Kinematic Representation of Ocean Eddy

Student: Dongwon ‘DW’ Han **Advisor**: Dr. Elaine Spiller

Department of Mathematics, Statistics and Computer Science – Marquette University

Introduction

Ocean processes play an important role in local and global environments. Because of inherent complexity of these processes, scientists study them with using numerical simulations. Computational Fluid Dynamics, CFD, provides the most realistic simulations, but are computationally expensive. Kinematic Models, KM, are easy to evaluate, but can not capture the same level of complexity. In this project, we compare KM to the CFD. Also we try to improve KM using particle filter and random function method.

Models

- **Computational Fluid Dynamic (CFD):** A system of partial differential equations solved numerically
- **Kinematic Model (KM):** A set of velocity functions (u,v,w) of parameters $(x,y,z,\alpha,\beta,\varepsilon_1)$

The Can Problem

- In ocean eddies, spiraling fluid is commonly observed
- Ocean eddy is modeled as a rotating cylinder with a differential rotating lid
- Rotating lid simulates a cyclonic wind pressure at the surface

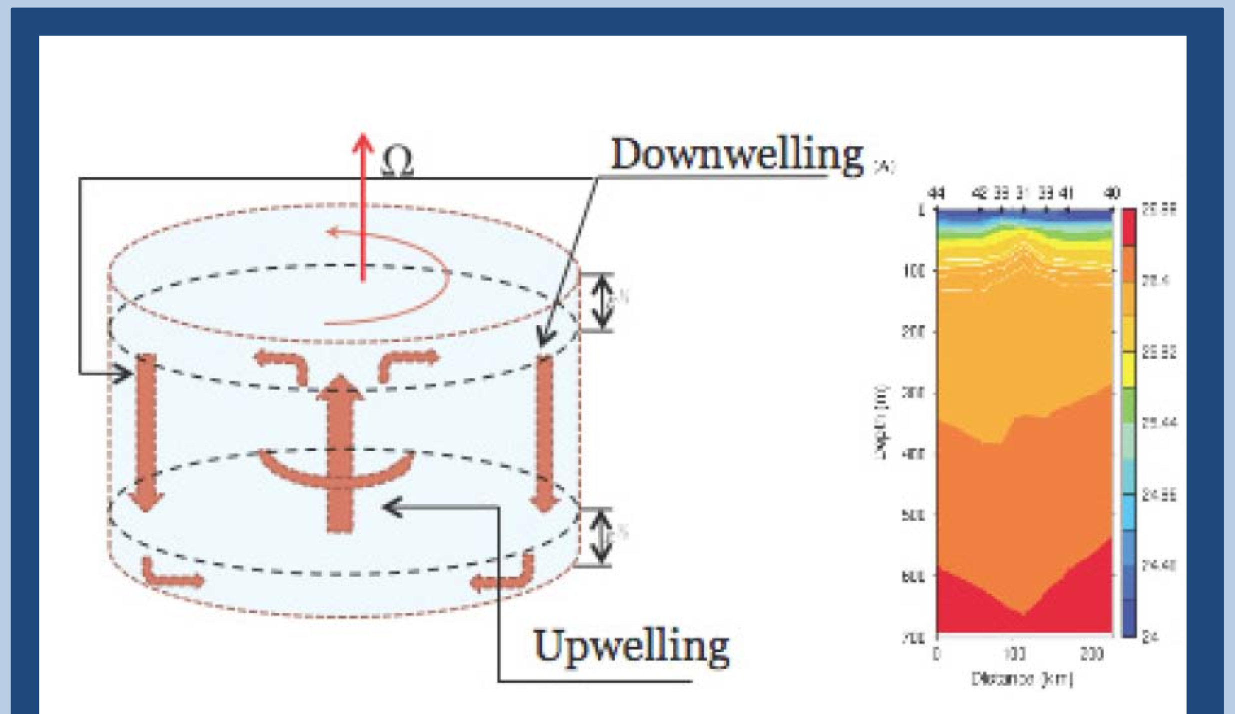

Figure 1: Image of the rotating can. On top, the rotating lid forces fluid outwards until it reaches the side wall, where the fluid is redirected downward. In the interior of the can, a cyclonic circulation recycles the fluid from the bottom and deliver it to the top. (Image Source: [1])

Method 1: Particle Filter

- A systemic method to optimize the model parameters
- Optimizes parameters α, β, and ε_1
- Rewards samples, or “particles”, that closely follow the observation.

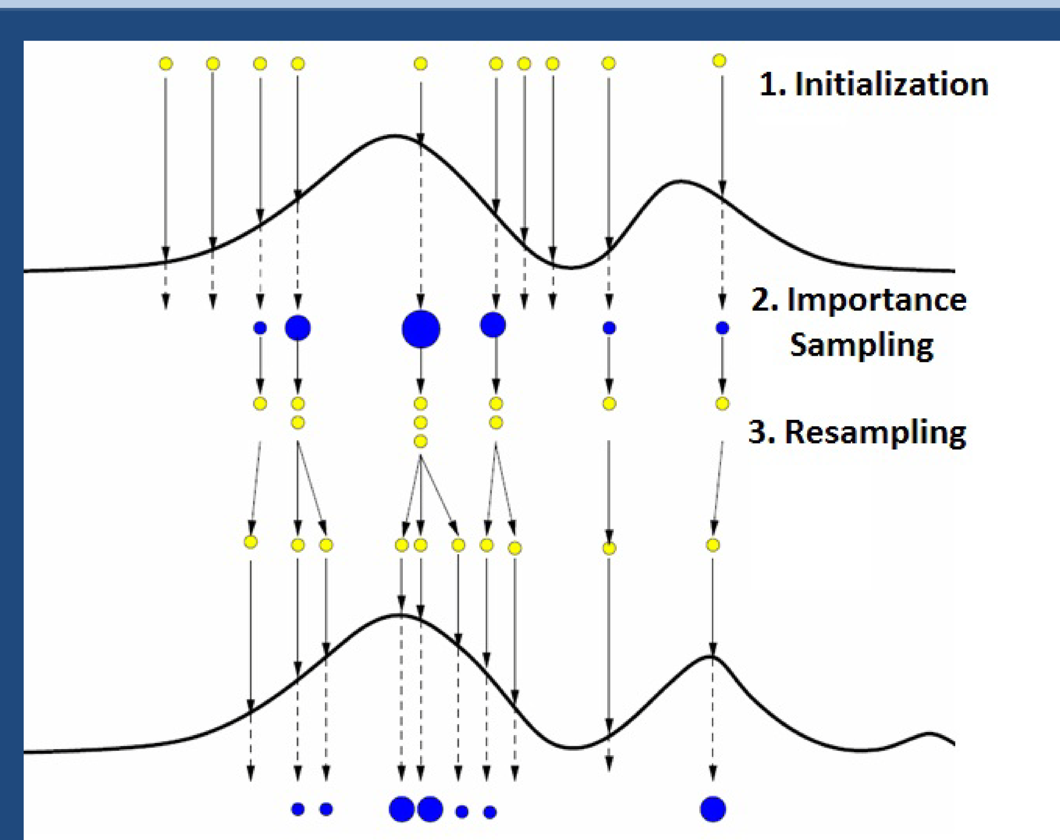

Figure 2: A diagram depicting particle filter algorithm.

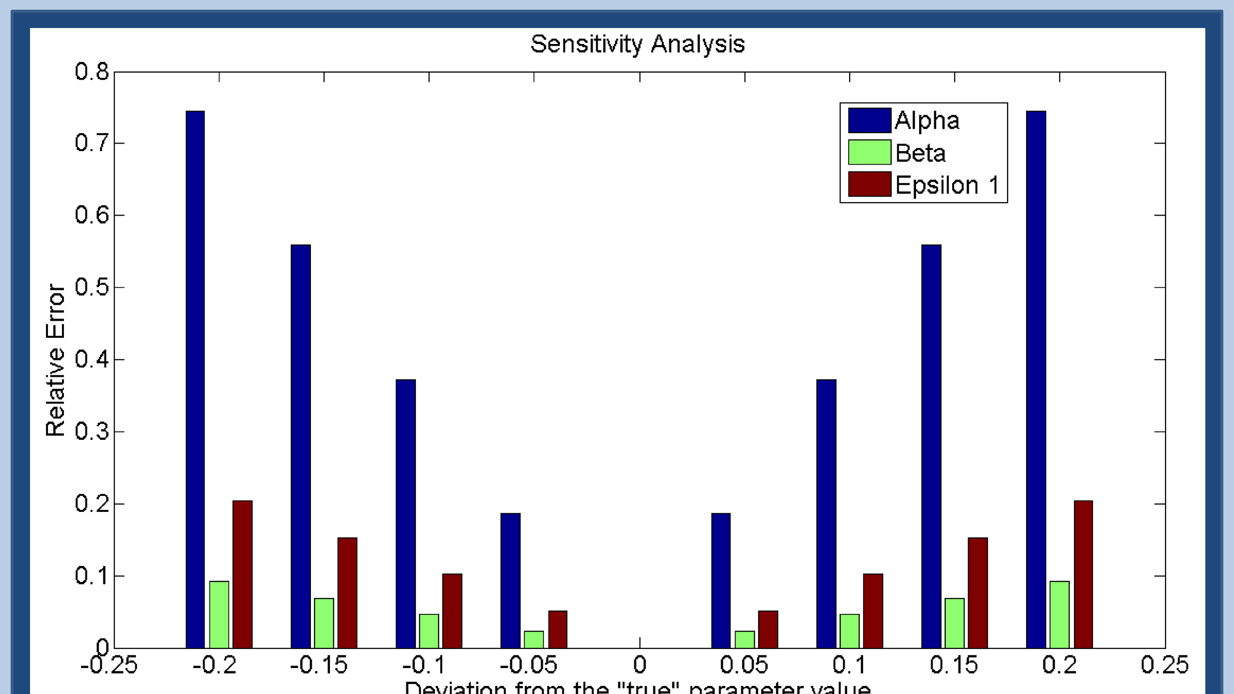

Figure 3 : Sensitive analysis shows how sensitive model output is to change in different parameters. “Truth” run is generated with the following parameters: $\alpha = 0.35$, $\beta = 1$, and $\varepsilon_1 = 0.45$.

Method 2 : Random Function method

- Model Error = CDF Prediction – KM Prediction
- Use random function method to “tune” a bias function
- A bias function estimates model error (Error ≈ Bias)
- Improved prediction = KM Prediction+ Model Bias

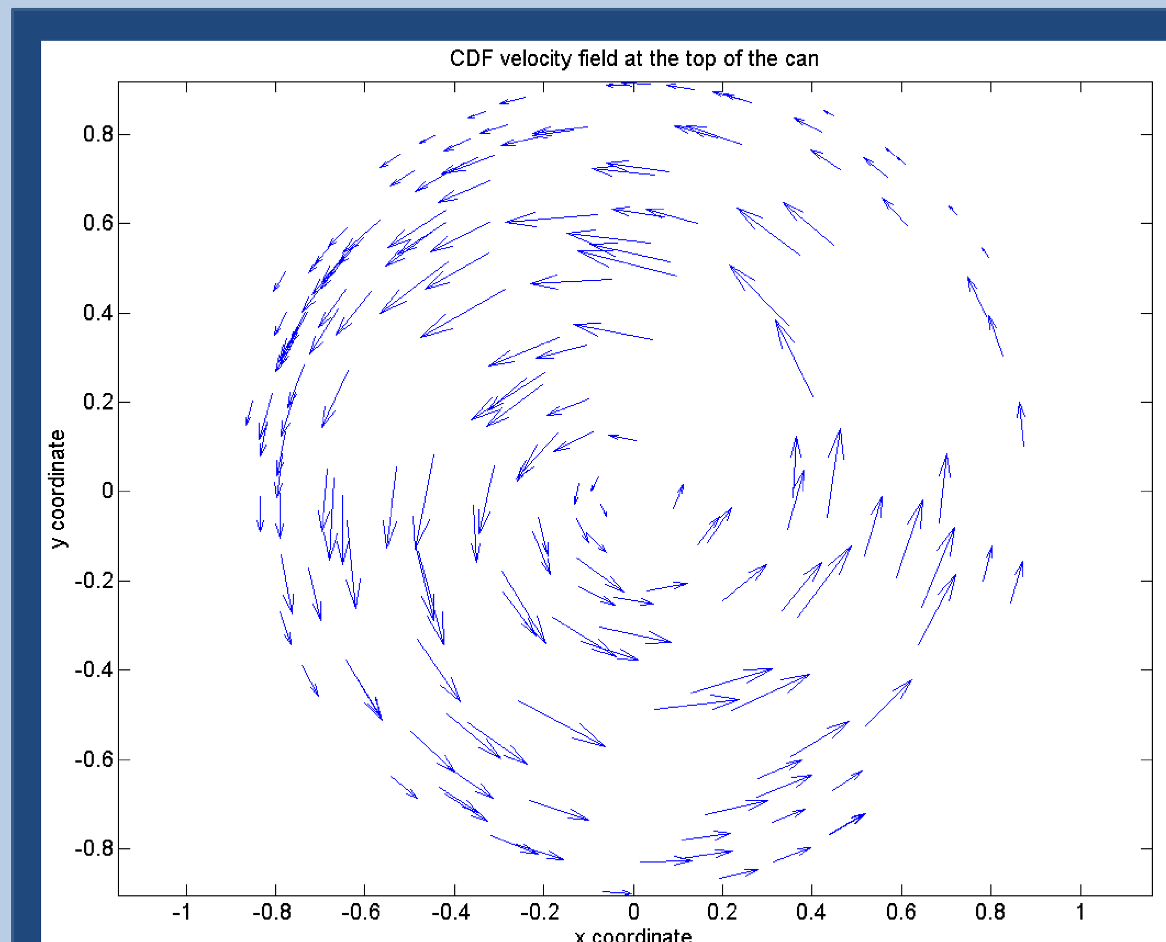

Figure 4: CFD velocity field, z > 0.8, projected on the top of the can.

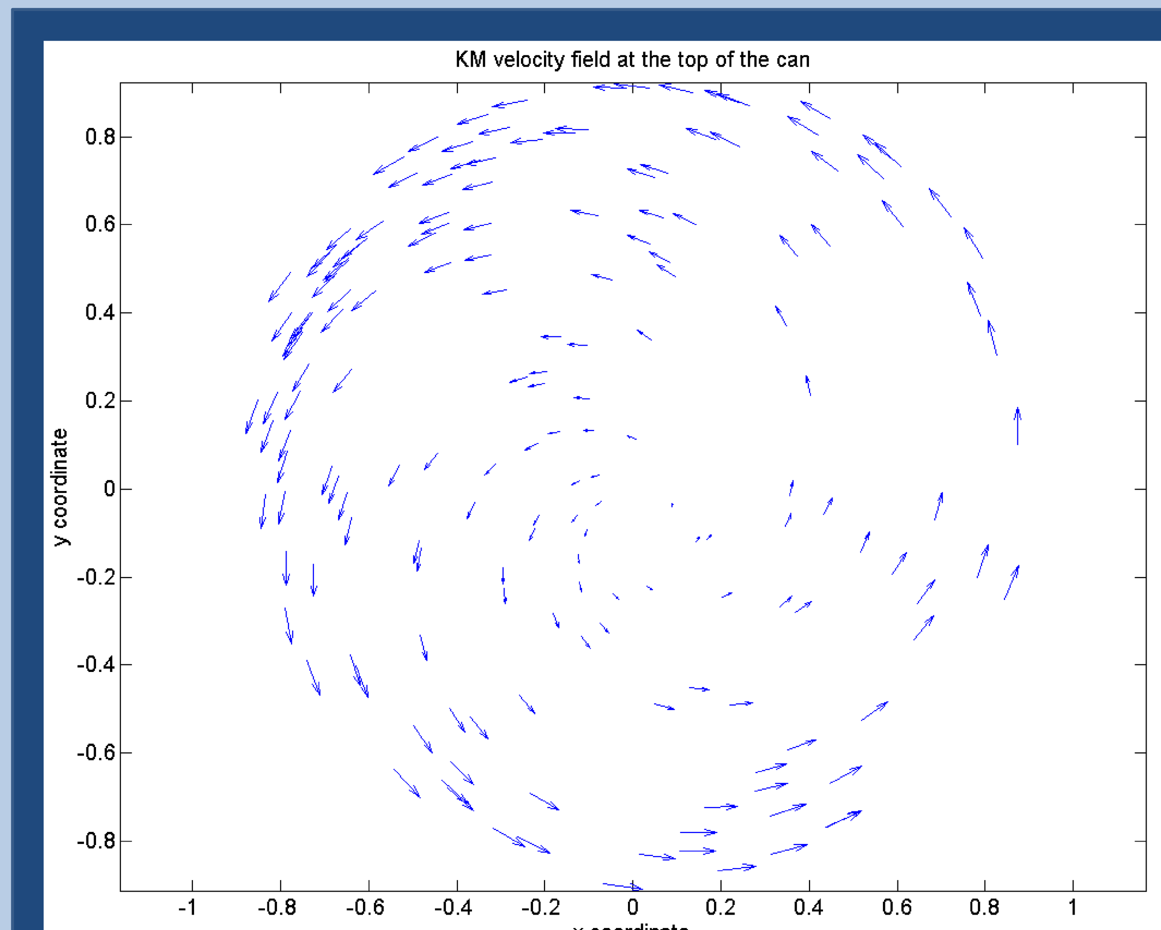

Figure 5: KM velocity field, z > 0.8, projected on the top of the can.

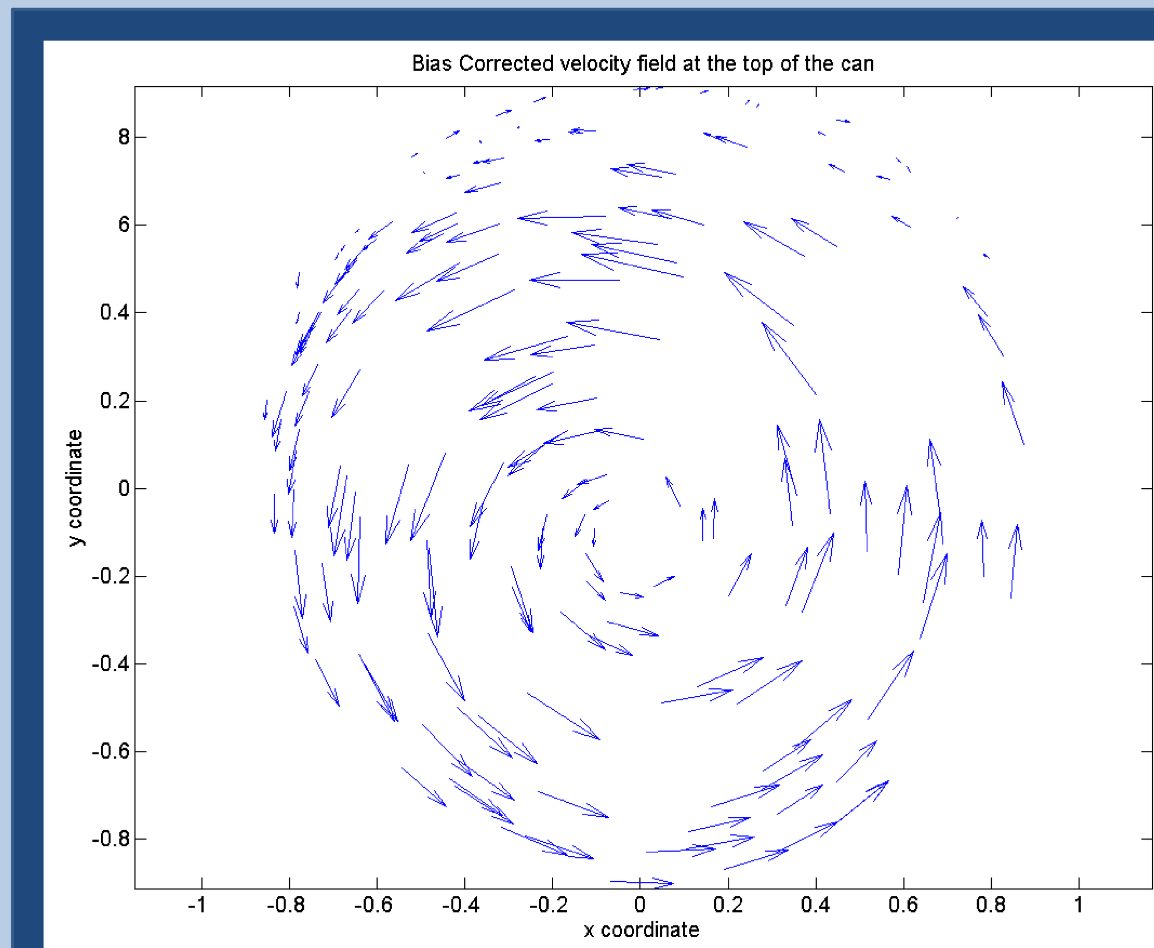

Figure 6: Bias Corrected velocity field, z > 0.8, projected on the top of the can.

Summary and Discussion

Finding

- Without a correction, KM has a significant error.
- Error is most visible on the sidewall and the top of the can
- α is the most important parameter in KM
- Bias correction, using Random Function, improves model prediction.
- Parameter optimization, using Particle Filter, is unsuccessful.

Problems

- Due to the scarcity of CFD samples, Random Function is not optimal
- Bias correction introduces boundary problem
  - Water particles leave the can

Reference

[1] Larry Pratt. The Rotating Can Problem. November 2011.
[2] Larry Pratt, Tamay Ozgokmen, Yana Bebieve, and Irina Rypina. The Rotating Can Flow.
[3] Jerome Sacks and William J. Welch. Design and Analysis of Computer Experiments. Lecture: Summer School on Computer Models and Geophysical Risk Analysis, August 2010.
[4] Elaine Spiller. Monsoon Summer School Lecture Notes on Data Assimilation. July 2011.