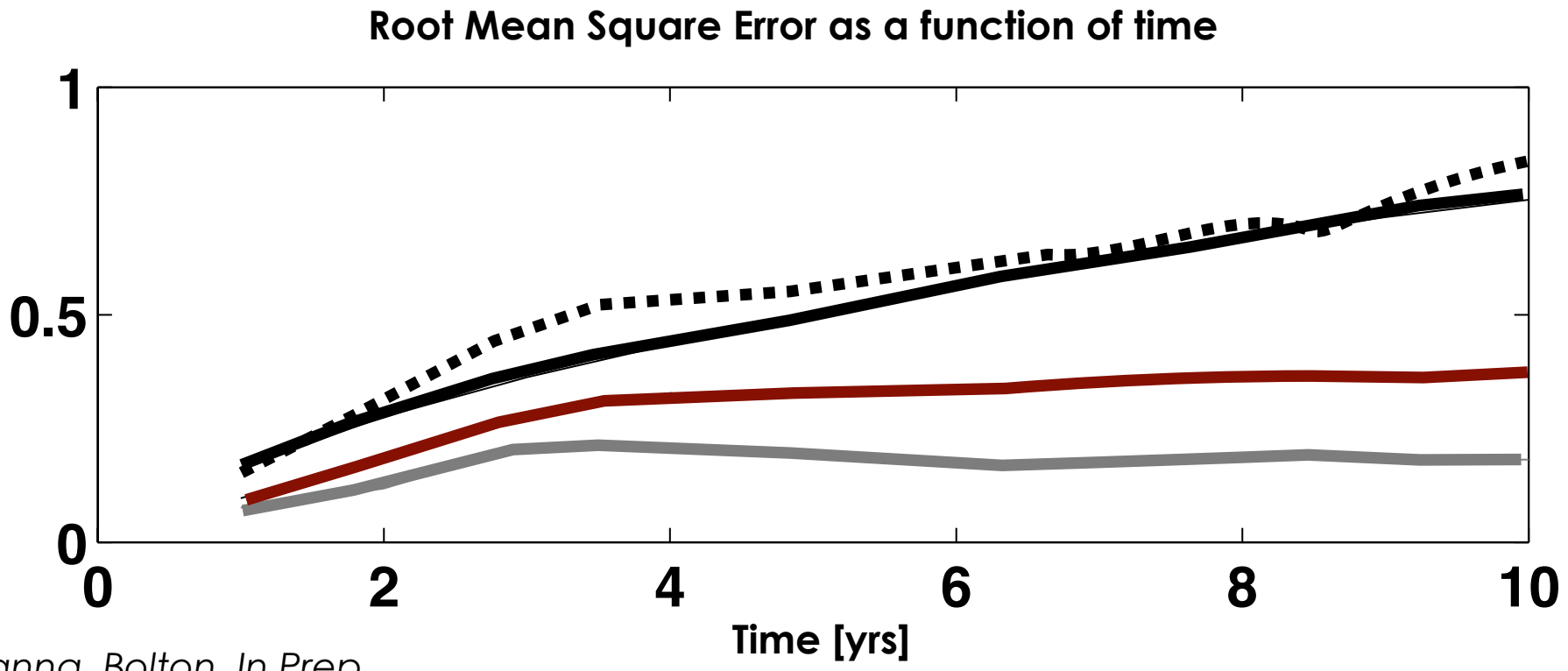




Bolton & Zanna, In Prep

Error in Predictions in QG

- Low-res without parametrization (black)
- Low-res + NN (dashed)
- Low-res + non-Newtonian (red)
- Low-res + NN + non-Newtonian parametrization (grey)



Zanna, Bolton, In Prep

Summary

- Complementary approaches to developing traditional parametrizations
- Need for good model + observational data
- Constant need for a combination of physics + human + machines
- Unconventional approaches can still teach us something about the physics of processes & their representation in models

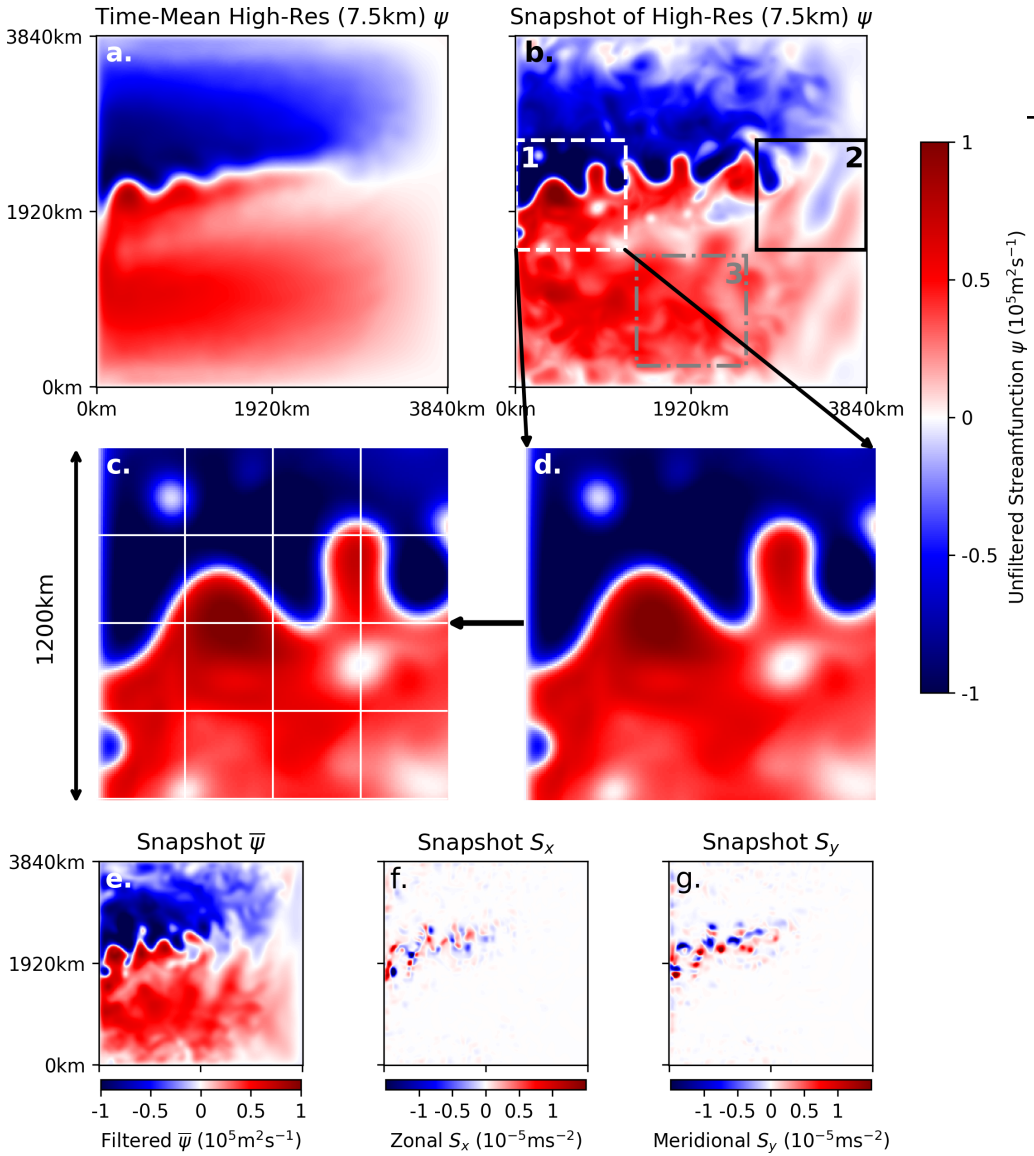
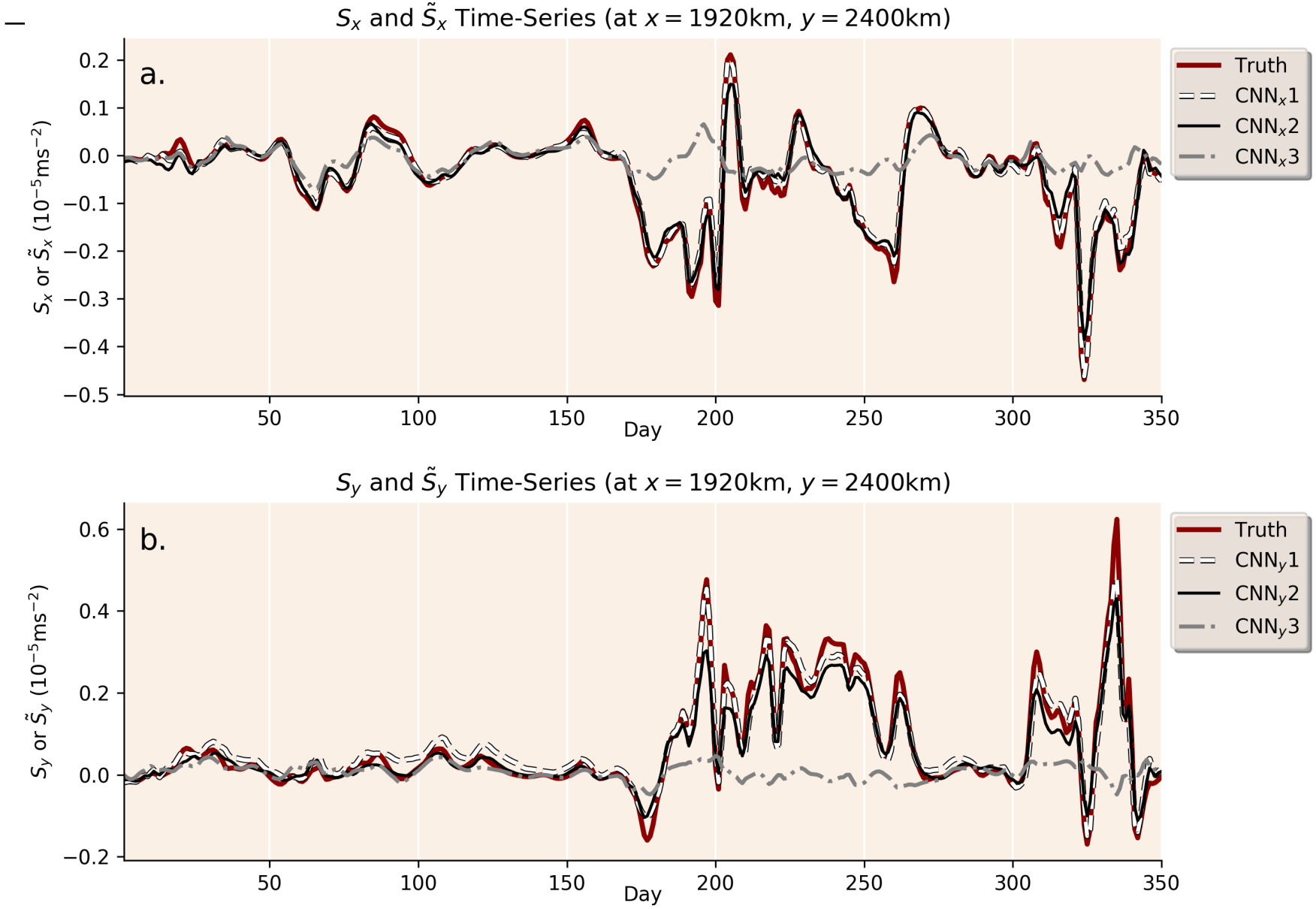


Figure 1. The time-mean and a snapshot of the upper-layer (un-filtered) streamfunction ψ are shown in (a) and (b) respectively. Training region 1 (whited-dashed), training region 2 (black-solid), and training region 3 (grey-dot-dashed), are illustrated in (b); data extracted from each region is used to train separate neural networks. A close-up of training region 1 is shown in (d), with the sixteen 40×40 sub-regions illustrated in (c). Each training region has length 1200km, with each 40×40 sub-region of length 300 km.


S_x and $\tilde{S}_x$ Time-Series (at $x = 1920$km, $y = 2400$km)
a.
S_x or $\tilde{S}_x$ $(10^{-5}\mathrm{ms}^{-2})$
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
50
100
150
200
250
300
350
Day
Truth
CNN_x1
CNN_x2
CNN_x3
S_y and $\tilde{S}_y$ Time-Series (at $x = 1920$km, $y = 2400$km)
b.
S_y or $\tilde{S}_y$ $(10^{-5}\mathrm{ms}^{-2})$
0.6
0.4
0.2
0.0
−0.2
50
100
150
200
250
300
350
Day
Truth
CNN_y1
CNN_y2
CNN_y3

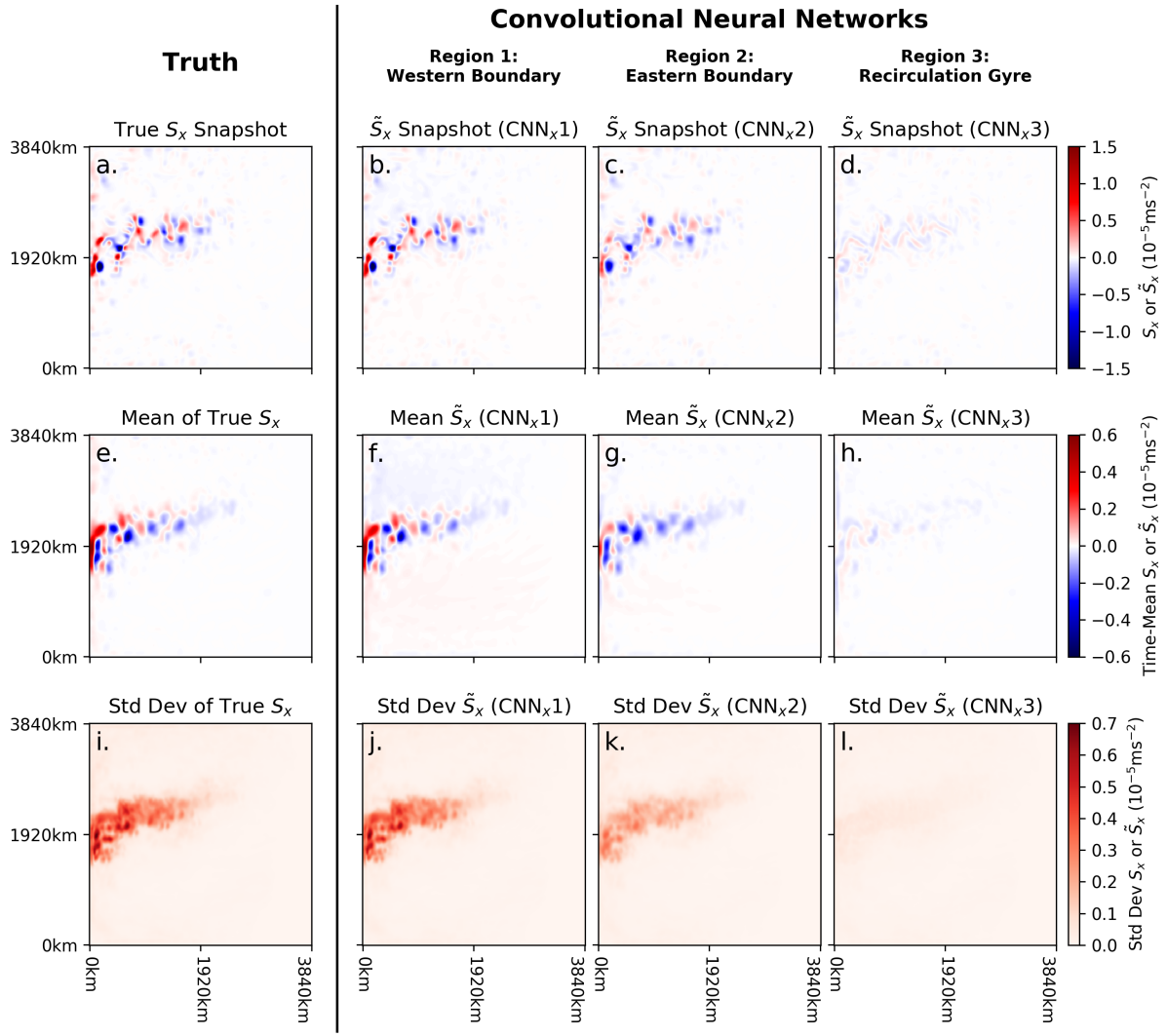


Figure 4. Comparisons of the true zonal component of the sub-filter momentum forcing S_x, with the neural networks trained using data from three different regions. The top, middle, and bottom rows compare a snapshot, the time-mean, and the standard deviation, respectively. The first column contains the diagnostics using the true zonal sub-filter momentum forcing S_x, while columns two, three, and four use predictions $\tilde{S}_x$ from the neural networks CNN$_x$1, CNN$_x$2, and CNN$_x$3, respectively. All diagnostics were calculated using the validation data.

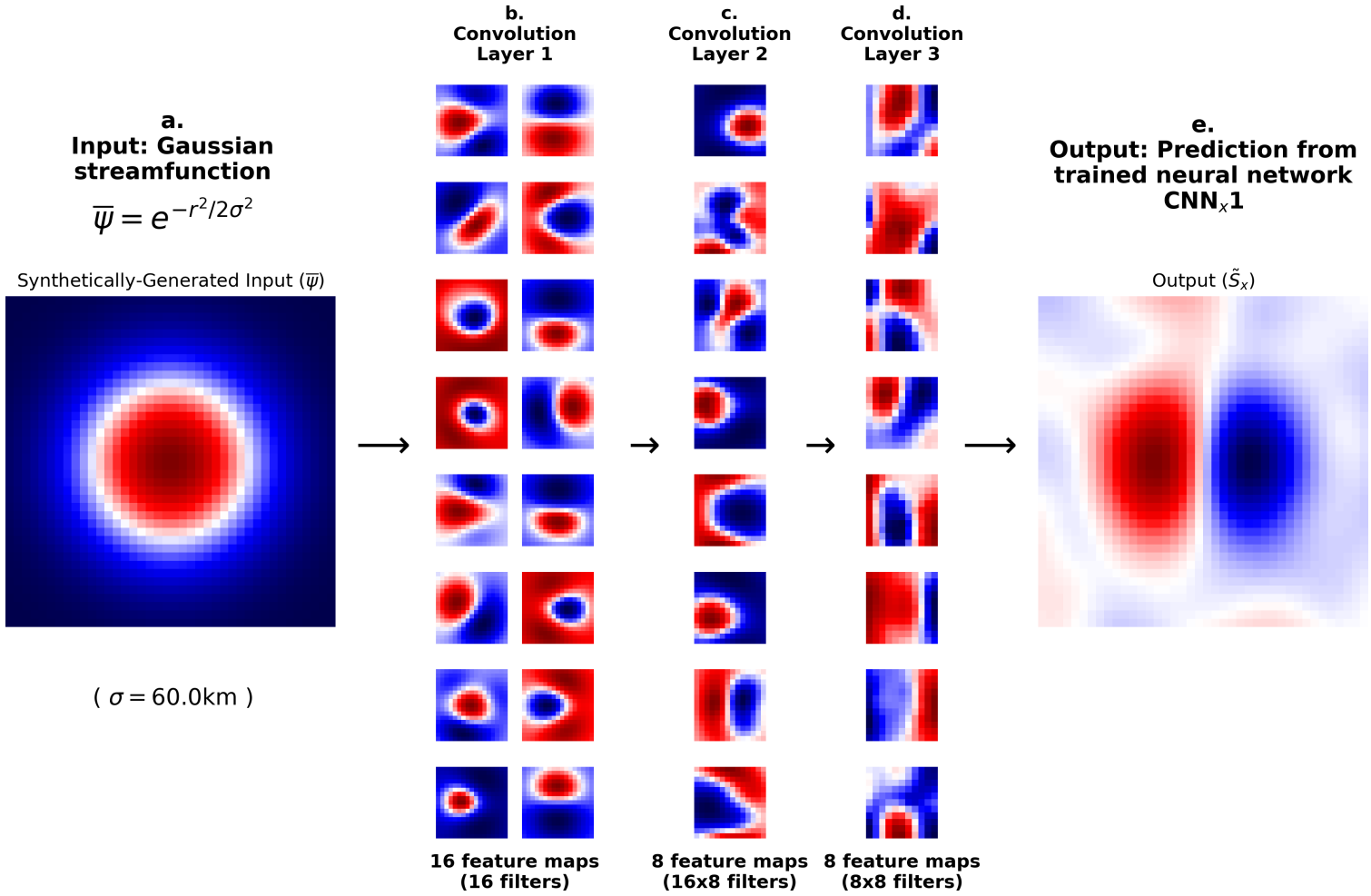
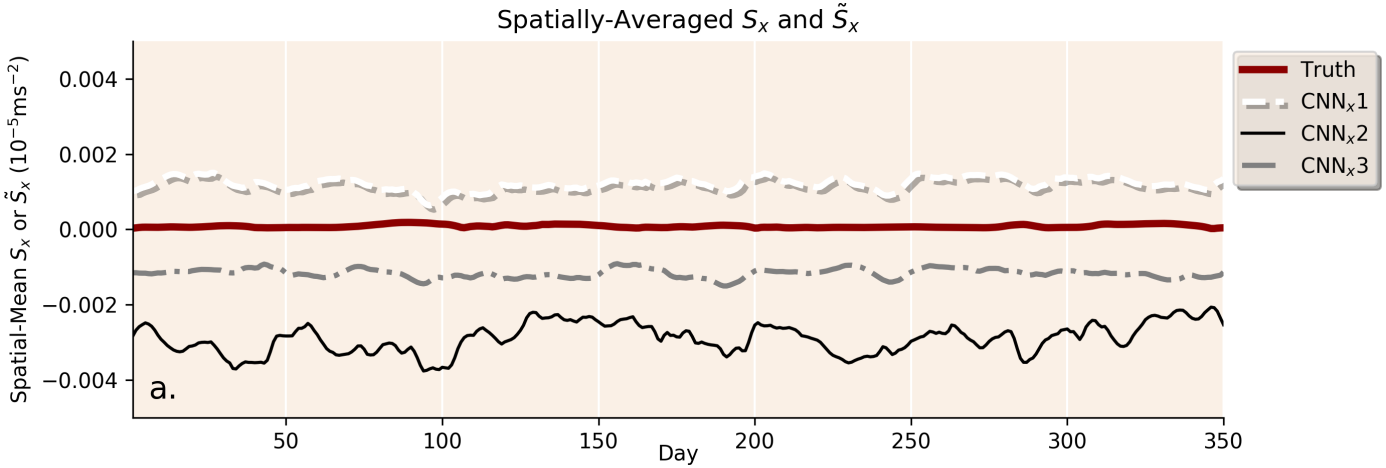
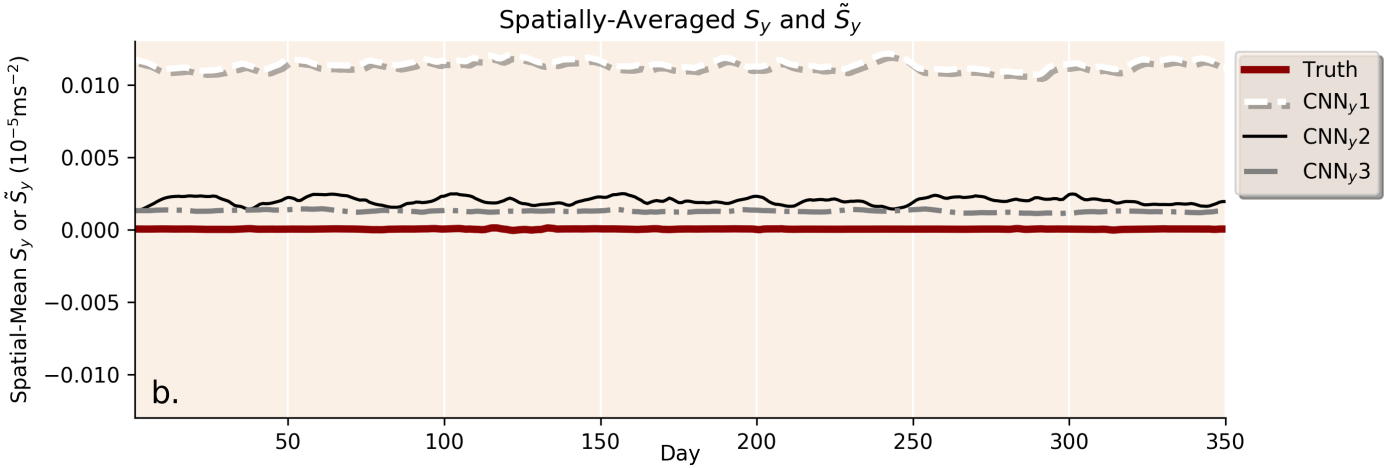


Figure 10. The feature maps at each stage of the neural network CNN$_x$1, for a synthetically-generated input streamfunction. Panel (a) shows the synthetically-generated input, where a radially-symmetric two-dimensional Gaussian function is used; the standard deviation is set to 60 km, in order to approximately match the length-scale of an eddy. Panels (b), (c), and (d) show the resulting feature maps of convolution layers 1, 2, and 3 respectively; there is a feature map

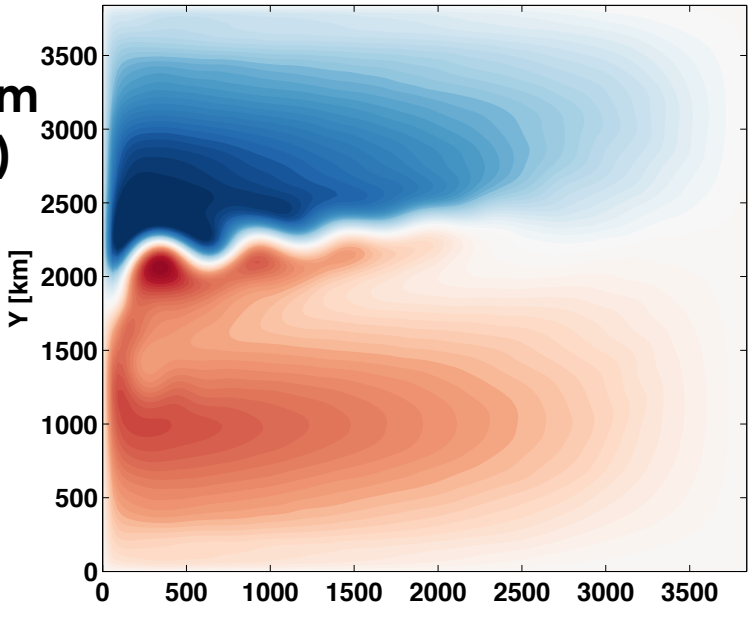

Spatially-Averaged S_x and $\tilde{S}_x$
Spatial-Mean S_x or $\tilde{S}_x$ (10^{-5}ms^{-2})
0.004
0.002
0.000
−0.002
−0.004
a.
50
100
150
200
250
300
350
Day
Truth
CNN$_x$1
CNN$_x$2
CNN$_x$3

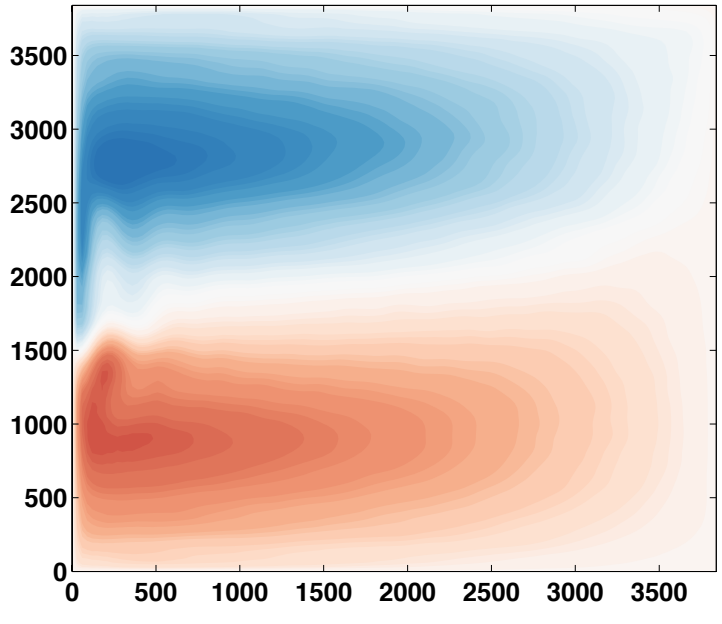

Spatially-Averaged S_y and $\tilde{S}_y$
Spatial-Mean S_y or $\tilde{S}_y$ (10^{-5}ms^{-2})
0.010
0.005
0.000
−0.005
−0.010
b.
50
100
150
200
250
300
350
Day
Truth
CNN$_y$1
CNN$_y$2
CNN$_y$3

Rethinking Subgrid Eddy Parametrizations

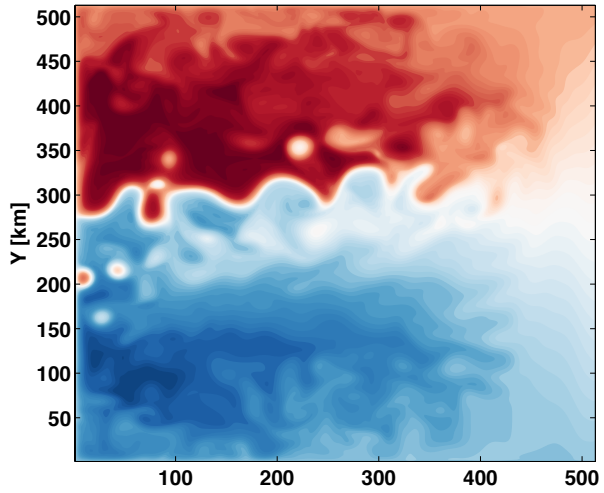
- Key aspects missing: energy backscatter from quasi-2D turbulence, jet sharpening, enhanced shear

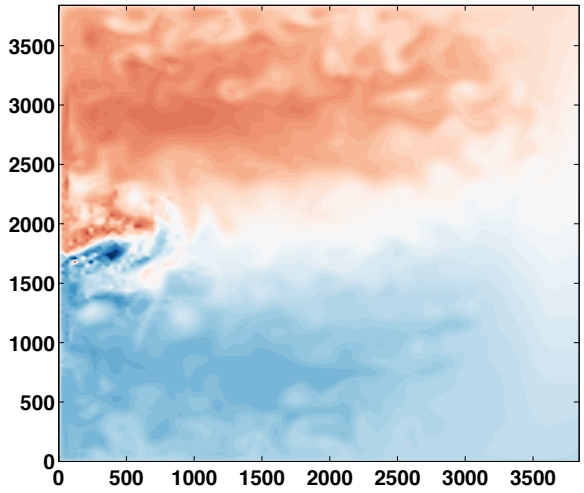
7.5 km (truth)





30 km (no param)





Rethinking Subgrid Eddy Parametrizations

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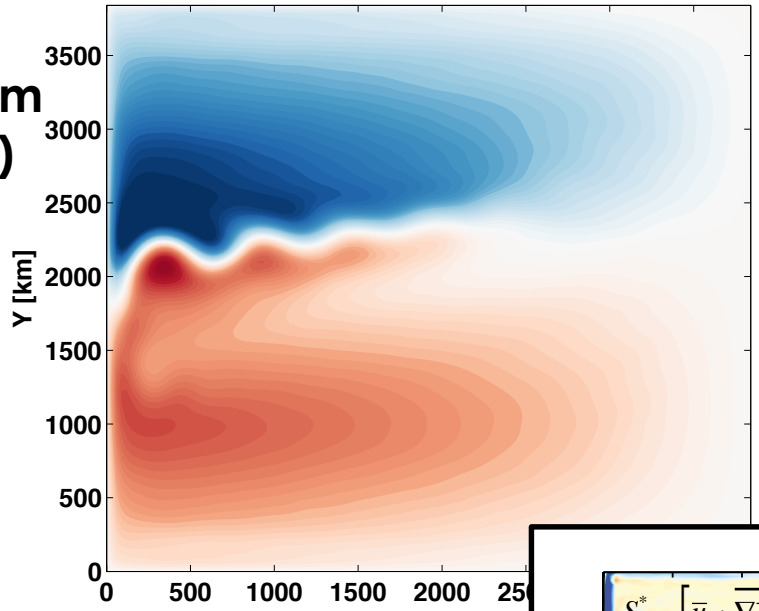
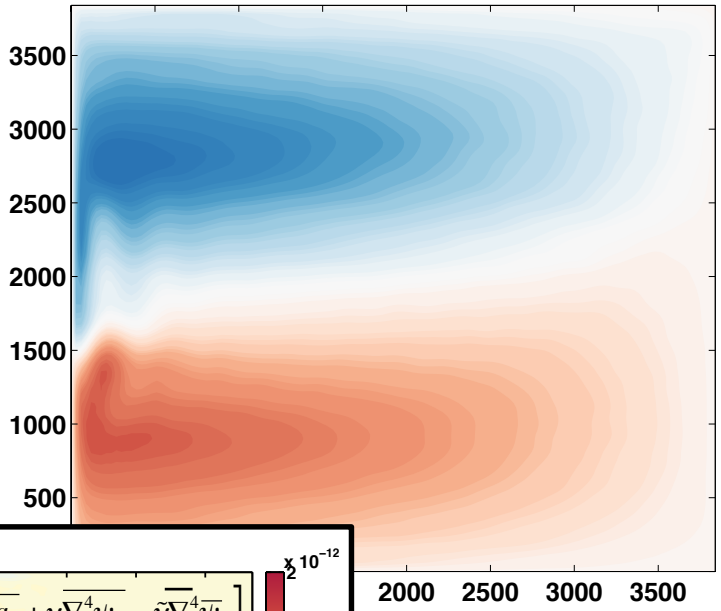
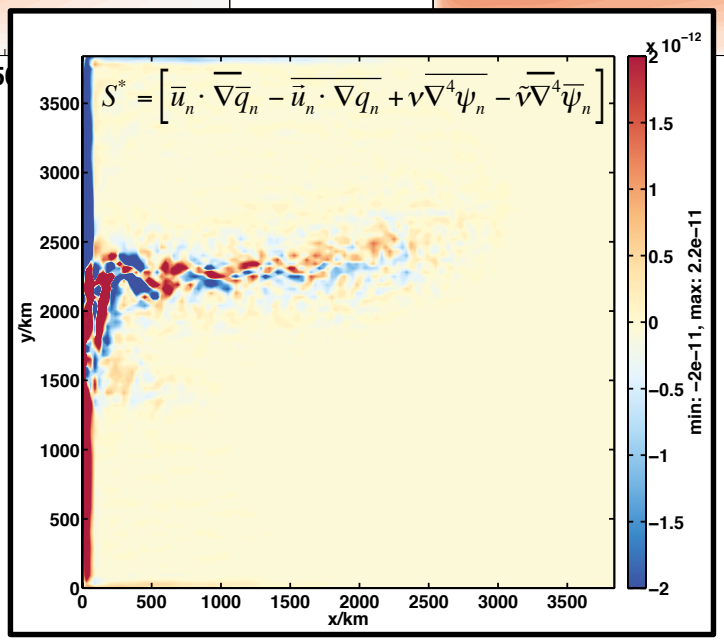


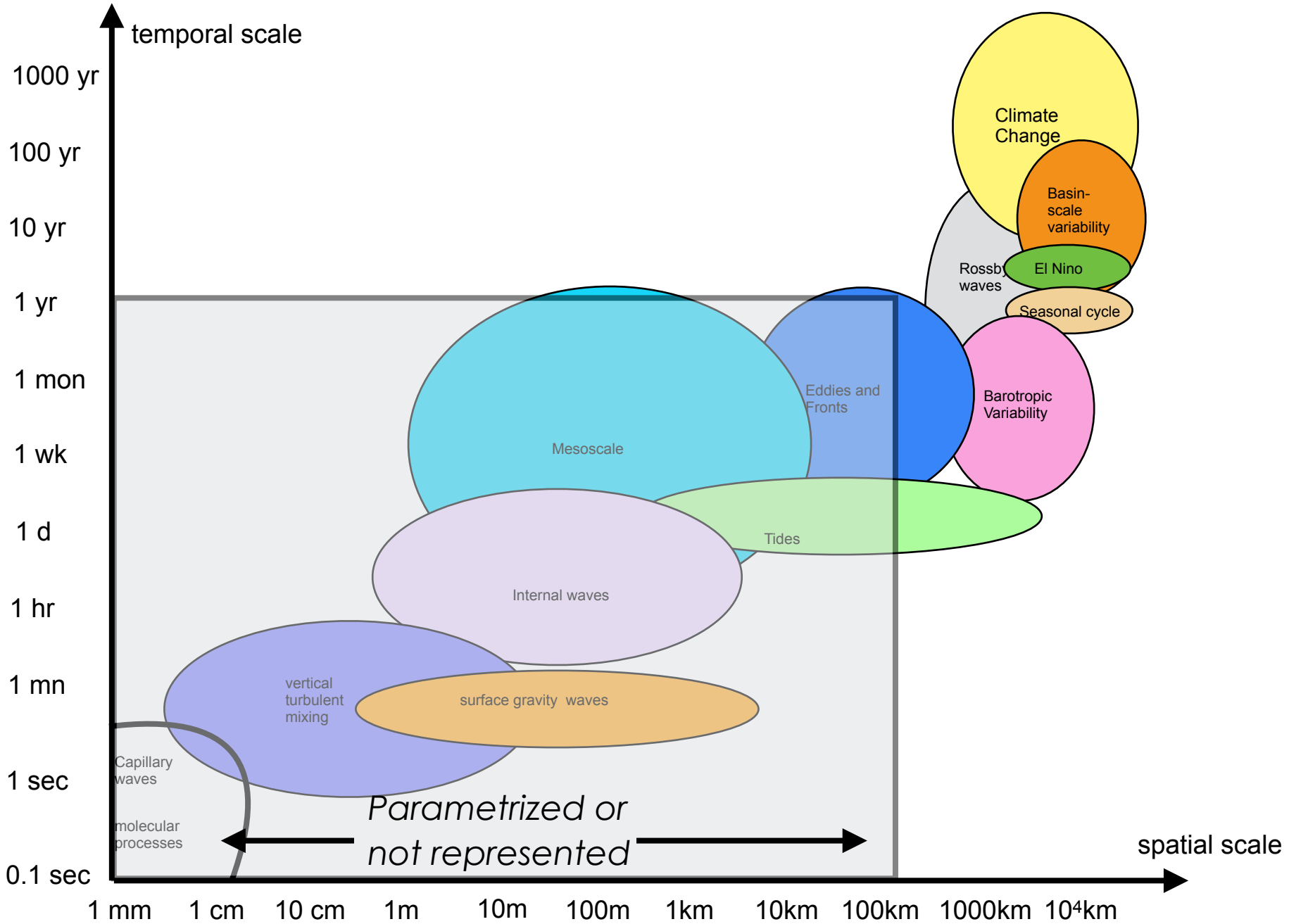


30 km (no param)

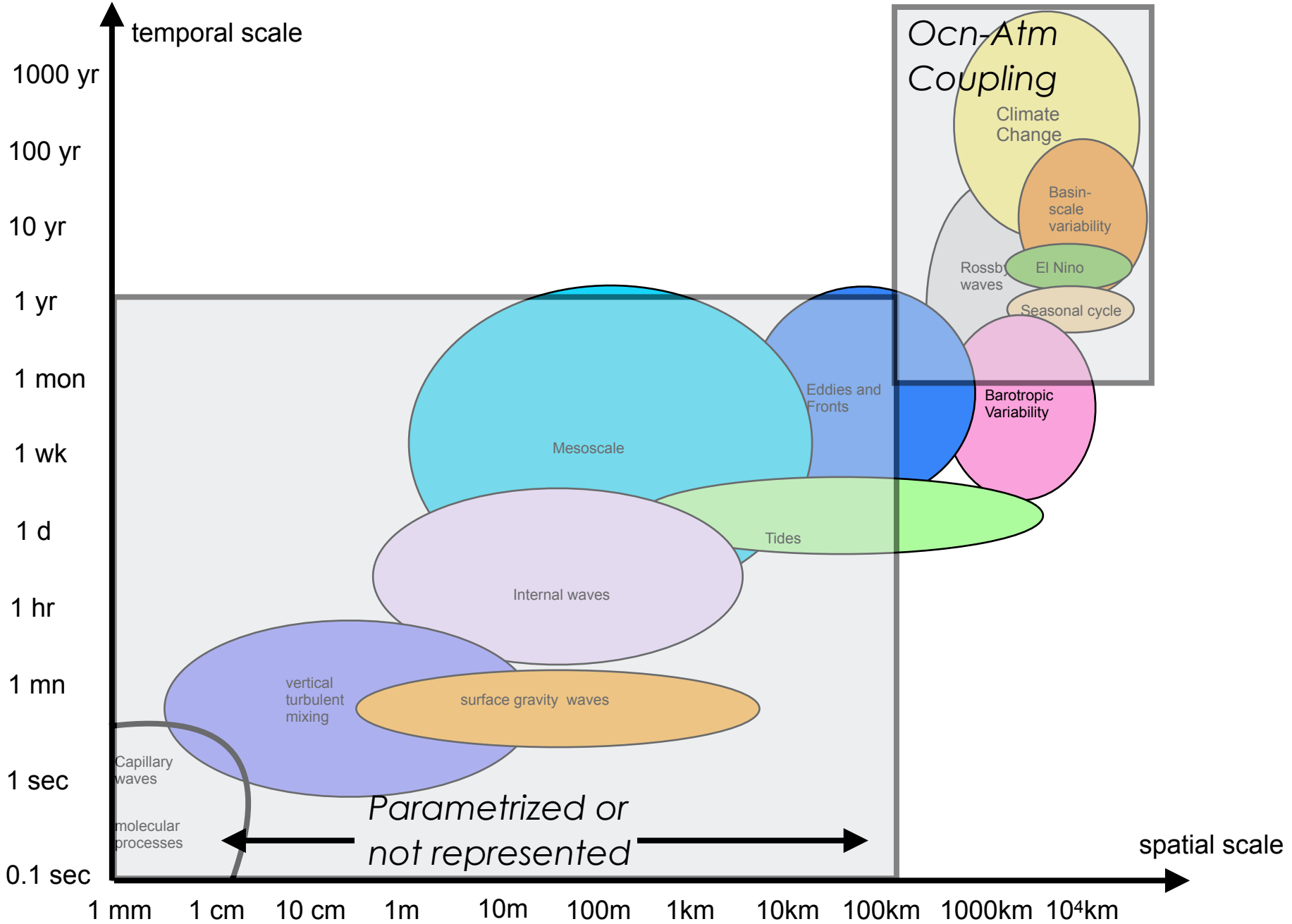


Mana & Zanna, 2014

Ocean Processes & Subgrid-scale parametrization

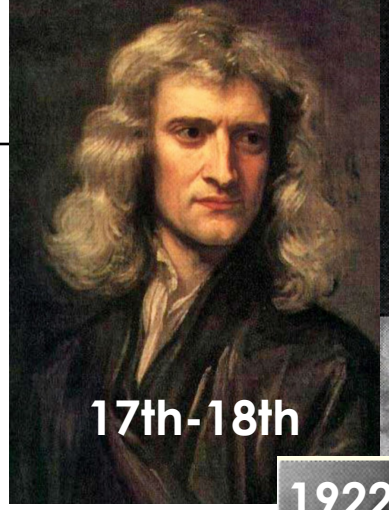


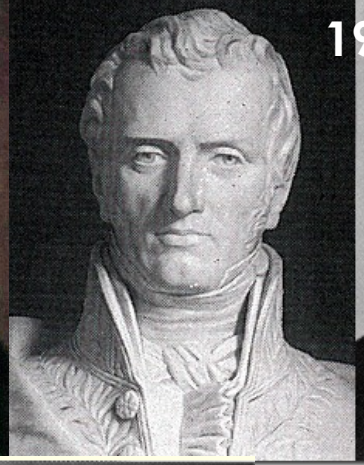
Ocean Processes: Temporal vs. Spatial Scales

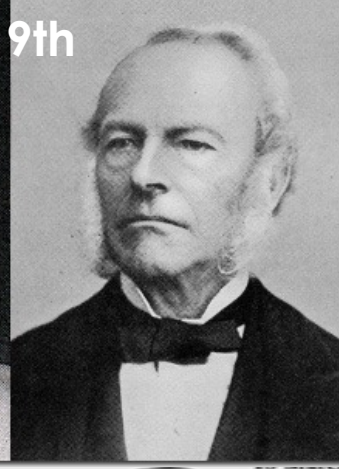


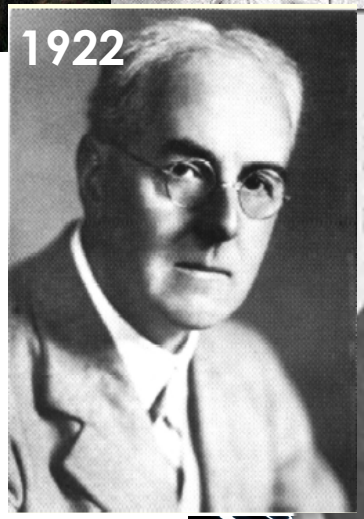
Outline

- Ocean/Climate physics & models

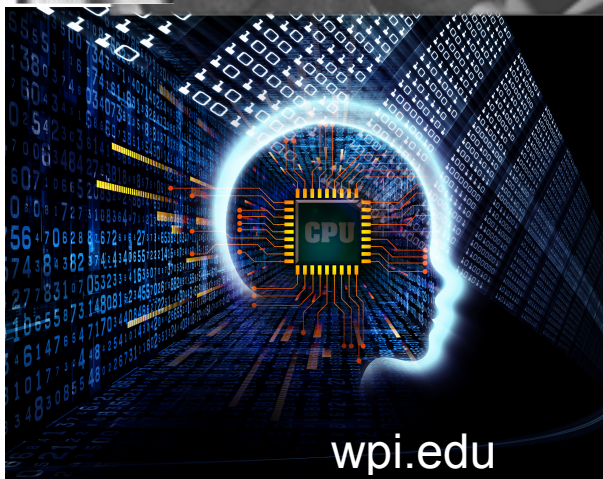








- Fundamental Problems in Ocean/ Climate, uncertainty and modelling:
  - Regional projections of Sea Level Rise
  - Uptake of heat, carbon, oxygen



- New avenues for ocean modelling: combining advances in machine learning together with our knowledge of physics and its modelling

Our governing equations

- **Newton's laws** (Navier-Stokes)

wind, gravity...

$$\frac{\partial \mathbf{v}}{\partial t} + \mathbf{v} \cdot \nabla \mathbf{v} = -\frac{1}{\rho}\nabla p + \nu \nabla^2 \mathbf{v} + \mathbf{F} + \mathbf{F}_c$$

$\mathbf{F}_c$ → Coriolis

- **Thermodynamics** - heat & salt for a stratified fluid (tracer equations),

$$\frac{\partial C}{\partial t} + \mathbf{v} \cdot \nabla C = \kappa \nabla^2 C + m_C$$

- **Conservation of mass/** continuity for incompressible fluid

$$\nabla \cdot \mathbf{v} = 0$$

- **Equation of state** for density (we don't know what it is really)

$$\rho = \rho(T, S, p) \approx \rho_0 (1 - \alpha T + \beta S)$$

Multi-scale Interaction

Energy Source

Wind + Buoyancy Work

Energy Transfer

Large-scale circulation + stratification 1000-10000km

Instability

Inverse Cascade

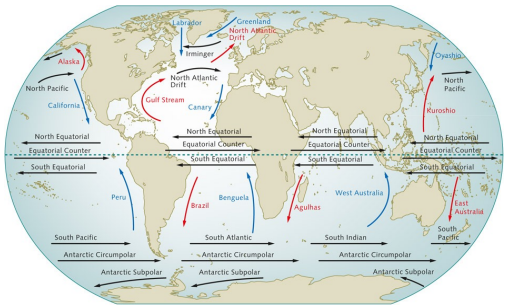
Mesoscale Eddies 10km-100km

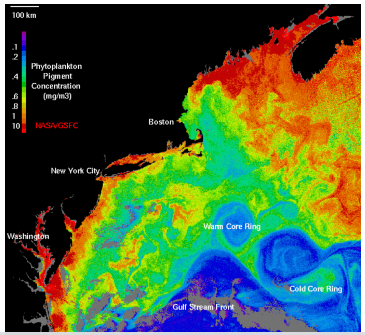
Inverse Cascade

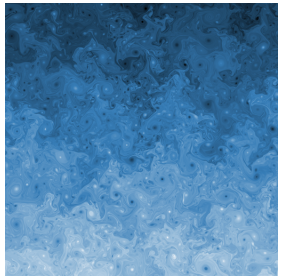
Sub-mesoscale, filaments … <10km

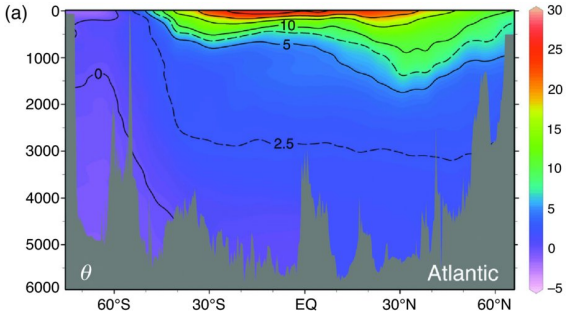
Energy Sink

Viscous Dissipation 1mm-1cm







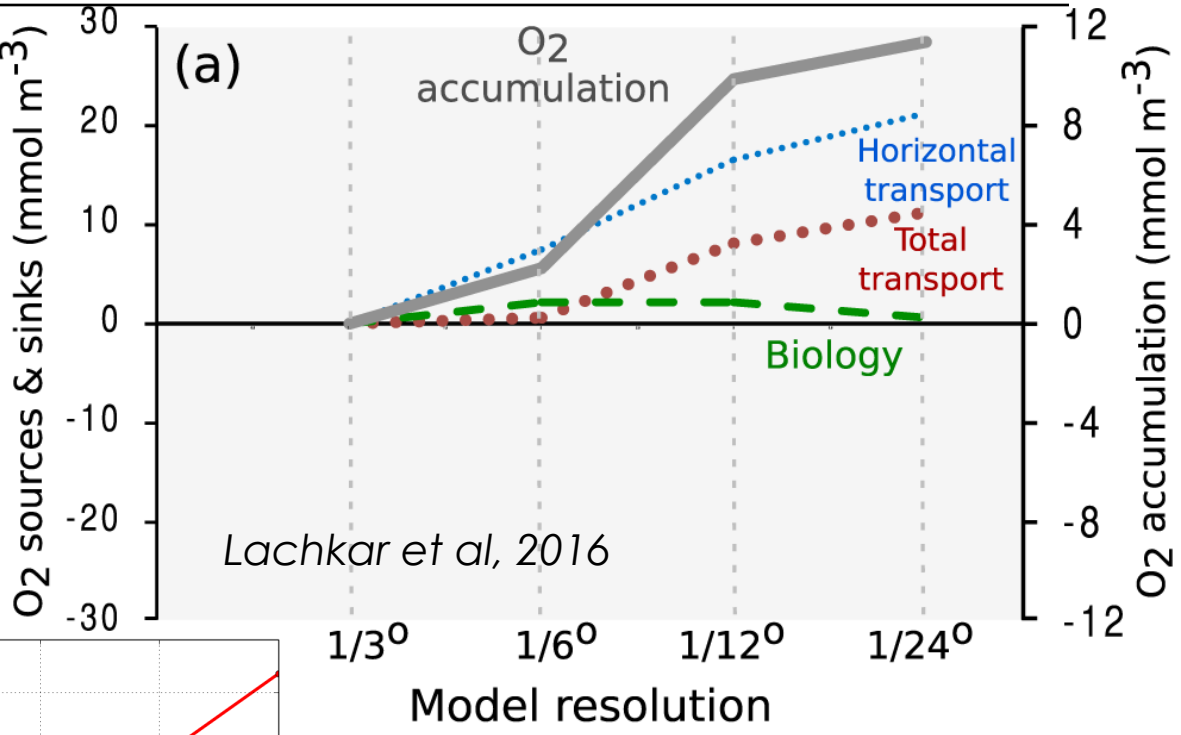


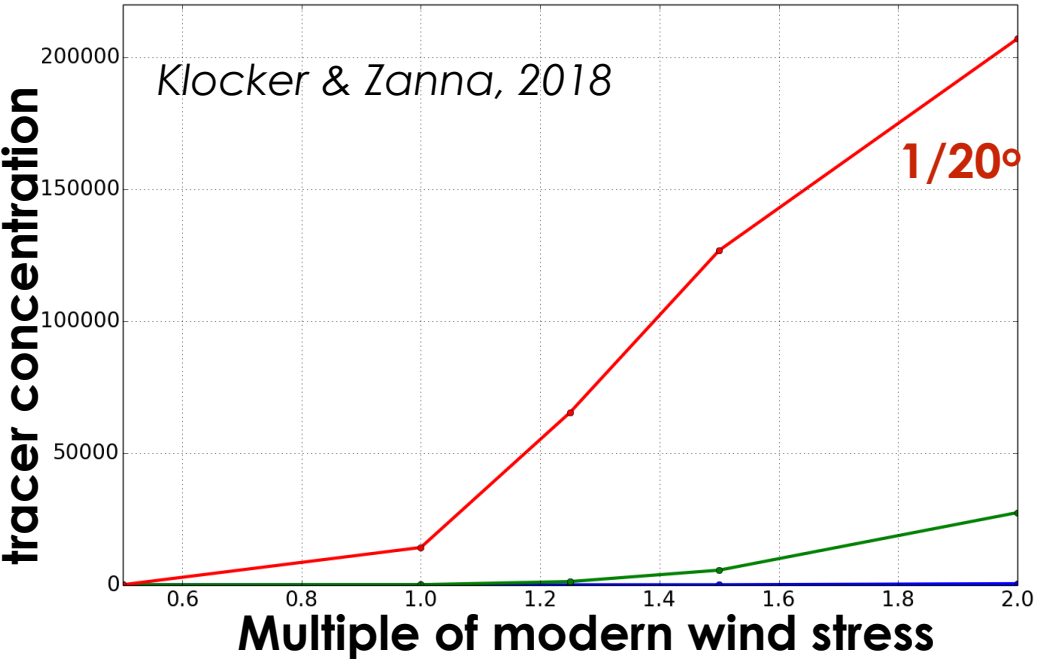
Many of these interactions are poorly represented in models, understood in nature, and their impact on climate (physics, biology, chemistry) is unknown

e.g. Wunsch & Ferrari 2004, Scott 2009

How much heat, carbon, oxygen are taken up?

- "Resolution" sets transport, accumulation of tracer

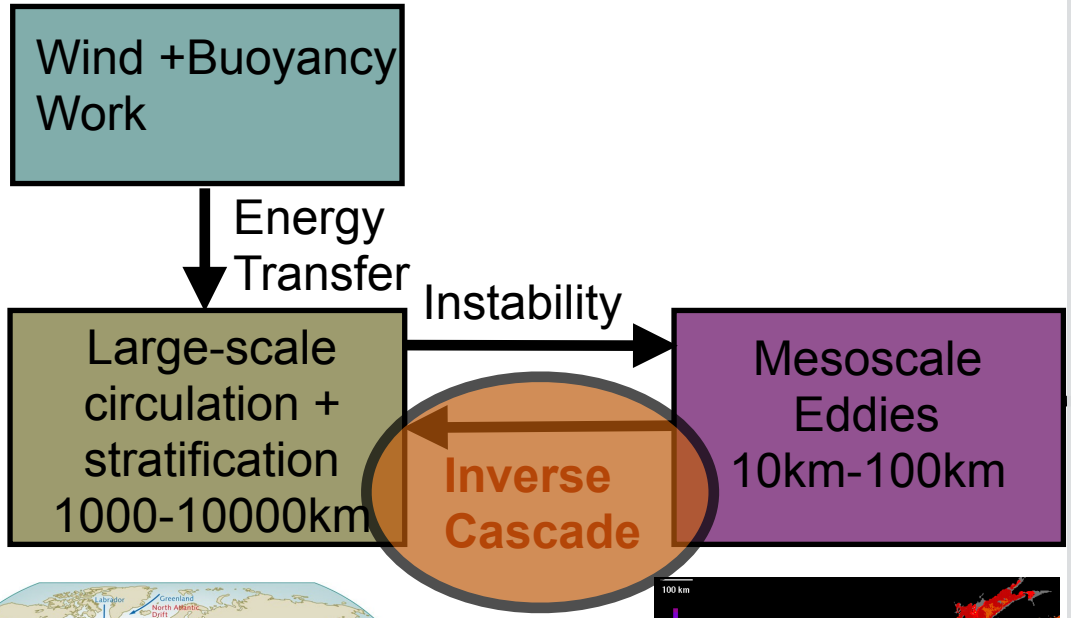


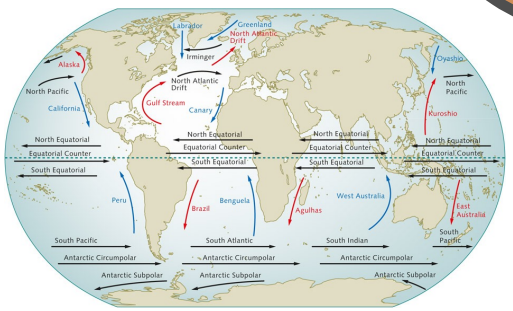


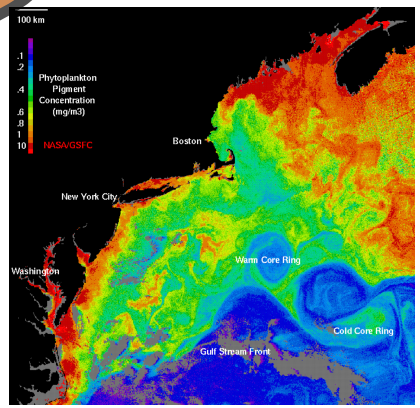
and its sensitivity to forcing (important for climate change)

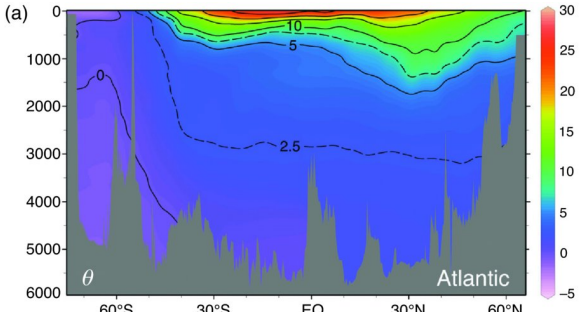
How to improve estimates of tracer uptake?

- or include missing mesoscale effects (10-100km)









Energy Sink

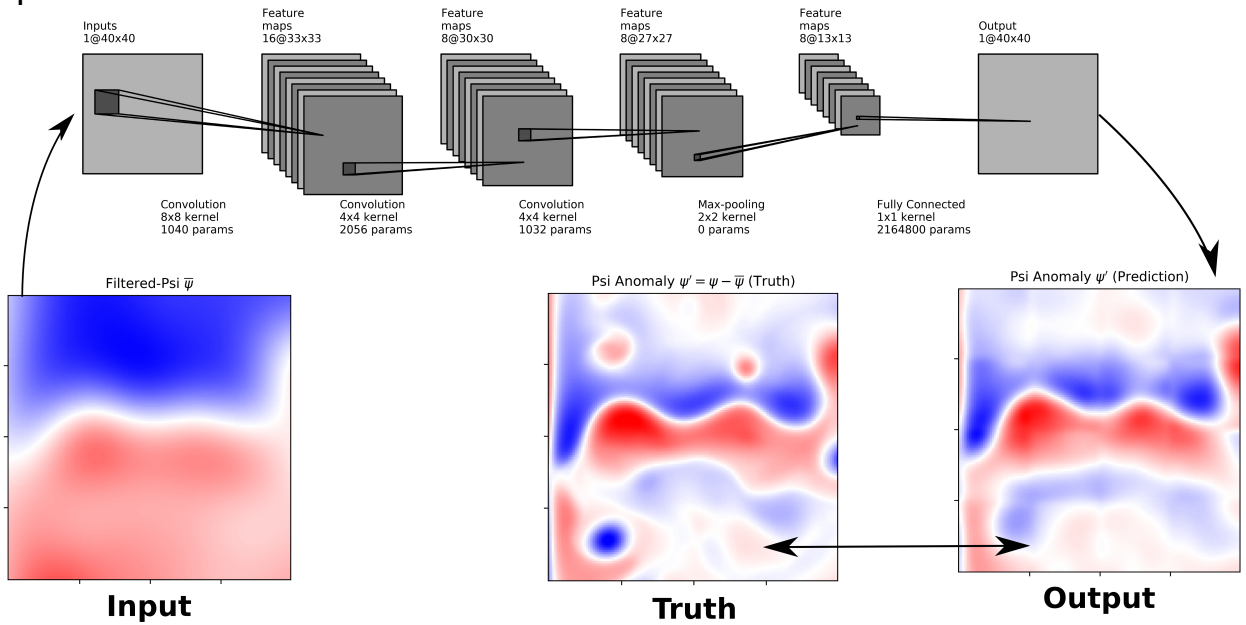
Viscous Dissipation 1mm-1cm

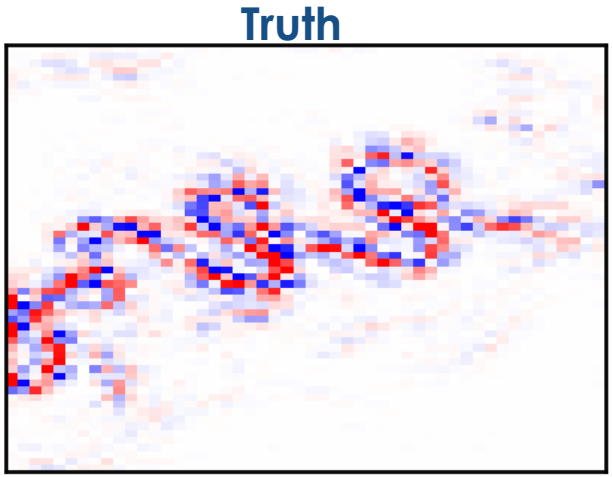
Sub-mesoscale filaments <10km

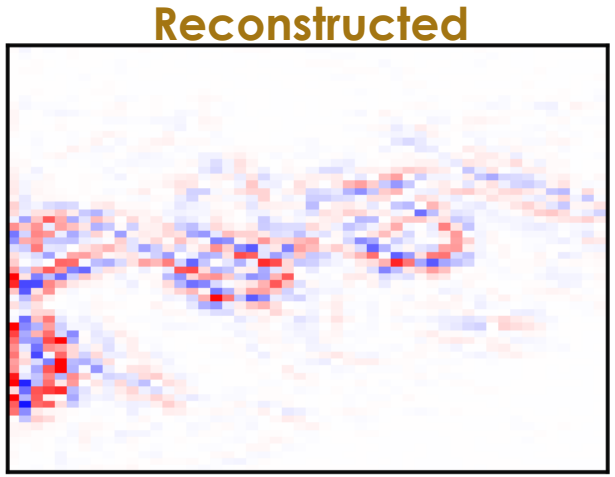
Wunsch & Ferrari 2008; Scott 2009

Neural Network to find Missing Forcing

- Can neural network help determining the missing forcing or optimise the parameters ?



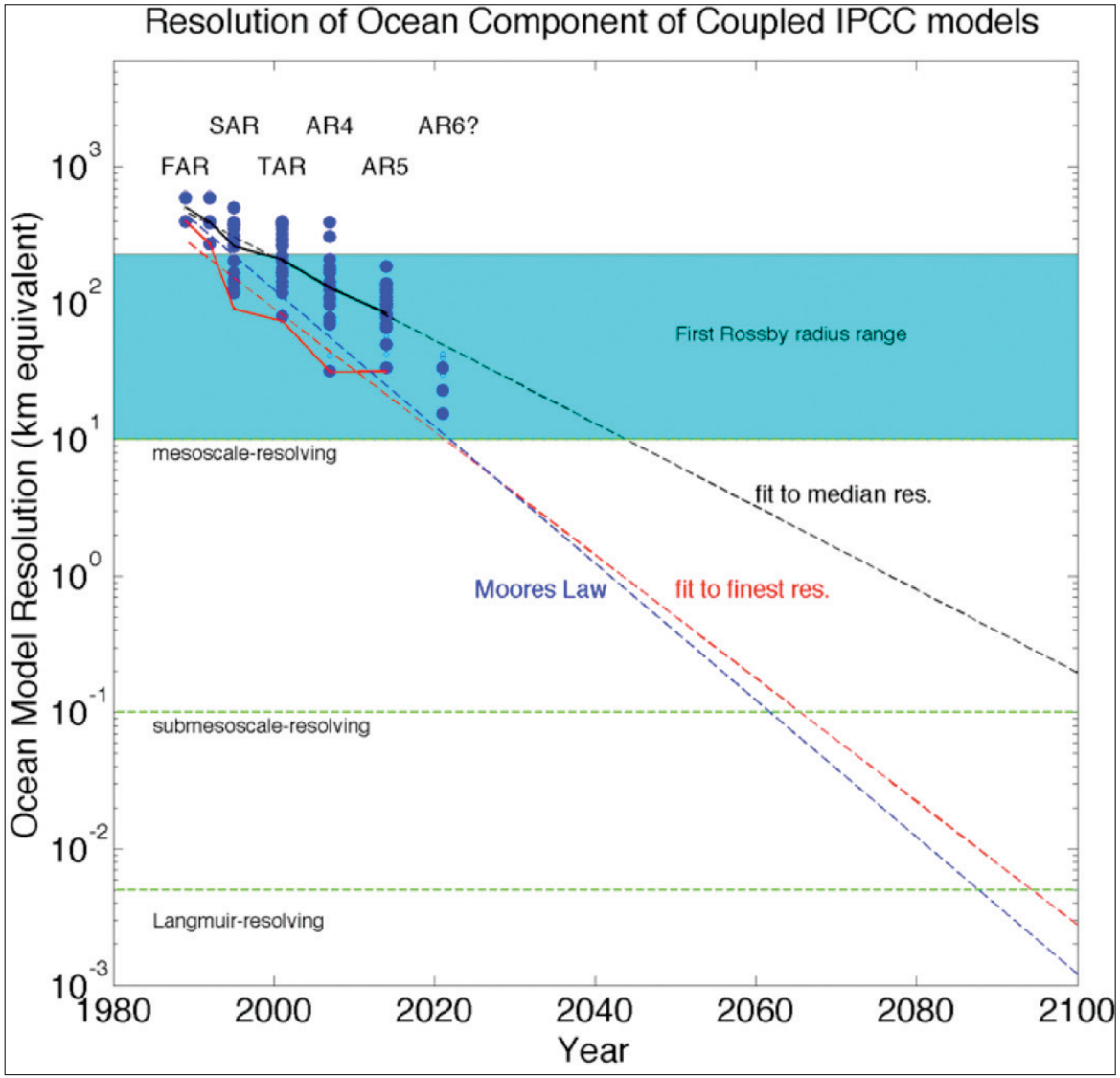




Bolton & Zanna, In Prep

Summary & New Avenues

- Limited computational resources for ocean-climate models

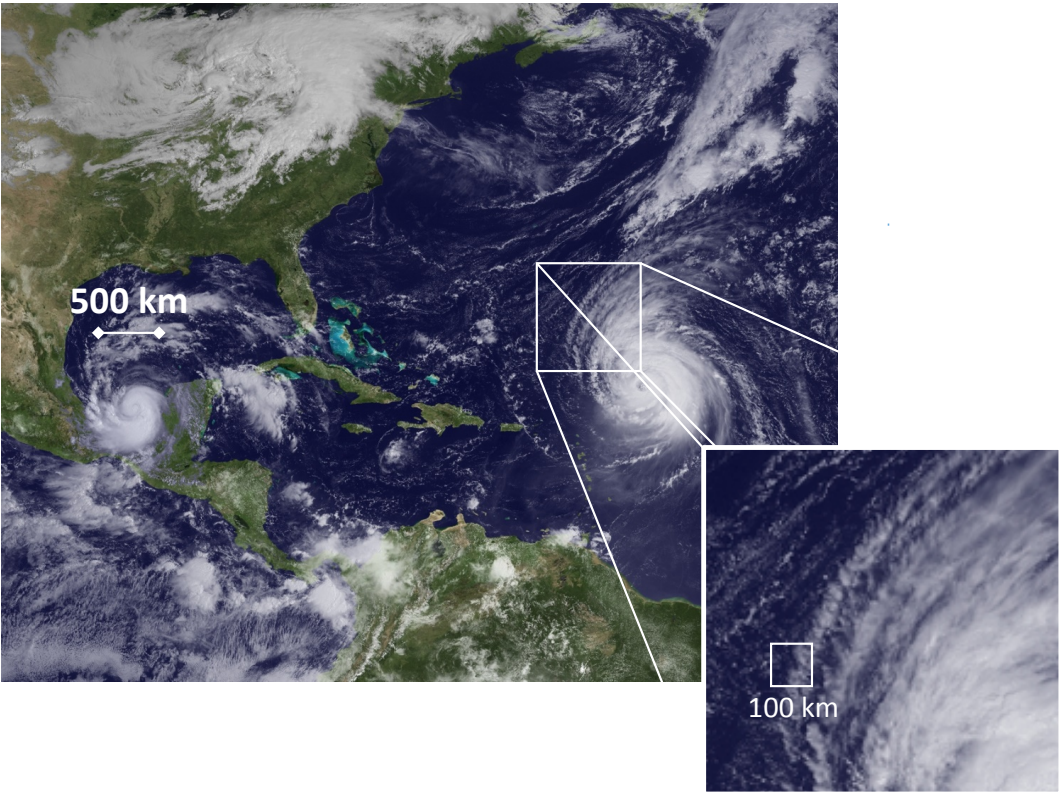


Fox-Kemper et al 2014

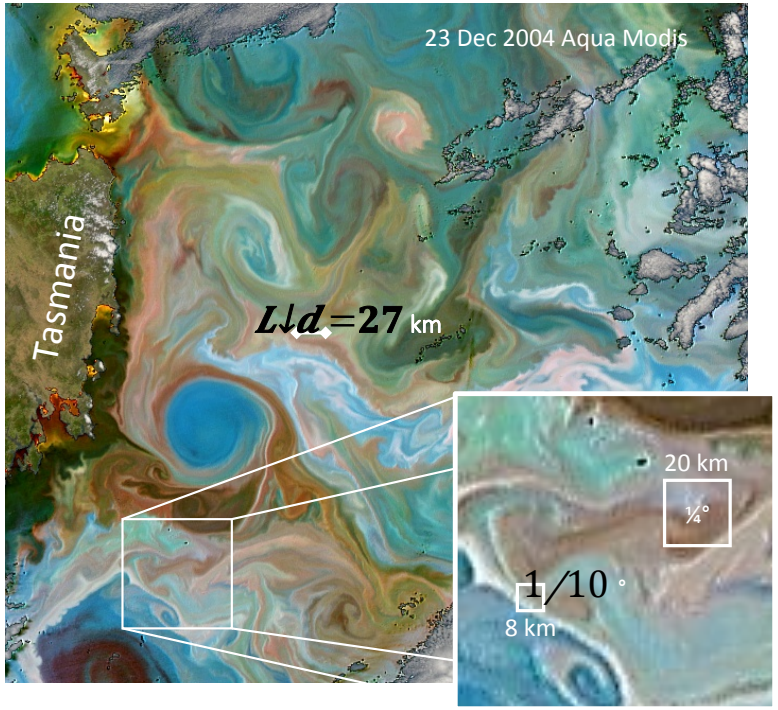
Summary & New Avenues

- Limited computational resources for ocean-climate models
- Scales to resolve in the ocean smaller than in the atmosphere

Clouds visualized from FV3 simulation (NOAA)

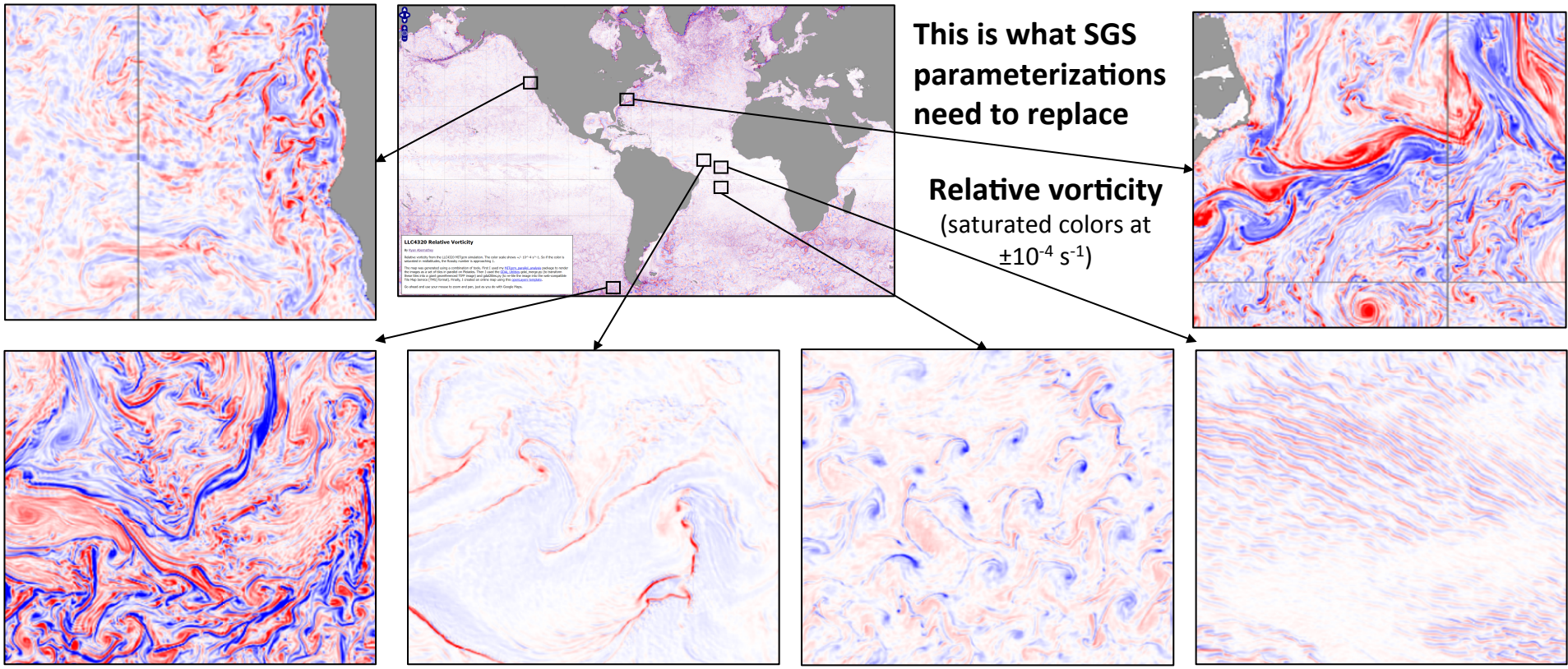


False color image from Aqua MODIS (NASA)



Summary & New Avenues

- Limited computational resources for ocean-climate models
- Scales to resolve in the ocean smaller than in the atmosphere
- Zoo of unresolved scales not accounted for, or represented in their bulk form - crucial for determining the temperature at the surface of the ocean



2km model from ECCO2 project (Menemenlis and Hill)

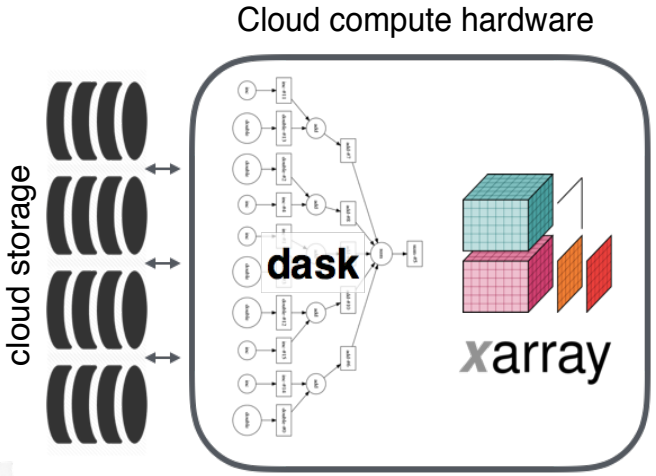
Thanks to Alistair Adcroft (Princeton/GFDL)

Data Storage & Fast Analysis

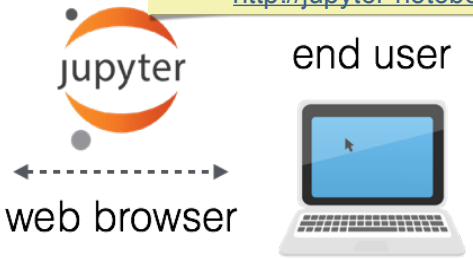
Pangeo Architecture

Led by Ryan Abernathey (Columbia University)

distributed file systems provide a scalable, shareable storage layer for climate Big Data



Jupyter notebook provides remote access to HPC / cloud systems
http://jupyter-notebook.readthedocs.io/



Xarray provides data structures and intuitive interface for working with climate datasets
http://xarray.pydata.org/

Dask sits beneath Xarray and provides distributed scheduling of "task graphs" on parallel hardware
http://dask.readthedocs.io

Cloud compute systems enable users to leverage large clusters of compute nodes for data processing. Our software will be deployed on NCAR's Cheyenne supercomputer and on Google Cloud Platform.

EarthCube NSF Google Cloud Platform Lamont-Doherty Earth Observatory Columbia University | Earth Institute

Ryan Abernathey, Chiara Lepore, Michael Tippet, Naomi Henderson, Richard Seager

Kevin Paul, Joe Hamman, Ryan May, Davide Del Vento NCAR

Matthew Rocklin ANACONDA Powered by Continuum Analytics

Many other collaborators around the world (also outside of geoscience)

Met Office ECMWF GFDL NASA NASA Goddard Institute for Space Studies

Summary & New Avenues

- The future: Increase Resolution ? Increase complexity? Increase ensemble size ?

Summary & New Avenues

- Limited computational resources for ocean-climate models
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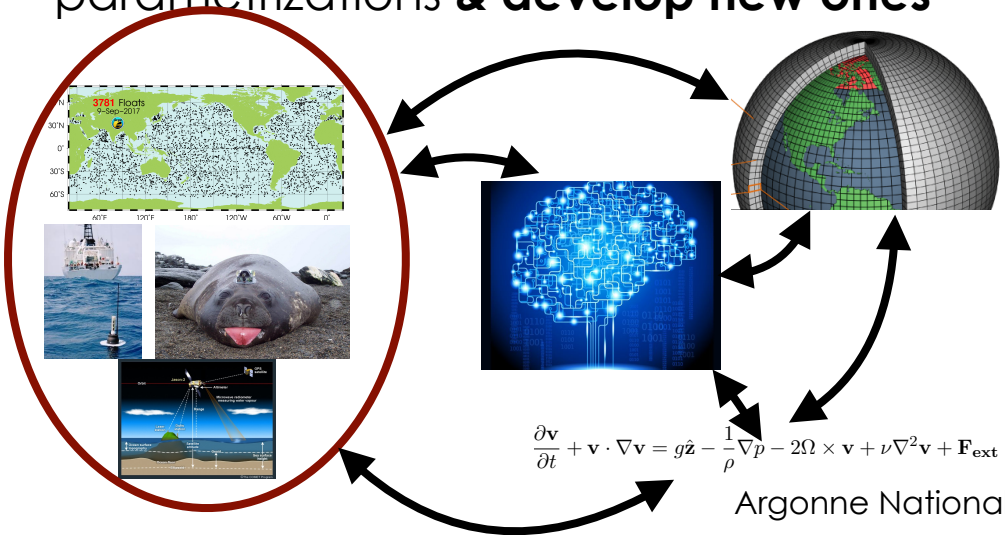
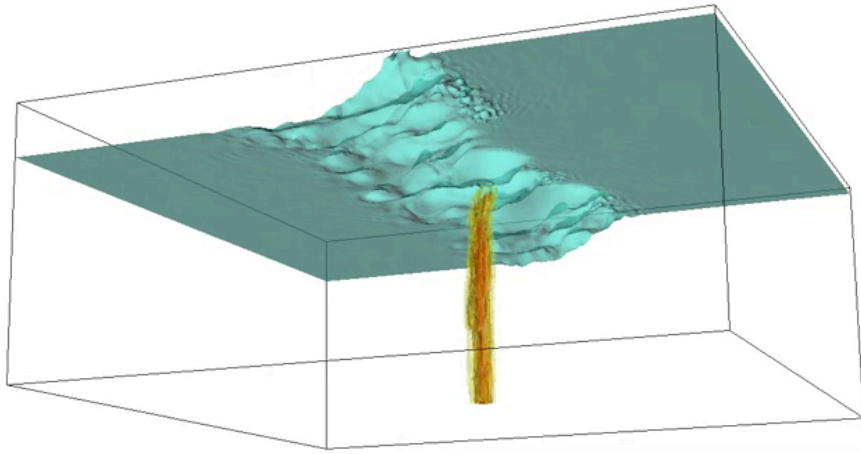
- The future: Increased Resolution ? Increased complexity ? Increase ensemble size ?
- My philosophy = back to basics. Use (idealised) high-resolution simulations, together with theory/first principle, and observations to inform current parametrizations **& develop new ones**



$$\frac{\partial \mathbf{v}}{\partial t} + \mathbf{v} \cdot \nabla \mathbf{v} = g\hat{\mathbf{z}} - \frac{1}{\rho}\nabla p - 2\Omega \times \mathbf{v} + \nu \nabla^2 \mathbf{v} + \mathbf{F}_{\mathbf{ext}}$$



Argonne National Laboratory. (Credit: Tamay Özgökmen and Paul Fischer)

Summary & New Avenues

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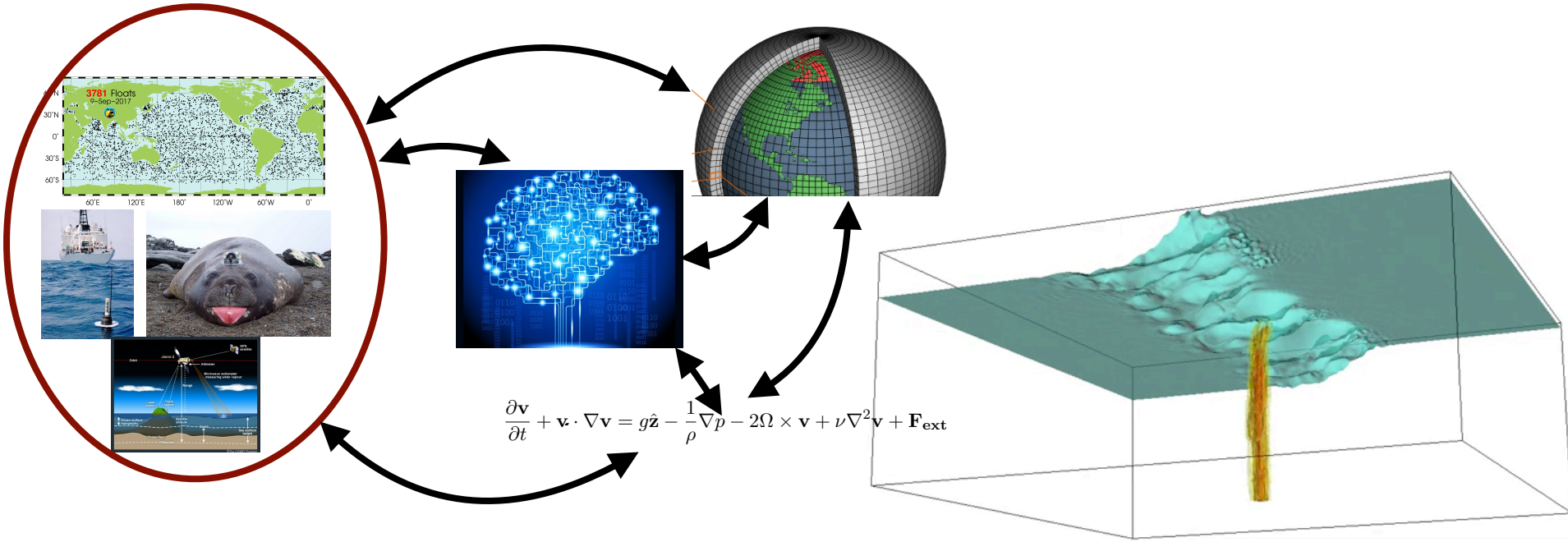
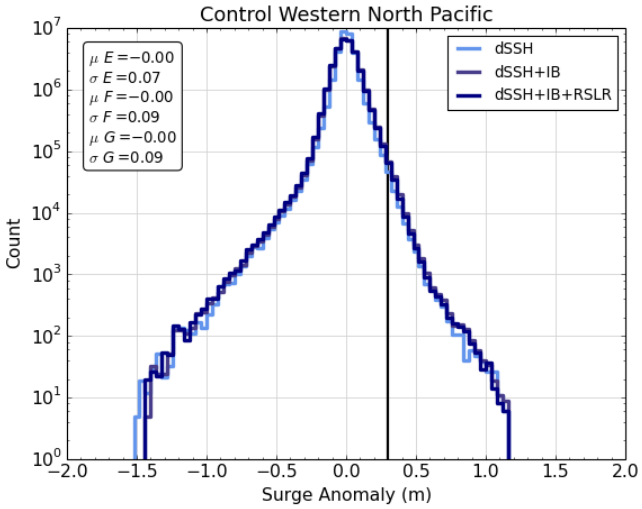
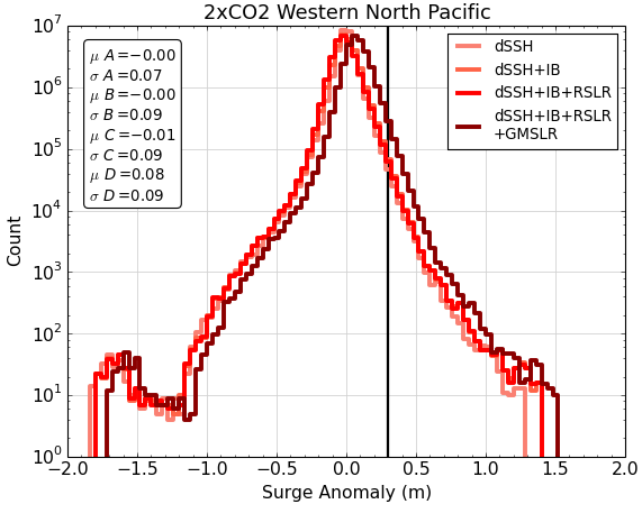
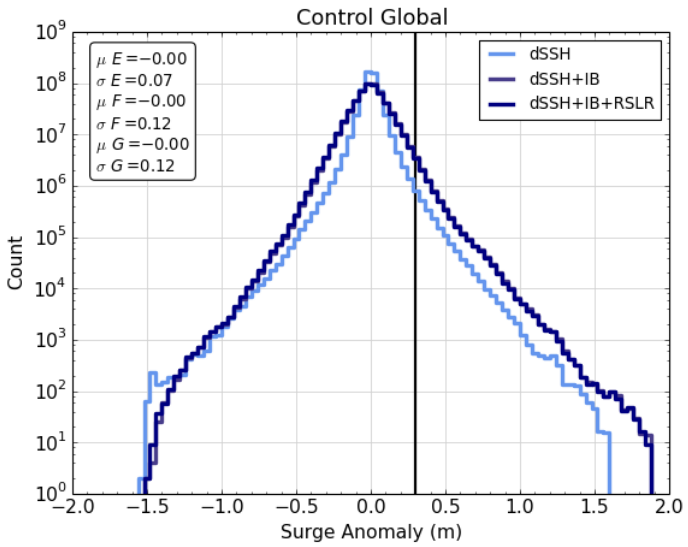


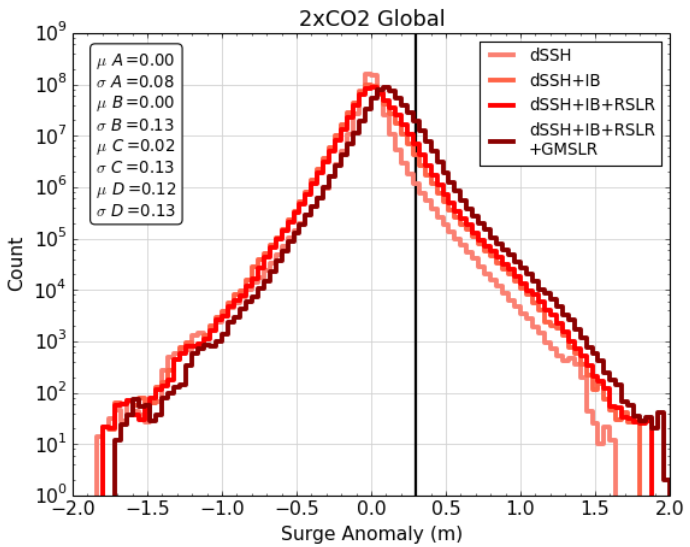
Argonne National Laboratory. (Credit: Tamay Özgökmen and Paul Fischer)

Motivation: How to Solve the Climate Problem?





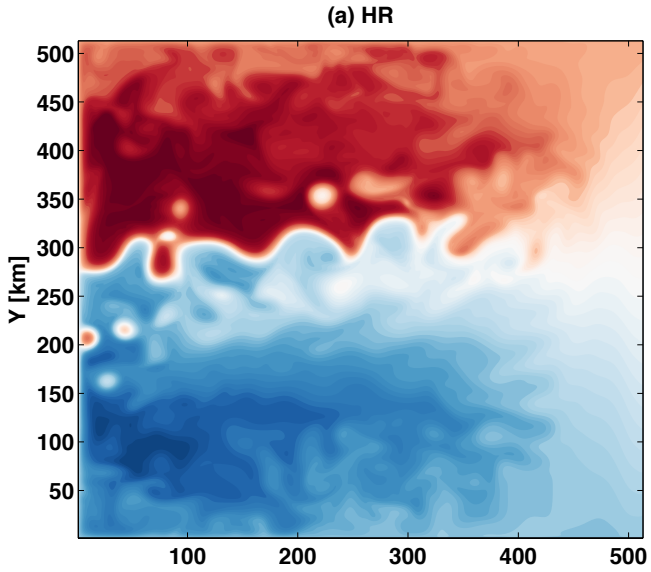


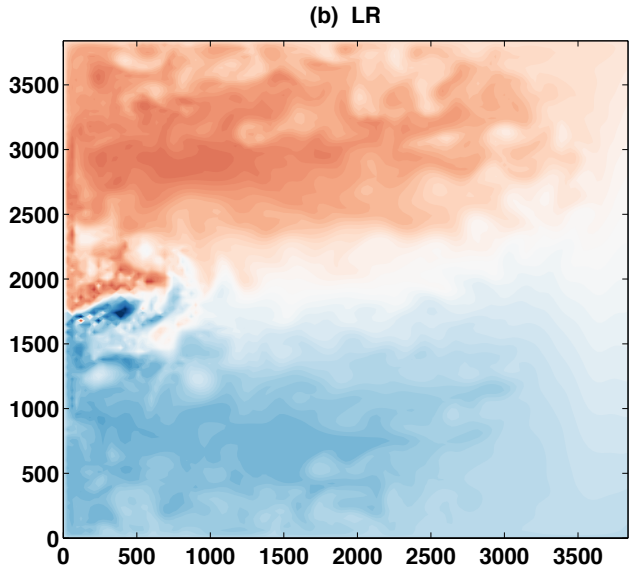


Turbulence in models

Zanna, Anstey, Mana, David, Bolton, 2016

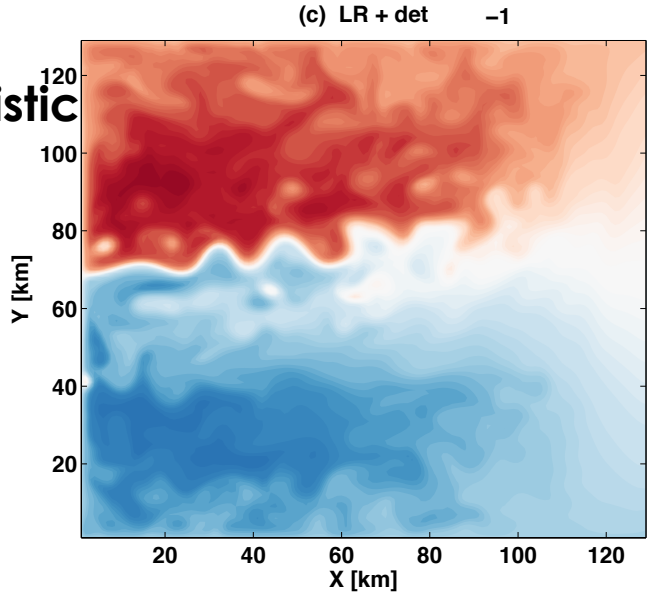
7.5 km ("truth")

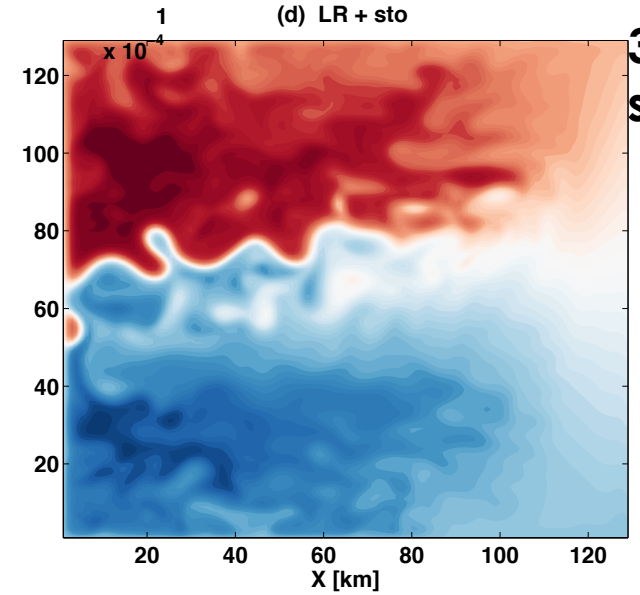




30 km (no param)

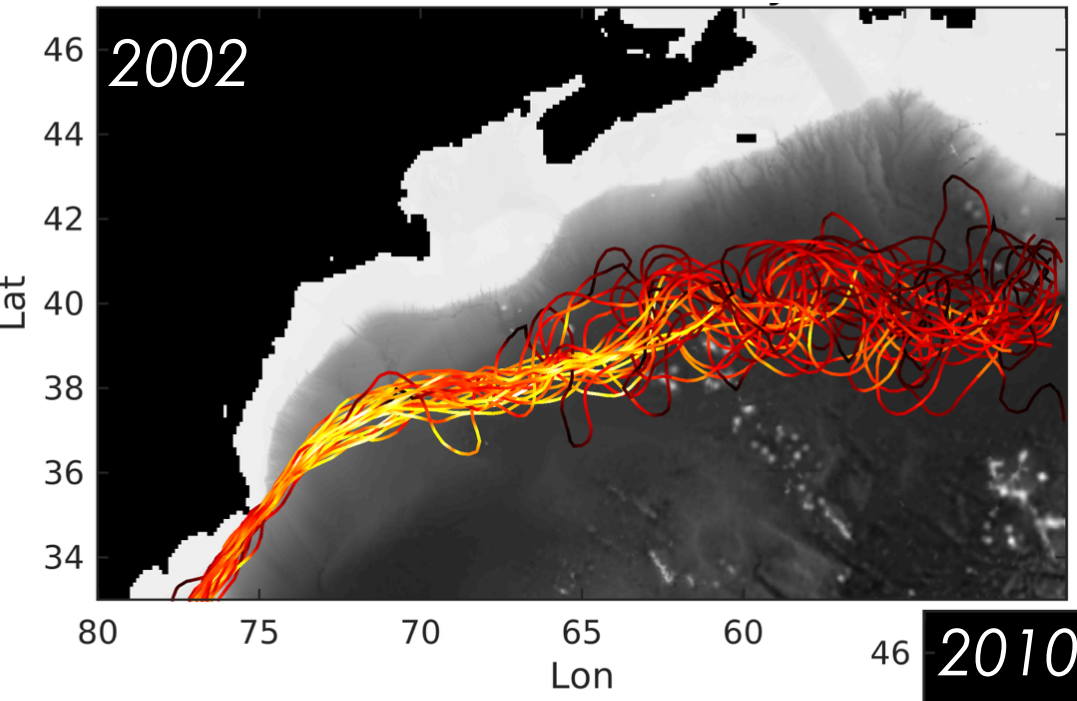
30 km + deterministic





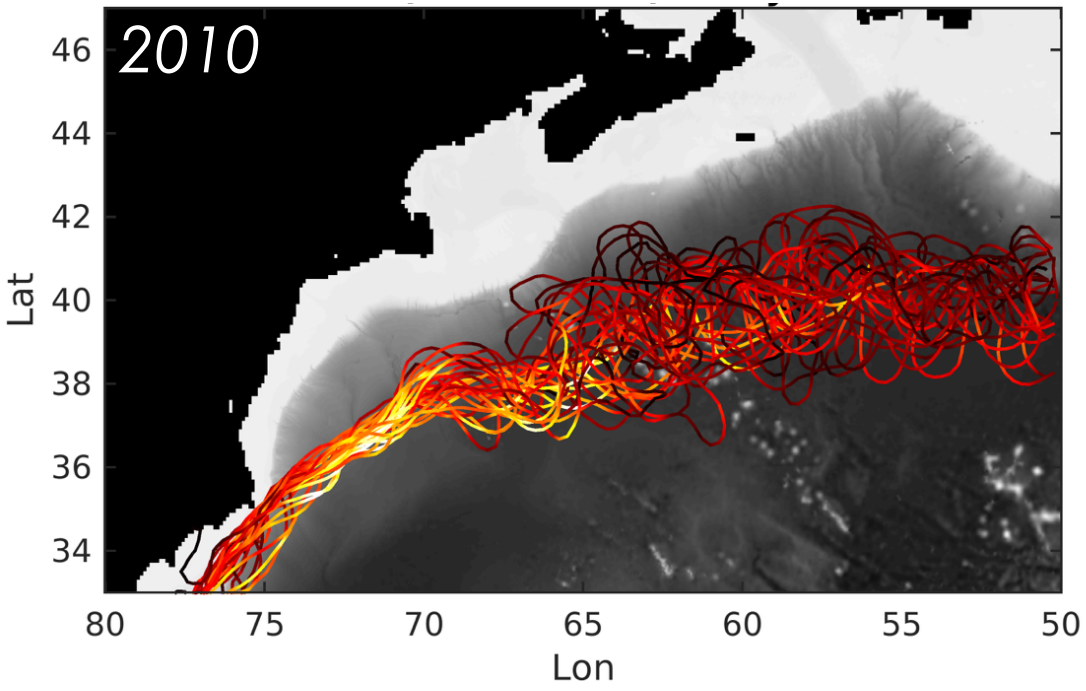
30 km + stochastic

Ocean Turbulence in the Gulf Stream



Bolton & Zanna, 2016

- Year - to - Year variability in Gulf Stream speed due to scale interaction



- Do we expect changes in the turbulent behaviour of the Gulf Stream & other currents & associated mixing?