REPORT OF AGU 2021 MEETING

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Lecture 1

Multi-scale Modeling of Oceanic Sub-mesoscale Lateral Dispersion

Main Question: How do inertia-gravity waves influence lateral dispersion?
Focus: 1. Waves play an indirect but critical role.
2. A specific class of interadtions involving waves increases the energy in the small-scale, linear potential vorticity (PV) field.
3. Thereby leading to noisier flow, and enhanced lateral dispersion, compared to flow without waves.
Boussinesq dynamiscs:

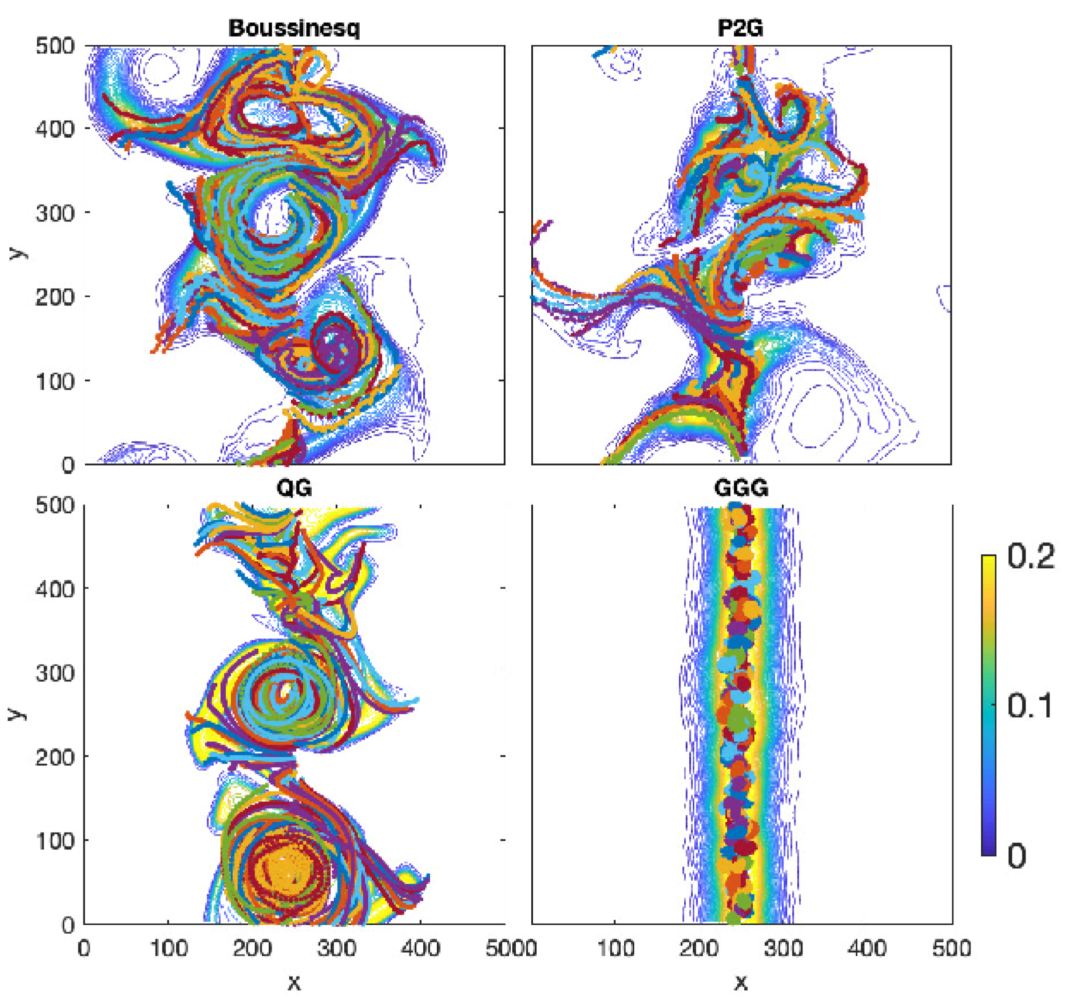
$$\begin{aligned} \frac{D\mathbf{u}}{Dt} + f\hat{\mathbf{z}}\times\mathbf{u} &= -\frac{1}{\rho_o}\nabla p - \hat{\mathbf{z}}\frac{g}{\rho_o}\rho', \\ \frac{D\rho'}{Dt} &= -w\frac{d\bar{\rho}}{dz}, \\ \nabla\cdot\mathbf{u} &= 0, \end{aligned} \tag{1}$$

with forcing of density anomaly ρ'.

Model	Interactions allowed
QG	vortical-vortical-vortical
PPG	vortical-vortical-vortical $\oplus$ vortical-vortical-wave
P2G	vortical-vortical-vortical $\oplus$ vortical-vortical-wave $\oplus$ vortical-wave-wave
Boussinesq (FB)	all

(2)

Visualization of dispersion using particles:



Q1: How do you subtract the three wave interactions from the full boussinesq system?
A1: They are doing their simulations in a periodic box. Then evervthing is easy because they can simply remove certain classes of wave vertical interactions in four years. Their method is as a projection onto classes of interactions. They actually do it in Fourier space and then they compute their nonlinear term in physical space in a sub-mesoscale computation.
Q2: Why the model P2G has more dispersion?
A2: When you the three wave interactions by themselves. It's pretty well known that they support afford cascade of energy. For example, in the other models, it would have three wave interactions. You have a nice for cascade of energy. If you remove that pathway for the forward cascade of energy, the energy has to go somewhere else. It wants to go down, you know, downscale and has to go somewhere else. So in the P2G model, it goes into the small-scale vortical modes instead of going into the small-scale wave modes. Therefore you have too much energy in the small-scale vortical modes and it's represents noisy flow. It's not coherent flow. And and so that's all these these noisy trajectories that you see in the P2G. They and their noisy are enough, that they've actually eroded the vort.

Lecture 2

Upscale Impact of Mesoscale Convective Systems on the Madden-Julian Oscillation and Its Parameterization in a Coarse-Resolution GCM

Step 1: Using cloud-resolving model. It's actually a system for atmosphere modeling (SAM model) and we consider a global 2D domain to mimic the tropical belt. So the resolution is quite fine.
Kinetic energy budget for planetary-scale systems:

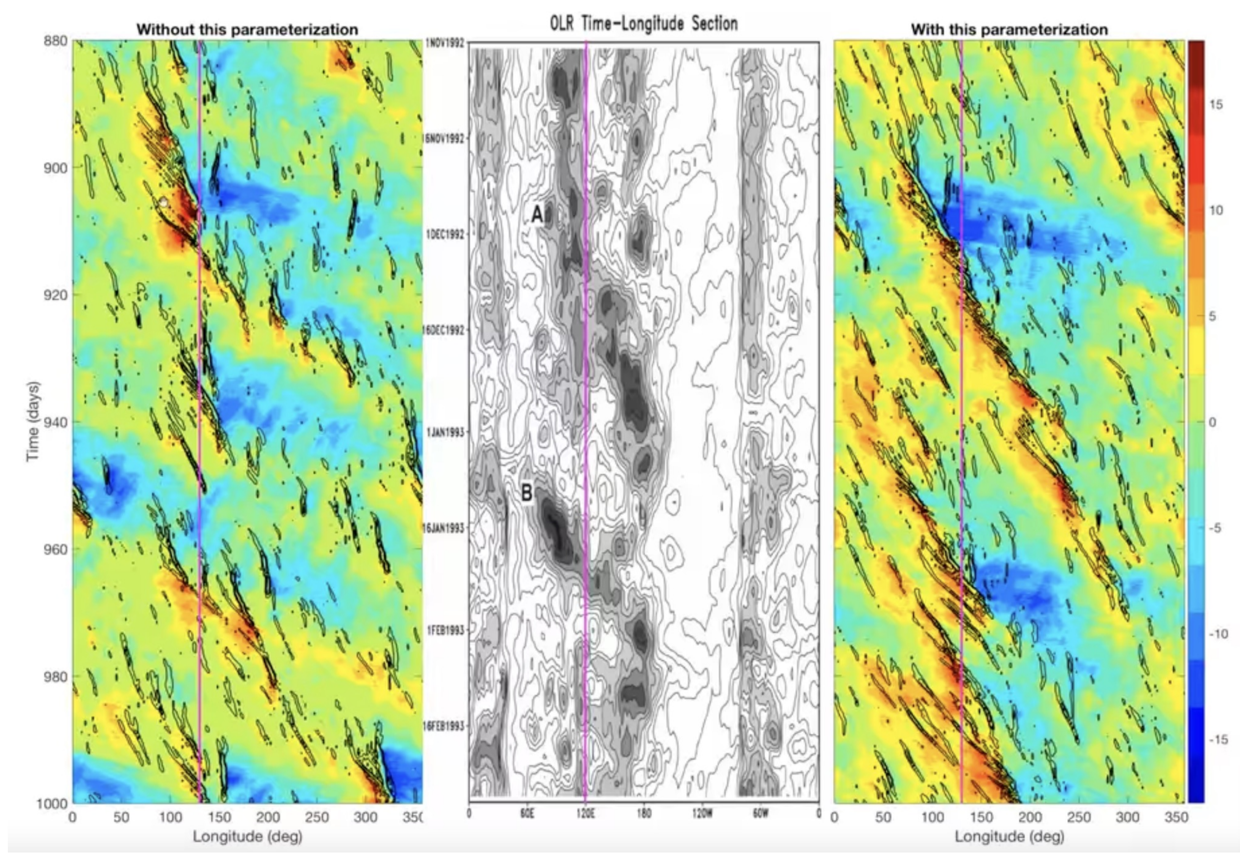
$$\left[\left(\frac{1}{2}\rho_0 u^2\right)_T\right] = \left[\rho_0 \hat{f} v_u\right] + \left[-\left(\rho_0\left\langle w^* u^*\right\rangle^{\rho}\right)_z u\right] + \left[-\left(\rho_0\left\langle w'u'\right\rangle^{\rho}\right)_z u\right] + \left[-\rho_0 p_x u\right] + \left[-\hat{\alpha}\rho_0 u^2\right]$$

The third term on the right hand is evolved productive between the mesoscale, fluctuations, and the appendix goes on the winds. And it has a maximum magnitude and also positive sign, meaning that this term behave like connecting energy source. They can conclude that MCSs are the main contributor to the kinetic energy of planetary-scale organization of tropical convection.
Step 2: Using multi-scale theoretical model.
Mesoscale Equatorial Synoptic Dynamics (MESD) model: It basically consists of two groups of equation. One for the mesoscale, fluctuation, one for the synoptic scale circulation.

Mesoscale fluctuations	Synoptic-scale circulation
$u'_\tau = -p'_{x'}$	$U_t - yV = -P_x - dU - \left\langle \overline{w'u'}\right\rangle_z$
$v'_\tau = -p'_{y'}$	$V_t + yU = -P_y - dV - \left\langle \overline{w'v'}\right\rangle_z$
$\theta'_\tau + w' = s'_\theta$	$\Theta_t + W = -d_\theta\Theta - \left\langle \overline{w'\theta'}\right\rangle_z + S_\theta$
$p'_z = \theta'$	$P_z = \Theta$
$u'_{x'} + v'_{y'} + w'_z = 0$	$U_x + V_y + W_z = 0$

(3)

These eddy terms $\left(-\left\langle \overline{w'u'}\right\rangle_{z'}, -\left\langle \overline{w'v'}\right\rangle_{z'}, -\left\langle \overline{w'\theta'}\right\rangle_z\right)$ are the upscale impact of MCSs on large-scale circulation.
The results show that the upscale impact of westward-moving MCSs at a slow speed provides favorable conditions for eastward propagation of the MJO analog, consistent with theoretical predictions by the multi-scale asymptotic model.
Step 3: Using global climate model. Compare the synoptic-scale circulation and the GCM model, GCMs have too coarse resolutions to explicitly resolve organized tropical convection, so their upscale impact $\left(-\left\langle \overline{w'u'}\right\rangle_{z'}, -\left\langle \overline{w'v'}\right\rangle_{z'}, -\left\langle \overline{w'\theta'}\right\rangle_z\right)$ is missing the parameterization. So their goal is trying to propose a parametrization for those upscale impact from the mesosphere and then add them into the GCM to see whether such edited parametrization will help improve that.

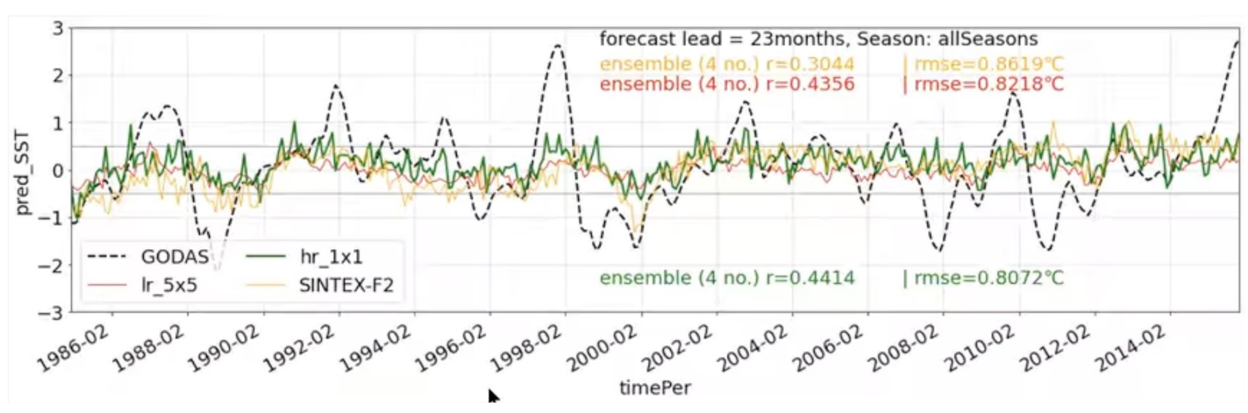


The preliminary results show that the parameterization for the upscale impact of MCSs promotes persistent eastward propagation of the MJO and helps to recover its realistic features of spatiotemporal variability in the GCM.

Lecture 3

Long Lead Predictions of ENSO Using Convolutional Neural Networks

For forcasting ENSO, there are dynamical models and data driven methods.
Dynamical models: Predictability is limited upto one year.
Data driven methods: 1. Traditional statistical - ANN, SVR, RF, Baysian, etc.
2. Latest deep learning - LSTM, CNN, ConvLSTM
Long-lead predictability is poor.
Seasonal ESNO prediction framework: 1. Training Inputs.
2. Convolutional neural network.
3. Hyper-parameter optimization. (Obtaining optimal model and hyper-parameters among 300 trials.)
4. Validation Inputs.
5. Ensembles. (Select 10 best performing models.)
Overall framework: 1. Select season.
2. Repeat seasonal framework.
3. Ensemble prediction for specific season.
4. Combine ensemble predictions from various seasons.
5. Reconstruct Allseason predicted ENSO index.



Conclusion: - Proposed CNN's exhibits higher skills at long leadtimes.
- The higher skills from the proposed CNN's were majorly due to more sub-surface information and hyper-parameter optimization.
- Proposed CNN's were least affected by 'Spring predictability barrier'.
- Changing climate dynamics are seen to to captured.
- Heatmaps suggest that regions contributing to higher skills are in con-current expected precursors.
- Proposed CNN's exhibit higher skills in comparison to dynamical models and past attempts using deep leanring techniques.

Lecture 4

Using Machine Learning to Detect Chaos Terrain on Europa

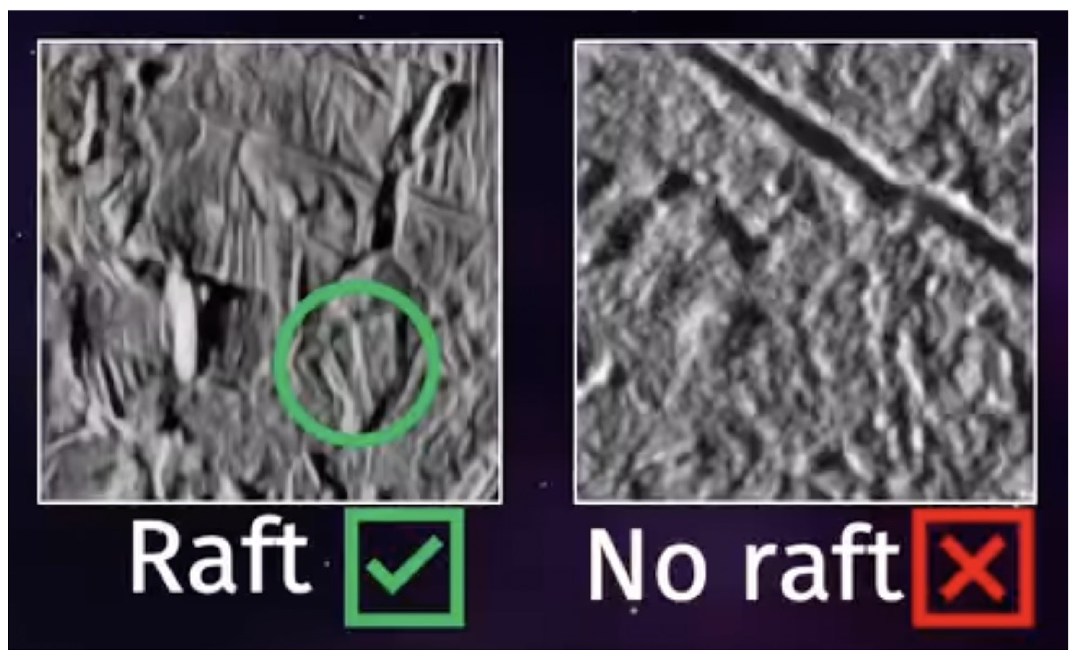
Ice raft: 'Linear-textured polygons' (ice rafts) have (a) 'recognizable linear textures'; (b) A well-defined perimeter; (c) Heavy shadow.
Imaging Processing: They use two steps (normalize and constrast) to process the image and make them easier to test the ice raft.
CNN: Convolutional neural networks are the most common type of machine learning algorithm used for image processing. They are designed to approximate the functionality of a human visual cortex. Sort of them like the human brain and use lavers of transformations and complex Matrix functions to do. So, these have been used in the past for a planetary surface feature studies.
U-nets: U-nets is derived from a CNN architecture and is used for image segmentation. According to the result, it has excellent performance with limited data. In order to solove the computer programing problem, they also use the google cloud platform.
Labeling: Before running anything through a program, labeling the data is necessary. They use labels to create those initial training and testing data sets. So initially they had trace two different versions of images, one is fuzzy label and one is no fuzzy label.

Lecture 4

They useuse the intersection over union as a metric to measure quality.

$$\text{IoU} = \frac{\text{area of intersection}}{\text{area of union}} = \frac{\text{TP}}{\text{TP+FN+FP}}$$

Since the value of IoU is low, this is not an ideal result.
Improved U-net Results: They then moved to using fuzzy labels, but the improvement in performance was initially fairly small. And because the detections were no longer binary, they no longer defined success based on true or false as they did before.
Resnet: This is the tvpe of alaorithm that looks at a picture and says raft or no raft. Based on whether there is a raft in the picture. It's a transfer learning.



One of the issues they had with their images is that there are widely varving resolutions, but with some simple image processing, residents are particularly good at handling discrepancies in image resolution. Each tile gets classified based on how confident the algorithm is that there's a raft. The result has 75% accuracy.