# Technical Talk - PhD Project

Kamal Sharma

Department of Mathematics, University of Hamburg

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Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

# Introduction

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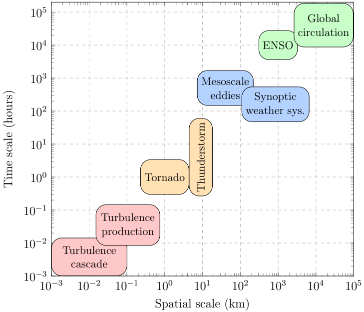
**We are solving stochastic PDEs which model ocean-atmosphere interactions!**

# Introduction

## Why add stochastic terms?

# Multiscale phenomena

- Earth's oceans and atmosphere are characterized by a rich hierarchy of interacting processes




Spatial and temporal scales of various meteorological phenomena[1]

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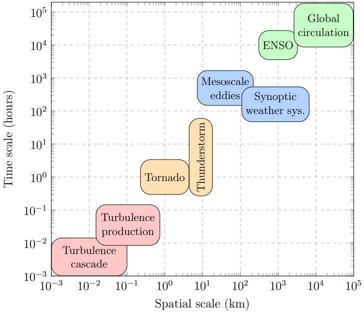


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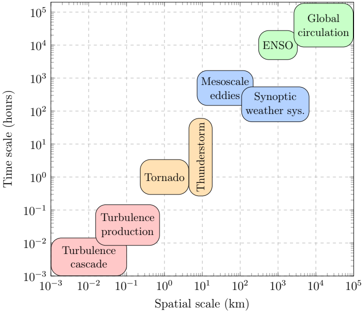


Spatial and temporal scales of various meteorological phenomena[1]

- Numerical models have fixed resolution
- Processes occurring below the model resolution are not captured $\rightarrow$ leads to prediction error!
- **Solution**: Parameterization or subgrid-scale modeling

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# Parameterization

- Additional terms are added to account for the missing effect of unresolved/small scales
- Parameterization techniques can be divided into two categories:
  1. Deterministic
  2. Stochastic
- We explored **stochastic parameterization** : stochastic advection by Lie transport (SALT)
- Why SALT?
  - preserves structure $\rightarrow$ conservation properties still hold
  - better forecast skills $\rightarrow$ uncertainty due to unresolved transport processes can be quantified
  - conducive to data-driven approaches $\rightarrow$ can be estimated from observations/satellite data

# Research objectives

# Objectives

1. Explore the efficacy of stochastic parameterization (in terms of UQ skills) for a climate model
   - Previous studies focused on Euler, quasi-geostrophic, and shallow water equations
2. Numerically solve the idealized stochastic climate model
3. How to model the noise/stochastic term effectively?
4. Compare the stochastic model results with other existing models/approaches

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# The climate model

# Model equations

2D climate model equations:

$$\text{Atmosphere}: \mathrm{d}\mathbf{u}^a + ((\mathbf{u}^a \mathrm{d}t + \sum_i \xi_i \circ \mathrm{d}W^i) \cdot \nabla)\mathbf{u}^a + \frac{1}{Ro^a}\hat{\mathbf{z}} \times (\mathbf{u}^a \mathrm{d}t + \sum_i \xi_i \circ \mathrm{d}W^i)$$

$$+ \sum_i (u_1^a \nabla \xi_{i,1} + u_2^a \nabla \xi_{i,2}) \circ \mathrm{d}W^i = (-\frac{1}{C^a}\nabla\theta + \frac{1}{Re^a}\Delta \mathbf{u}^a)\mathrm{d}t,$$

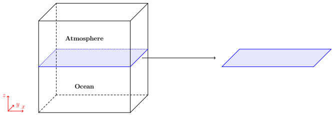
$$\mathrm{d}\theta^a + \nabla \cdot (\theta^a(\mathbf{u}^a \mathrm{d}t + \sum_i \xi_i \circ \mathrm{d}W^i)) = (\gamma(\theta^a - \theta^o) + \frac{1}{Pe^a}\Delta\theta^a)\mathrm{d}t,$$

$$\text{Ocean}: \frac{\partial \mathbf{u}^o}{\partial t} + (\mathbf{u}^o \cdot \nabla)\mathbf{u}^o + \frac{1}{Ro^o}\hat{\mathbf{z}} \times \mathbf{u}^o + \frac{1}{Ro^o}\nabla p^a = \sigma(\mathbf{u}^o - \mathbb{E}\mathbf{u}^a_{sol}) + \frac{1}{Re^o}\Delta \mathbf{u}^o,$$

$$\nabla \cdot \mathbf{u}^o = 0,$$

$$\frac{\partial \theta^o}{\partial t} + \mathbf{u}^o \cdot \nabla \theta^o = \frac{1}{Pe^o}\Delta\theta^o.$$

Incompressible/compressible Navier-Stokes + Advection-diffusion eqs.




Model domain

$\mathbf{u}$ : velocity,
$\theta$ : temperature,
$p$ : pressure

# How to get the stochastic terms?

- Difference between Lagrangian trajectories at different resolutions:

$$\sum_i \xi_i \, \mathrm{d}W^i \approx \mathbf{u}_{true} \, \mathrm{d}t - \mathbf{u} \, \mathrm{d}t$$

$\mathbf{u}_{true}$ : true velocity
$\mathbf{u}$ : mean flow velocity i.e. the large-scale component of $\mathbf{u}_{true}$

- Ways to estimate the true velocity $\mathbf{u}_{true}$:
  1. Observation data (for example, from satellites)
  2. Synthetic data (from high-resolution numerical simulations)

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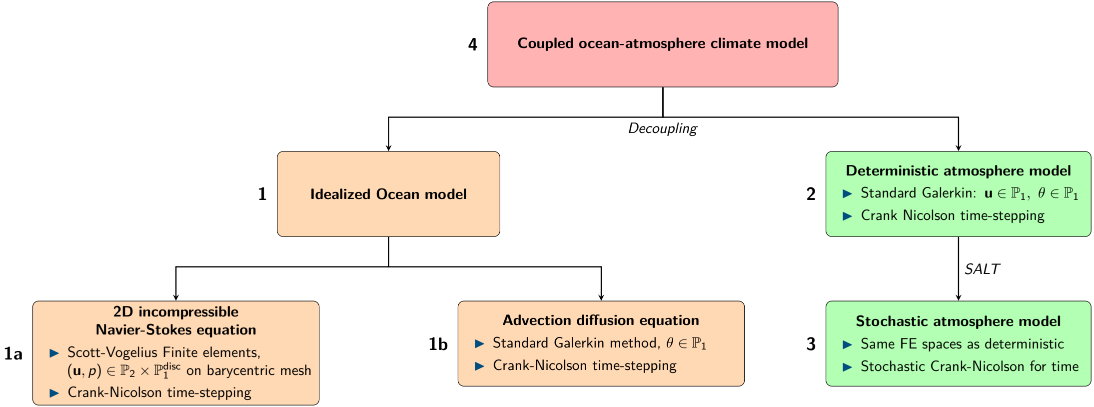
- **We use synthetic data!**

# Our methodology

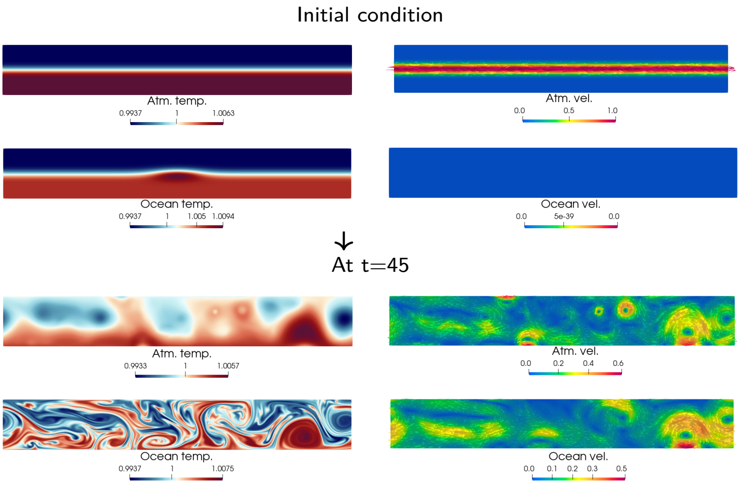



We used an open-source Python Finite Element package for numerical implementation and simulation

# Numerical simulation of the climate model

# Deterministic model simulation and model calibration

- We run the climate model in high-res. ($\Delta x = 1/128 \sim 30$ km) for 45 time units ($\sim 25$ days)



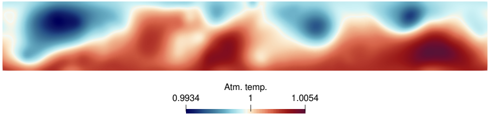

- Analyze data $\rightarrow$ extract small-scale features (using statistical algorithms) $\rightarrow$ obtain $\xi_i$

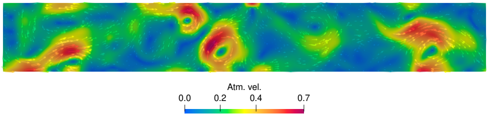
# Numerical simulation of the climate model

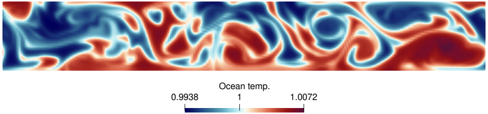
## Stochastic model simulation

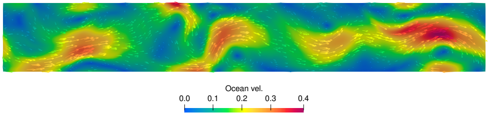
# Stochastic model simulation

- We run the stochastic model on a coarse grid ($\Delta x = 1/32 \ \sim 120$ km)
- Initial conditions correspond to coarse grained velocity and temperature fields at $t = 25$

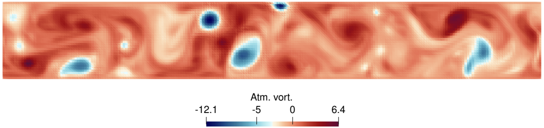


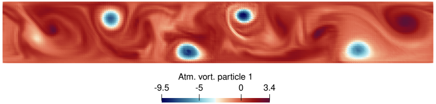

Atmospheric vorticity at $t = 25$



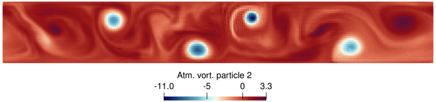
# Simulation results

- Stochastic model is simulated for 20 time units ($t = 25$ to $t = 45$)
- Stochastic vs. deterministic (without parameterization) model results at $t = 35$

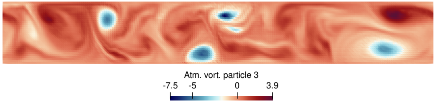
Particle 1



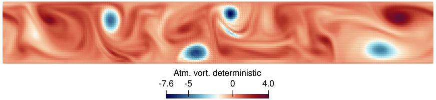

Particle 2



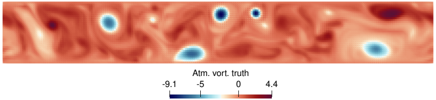

Particle 3




Deterministic solution



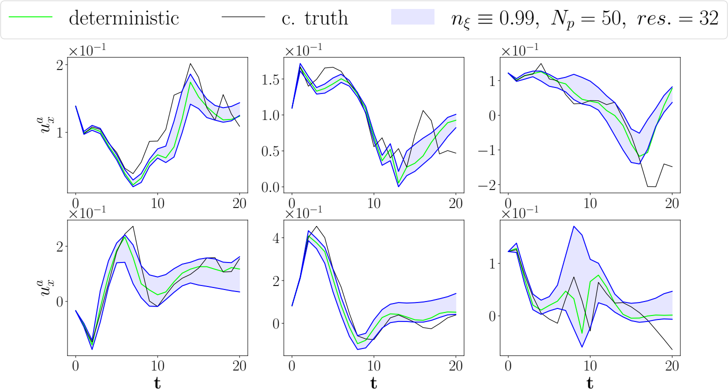

**True solution**



# Simulation results

- Comparison between the stochastic ($\mu \pm 1\sigma$) and deterministic sol. at 6 grid points:

**Atmospheric velocity** ($x$ component)

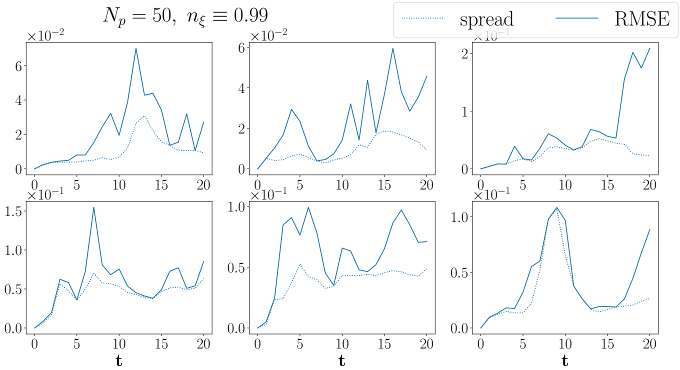



1. Ensemble spread increases over time
2. Stochastic model captures the truth for 5 to 10 time units

# Uncertainty quantification

- Plots for the evolution of ensemble spread and RMSE at six different locations on the grid

**RMSE vs. spread** for $u_x^a$




- The size of ensemble spread is proportional to the RMSE (for at least 15 time units)
- Error in the stochastic solution can be estimated by its own spread
  - SPDE solution is suitable for data assimilation methods!

# Summary

# Summary & outcomes

- Aim: solve a stochastic coupled ocean-atmosphere climate model
- Novelty: Data-driven model
  - stochastic terms (modelling unresolved processes) are obtained from observation data
  - has desired properties: structure-preservation
  - We used high-res. model sim. data to estimate $\xi_i$ $\rightarrow$ data analysis & statistical modelling
- Methodology for solving the model equations:
  - Solve simpler models first
  - build the climate model step-by-step
  - verify numerical schemes at each step
- Results:
  - Stochastic model solution capture the truth for some time units
  - Shows promising UQ test results: ensemble spread size $\propto$ RMSE
- Outcome: first step towards using SALT in a highly complex coupled system!

Thank you for your attention!