GODAE OceanView International School

New Frontiers in Operational Oceanography

2-13 October 2017, Club Pollentia Resort, Mallorca, Spain.

New frontiers in ocean circulation modelling

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About the lectures

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Lecture #1 : Ocean circulations models : scope, usage and fundamentals.

- Thursday: 11:45-12:30

Lecture #2 : Representation of physical processes ocean circulation models

- Saturday: 9:45-10:30

Lecture #3 : Towards data-driven, probabilistic ocean circulation models

- Saturday: 11:45-12:30

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Slides of the lectures :

https://github.com/lesommer/2017-lectures-godae-ocean-view

Book chapter :

https://github.com/lesommer/2017-book-chapter-godae-ocean-view

Lecture #1

Ocean circulations models : scope, usage and fundamentals.

Ocean circulation models

- are based on **first principle physics**;
- are used for a **wide range of applications**;
- are a key **building block of operational oceanography**;
- require **group effort and collaborations** over long time scales.

We have also learned that :

- **subgrid closures are rate controling** components of ocean models;
- **numerical discretization is a key** aspect of ocean circulation modelling;
- besides the numerical kernel, **interfaces are also important** (forcing function, coupling interfaces, etc…)
- ocean models are now (arguably) **able to describe mesoscale motions at global scale**;
- new frontier : **submesoscale-permitting modelling at global scale**.

Lecture #2

Representation of physical processes ocean circulation models

- ocean circulation models are **continuously increasing the range of physical processes** they account for;
- but defining objectively **what fraction of ocean variability is adequately represented** in ocean model solution is difficult;
- the **notion of effective resolution** is a simple (simplistic ?) concept that serves as a rationale for separating resolved and unresolved scales in ocean models;
- Interaction with **computer scientist and applied mathematicians will be essential** to further increasing the range of scale resolved in ocean models (schemes, HPC, …)
- the design of **SGS closures is a key activity** of ocean model design but (1) this is not an easy task (2) the problem is not that well posed (average ?, LES, RANS ?)
- the **coupling with third party models** is likely to become a natural way for ocean circulation model to account for certain classes of physical processes

Lecture #3 :

Towards data-driven, probabilistics ocean circulation models

Topics covered

- the **ill-posed nature of deterministic** geoscienctific modelling
- **stochastic closures** in ocean circulation models
- **stochastic modelling** to deal with various sources of uncertainties
- **ensemble simulations** in ocean circulation modelling
- the Bayesian framework for **dealing with uncertainty in models**
- **data-driven development** of ocean circulation models
- ocean modelling at the age of **data science**

Outline of Lecture #3

Part 1. Stochastic modelling in ocean circulation models

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Part 4. Towards data-driven ocean modelling

Part 1.

Stochastic modelling in ocean circulation models

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- Stochastic parameterizations seem in particular well suited to the representation of **the cross scale exchanges of energy and momentum** for SGS balanced turbulence (in particular energy backscatter)
- notable improvment of Gulf stream dynamics have also been obtained through the stochastic representation of upscaling due to the **nonlinear** nature of the **equation of state** of sea-water.

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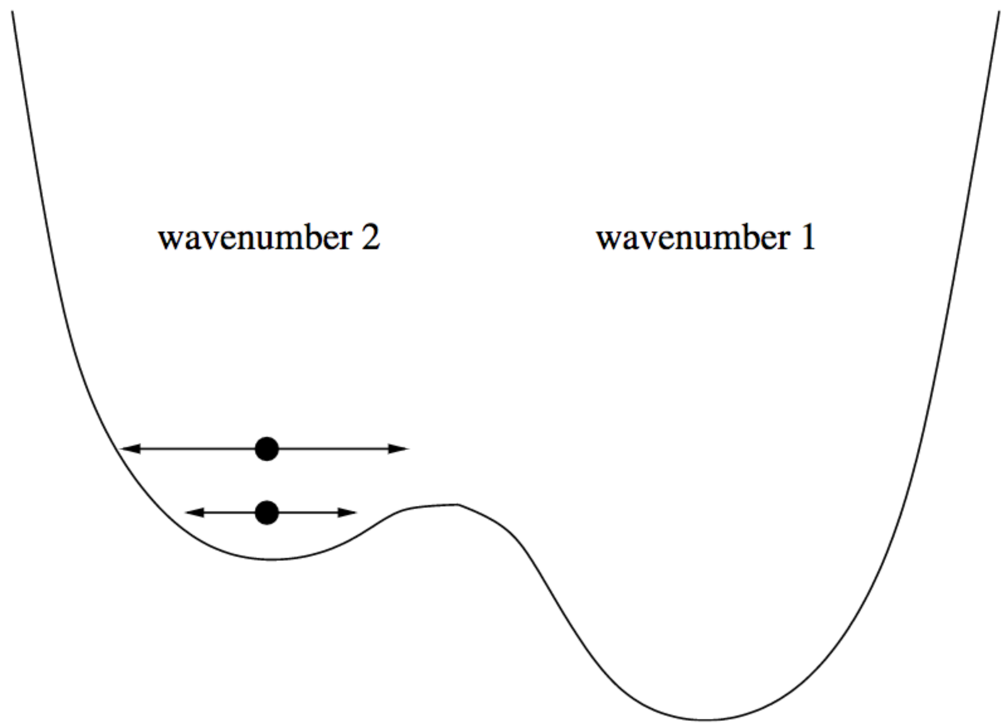
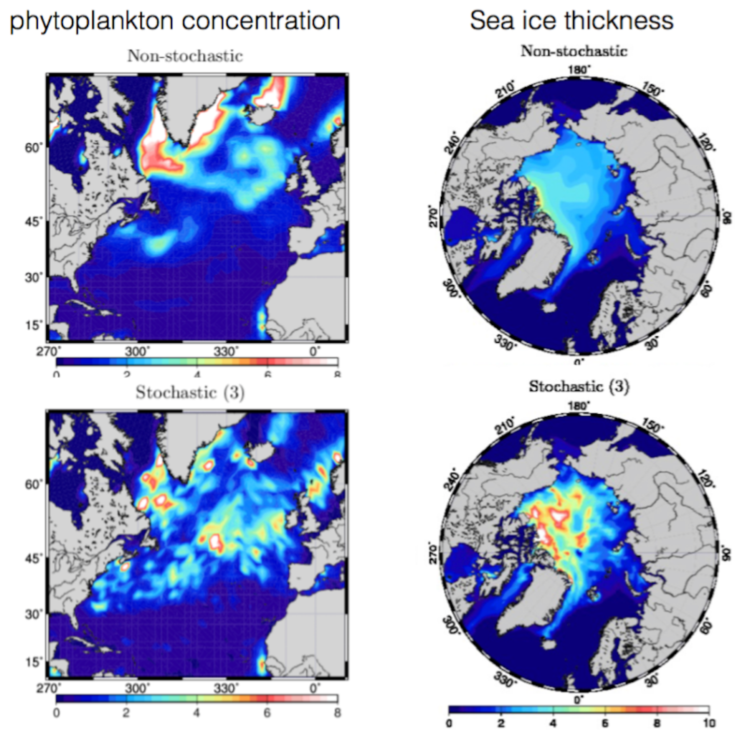


The idea is that **perturbations could allow your system to escape from local potential wells** and therefore explore more reliably the range of possible states.

Range of applications of stochastic ocean modelling

Stochastic approaches are therefore not limited to the representation of subgrid processes, they have been suceesfully applied to account for :

- the **uncertainty** in sea ice model parameters
- the **uncertainty** in biogeochemical models parameters



Brankart et al. (2015)

Part 2.

Uncertainty in ocean circulation modelling

Multiple sources of uncertainty in ocean models

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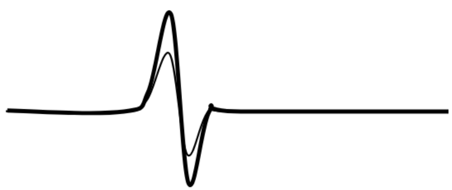
Overall, **uncertainty is a major property of ocean circulation models** that physicists tend to neglect to often.

The complex nature of numerical discretization errors

- numerical discretization errors can be classified in two categories :



dissipative errors affect the amplitude

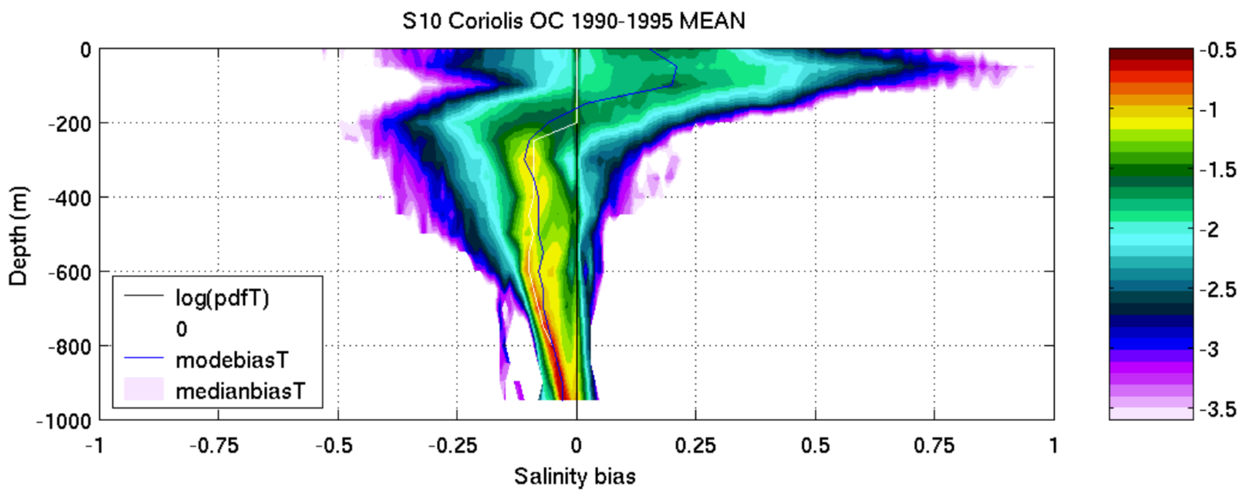
dispersion errors affect the phase of the solution

- numerical discretization errors may **propagate spatially** in the solution
- numerical discretization errors may **accumulate over time**

after integration over long times, **numerical discretization errors can show complex patterns**.

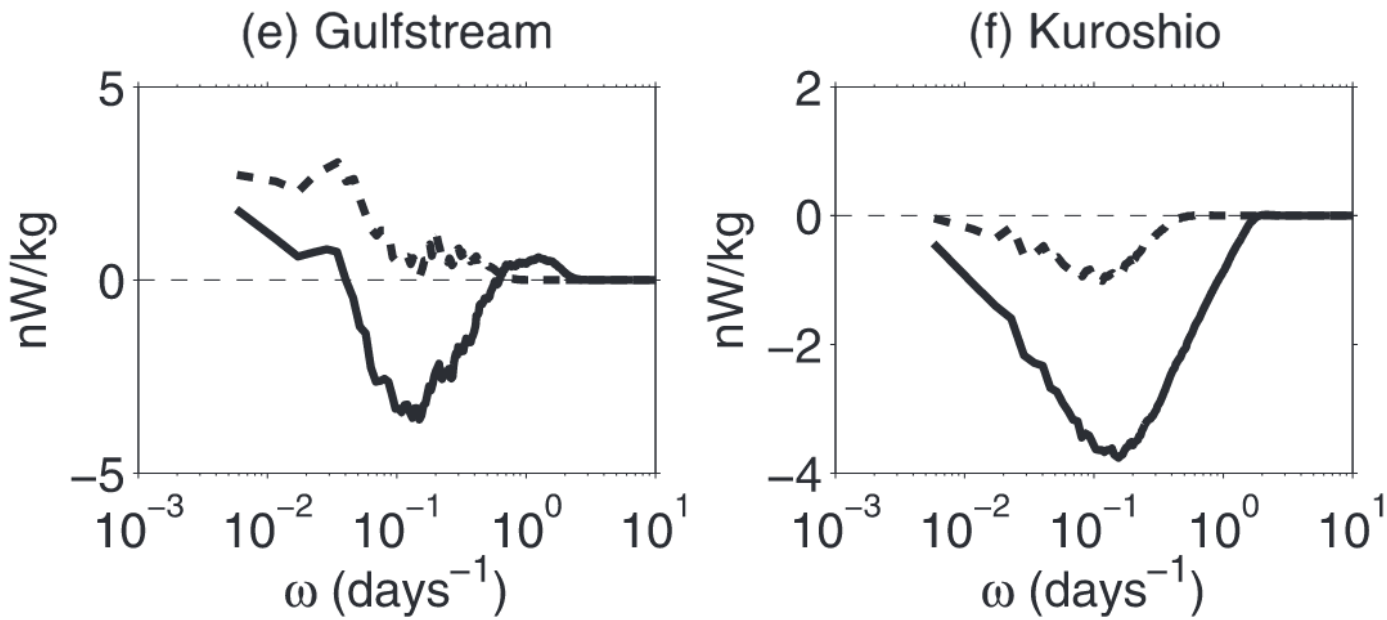
Practical expression of errors in ocean model solution

(Melet et al.)



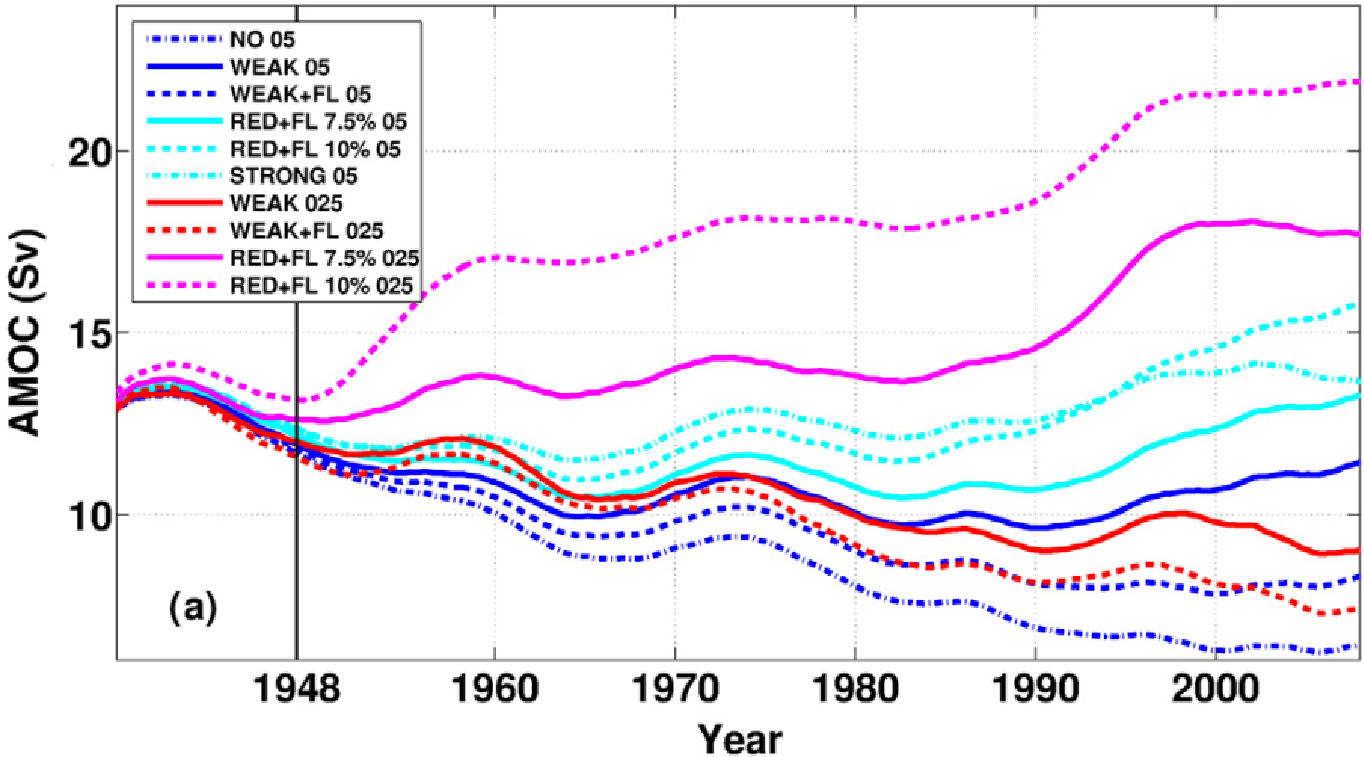
- In practice, ocean model error manifest itself through the **time-mean state** of the model solution, its **trend** at its **variability** at all time scale.
- Model errors are also usually **correlated both in space and in time** (see above).
- Model error is usually due to a combination of different factors

Example 1 : the phase of mesoscale eddy variability



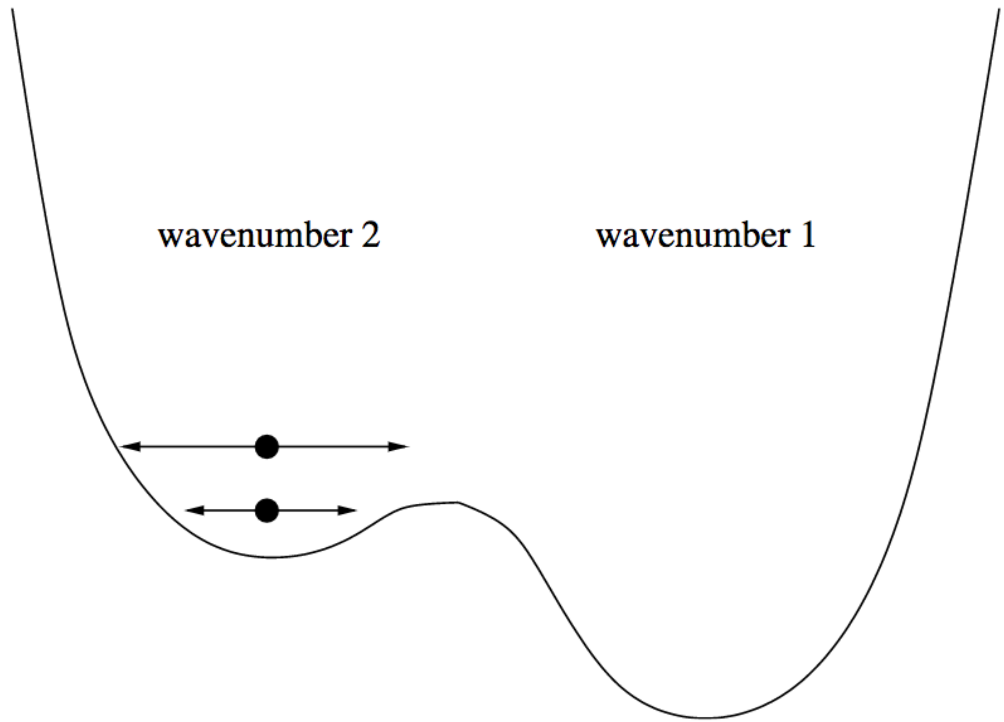
- the **phase of mesoscale** variability is obvioulsy **not predicted** by forced, non-assimilated ocean models.
- but implicitely, it is tempting to think that the phase of mesoscale flow features is not affecting too much the low frequency variability.
- Arbic et al. (2012) have shown that energy cascades in time to long time scales so that the phase of **mesoscale may actually affect long time scales**…

Example 2: AMOC in forced ocean models



- A key prediction that is expected from ocean models is **how the atlantic meridional overturning circulation (AMOC) varies** in time.
- Behrens et al. (2013) have shown that although the interannual variability of the AMOC is rather predictable, **surface salinity restoring is a major control** of the decadal trend of AMOC.

Multimodality of ocean states



- The **topology of the phase space of non-linear system** can be rather complicated, possible showing muliple possible local energy minima.

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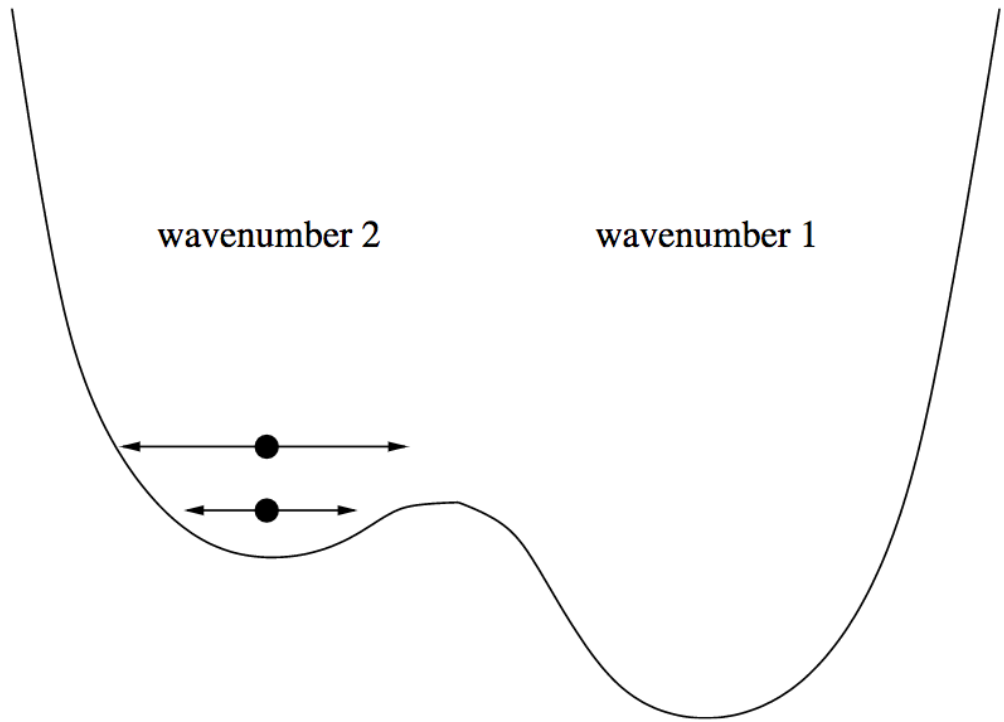
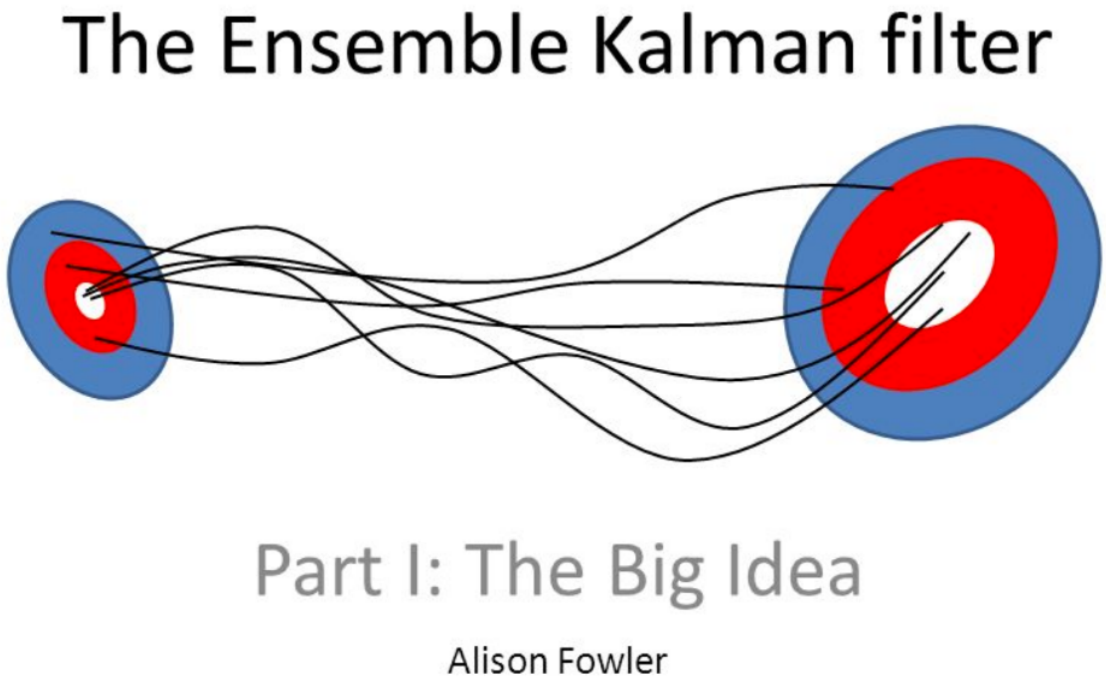


- The **topology of the phase space of non-linear system** can be rather complicated, possible showing muliple possible local energy minima.
- Deshayes et al. (2013) found in a global model that the freshwater transport in the southern atlantic was such that the **AMOC could be unstable to forcing perturbations**. *but can we trust this model prediction ?*

Part 3.

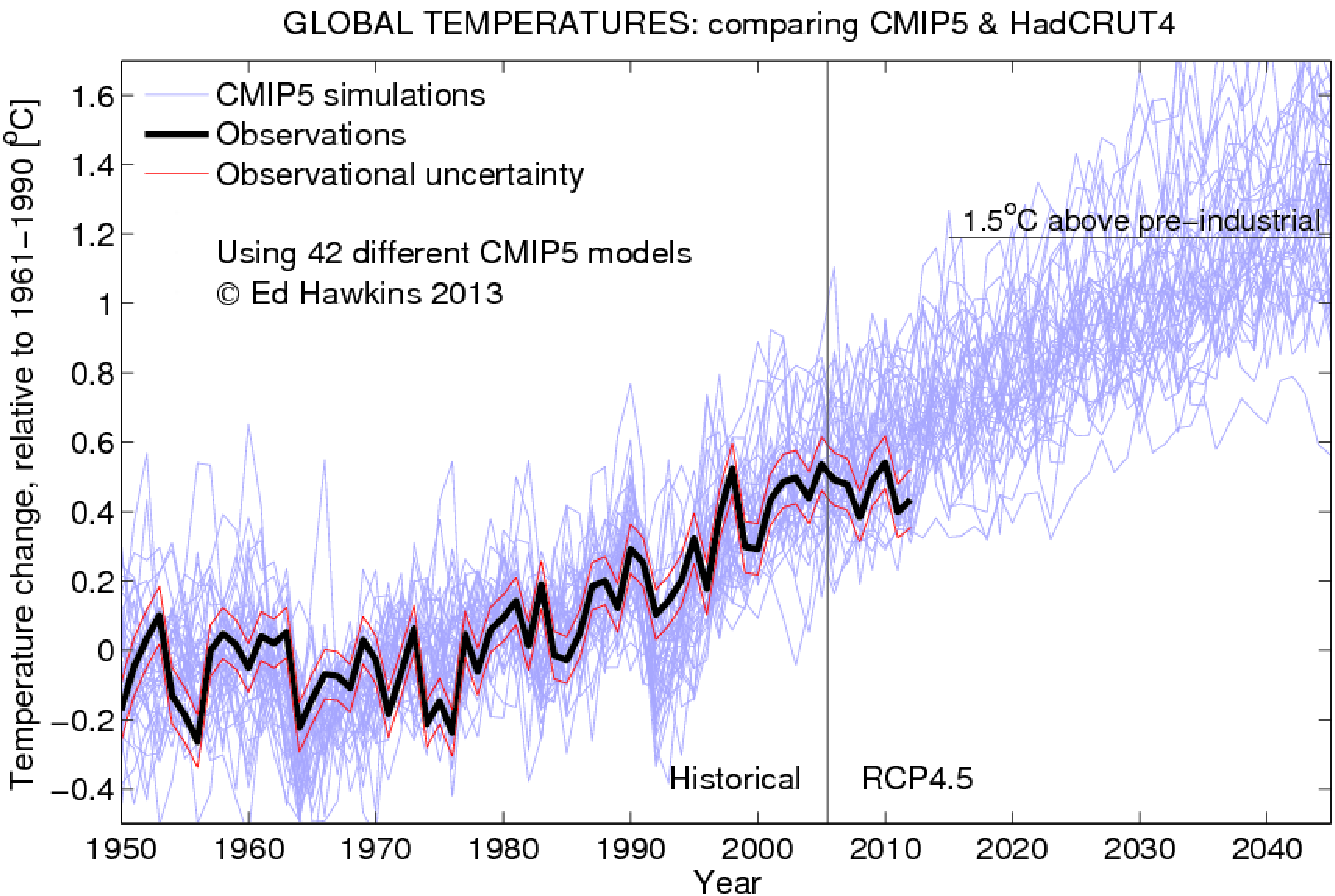
Probabilistic ocean modelling with ensemble simulations

Ensemble simulation in data assimilation



Ensemble modelling is used in data assimilation for sampling the possible likely states of the system.

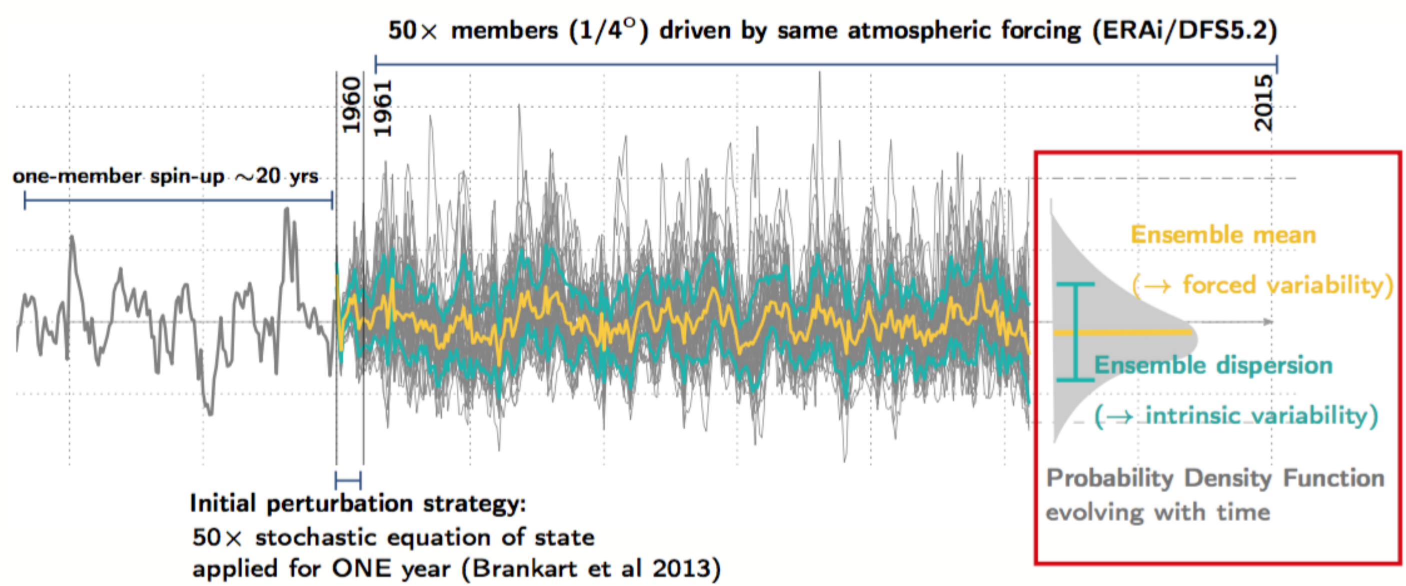
Ensemble simulation in climate modelling



Ensemble modelling is climate projections in order to reduce the uncertainty associated with spurious individual model bias/sensitivity.

Intrinsic ocean chaos revealed by ensemble simulation

The OCCIPUT ensemble of global eddying ocean model solutions



this set of simulation allows to investigate wjat fraction of oceanic variability is **governed by the atmosphere** versus the spontaneous **variability due to oceanic chaos**

see the posters by **Stephanie Leroux** and **Ixetl Garcıa Gomez**.

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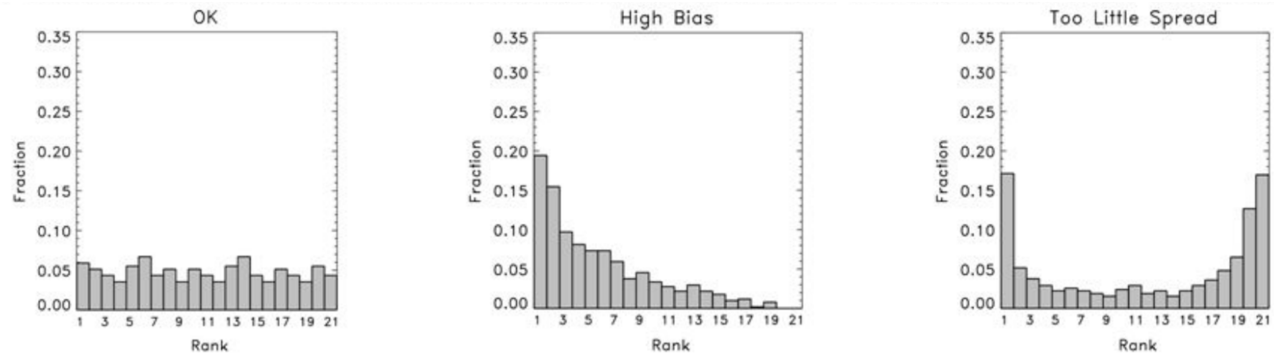
example : Rank histograms and model reliability



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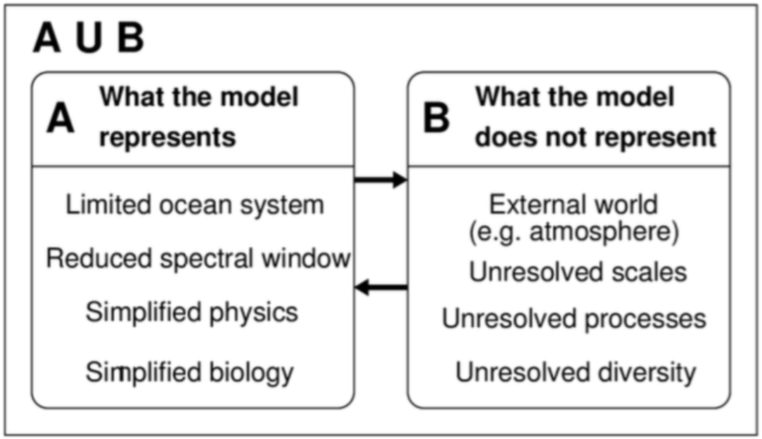

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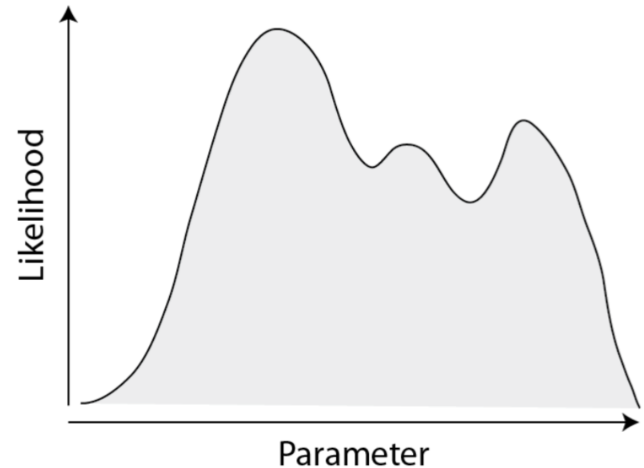

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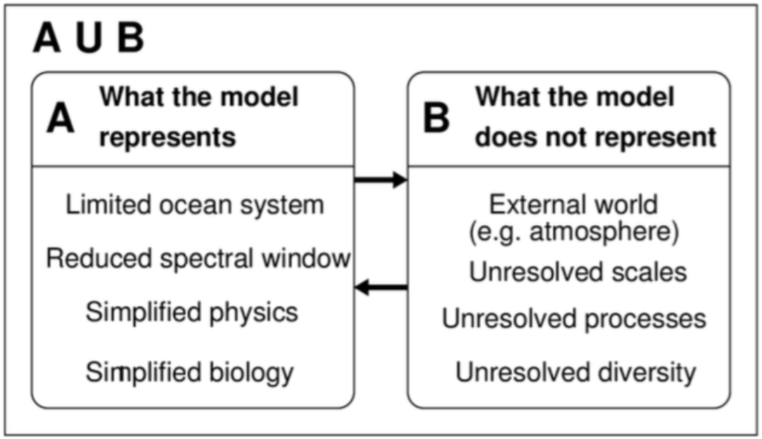

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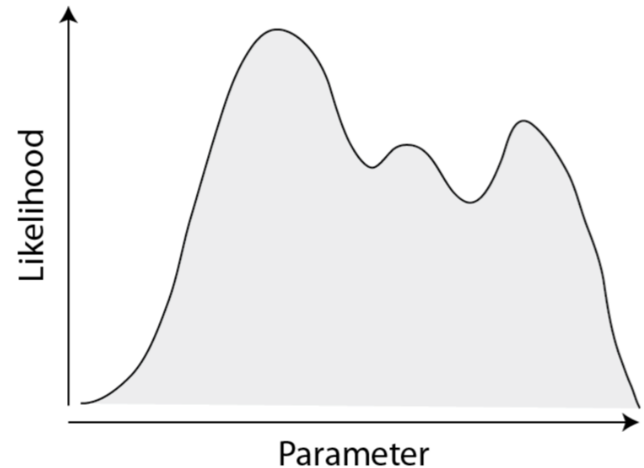

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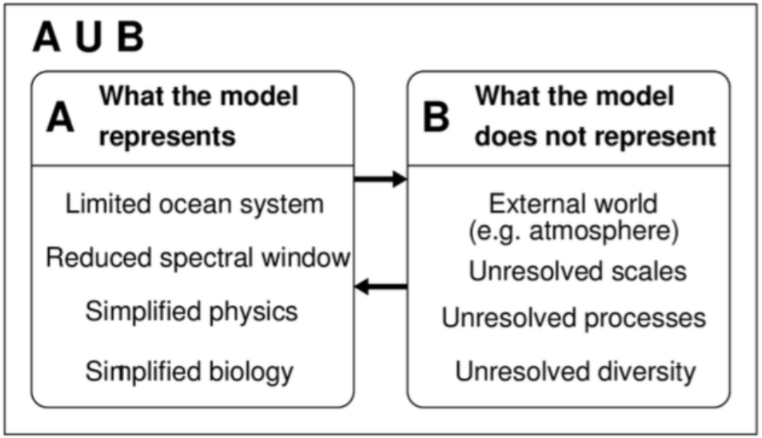

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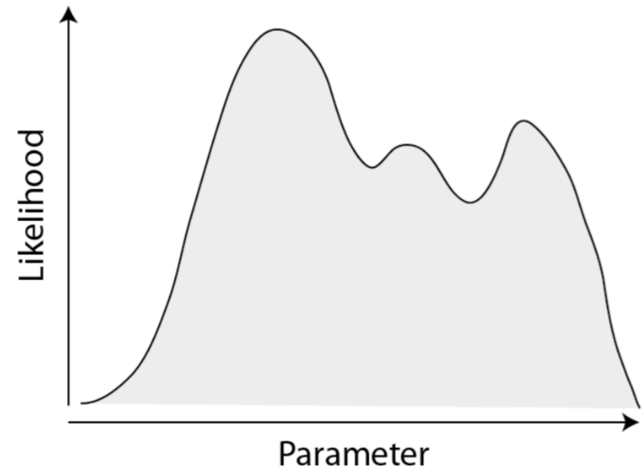

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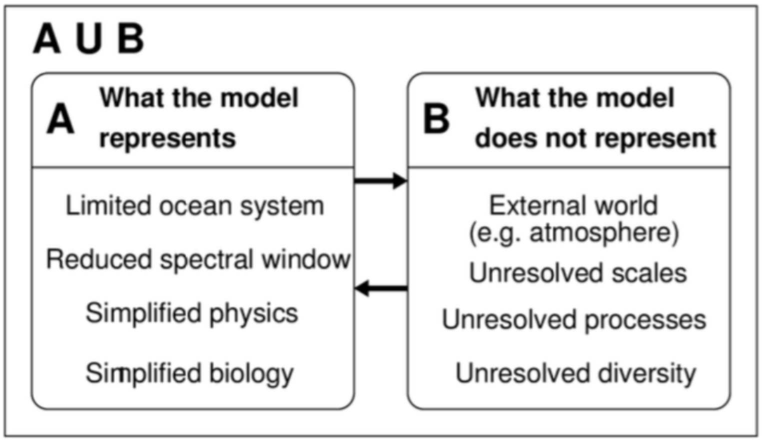

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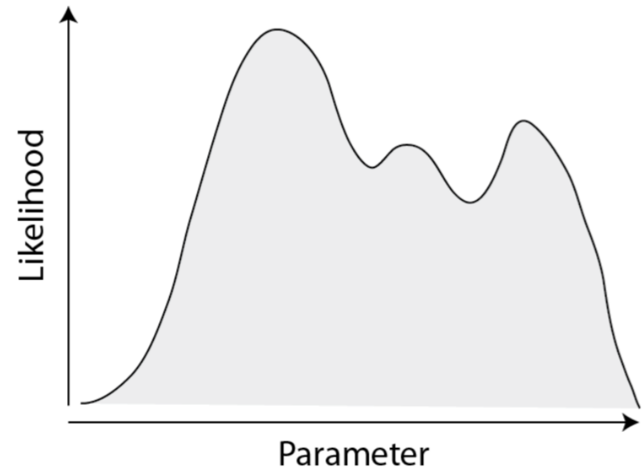

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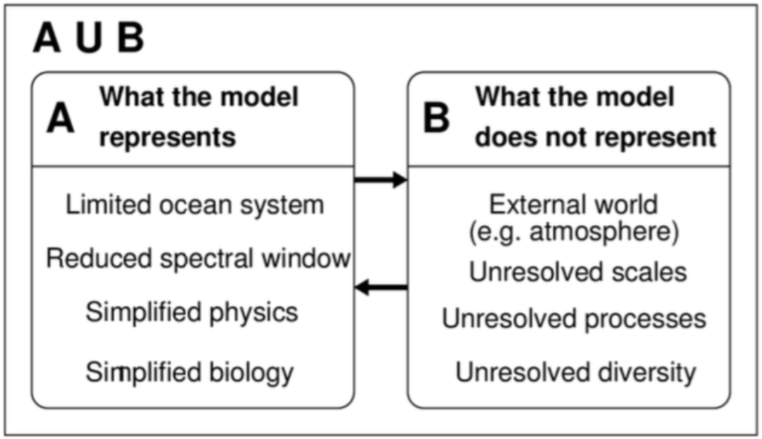

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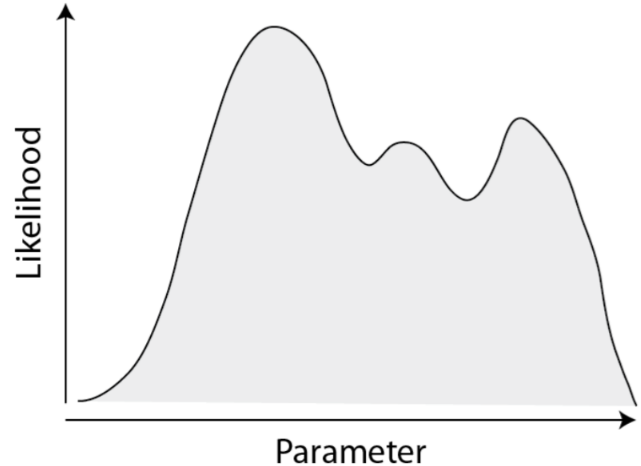

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- but still unclear how to deal with the **daemon of dimensionality** (sampling a 10^n degrees of freedom pdf with 50 members...)

Part 4.

Towards data-driven ocean modelling

The changing usage of geoscientific data

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Will the change in the flow of data we experience in geoscience change the way how we produce knowledge in the future ?

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- Observational data are used for constraining ocean model **forcing functions at the surface**; this is based on satellite data and atmospheric reanalysis data (not technically speaking observations)

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But overall, usages of observational data are pretty straighforward.

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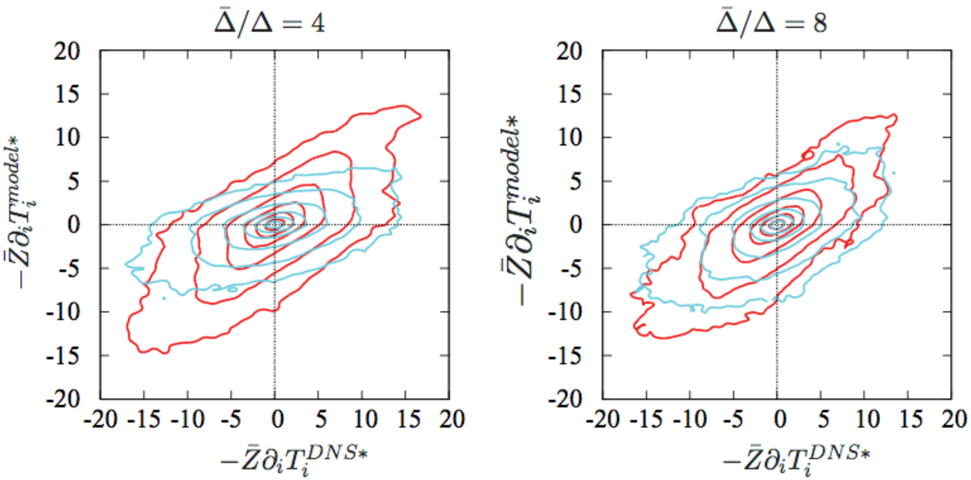
Arguably, ocean model design and usage is gradually using more methods coming from data science.

Data-driven design of subgrid scale closures



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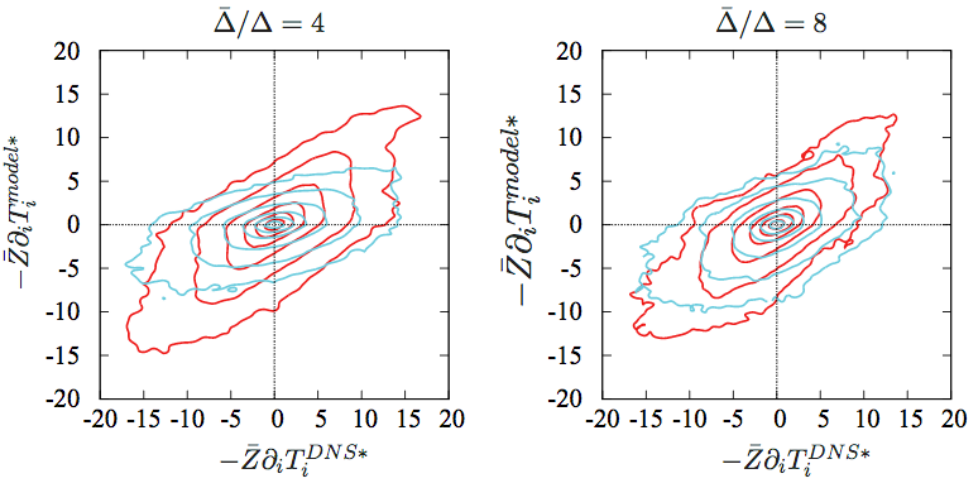

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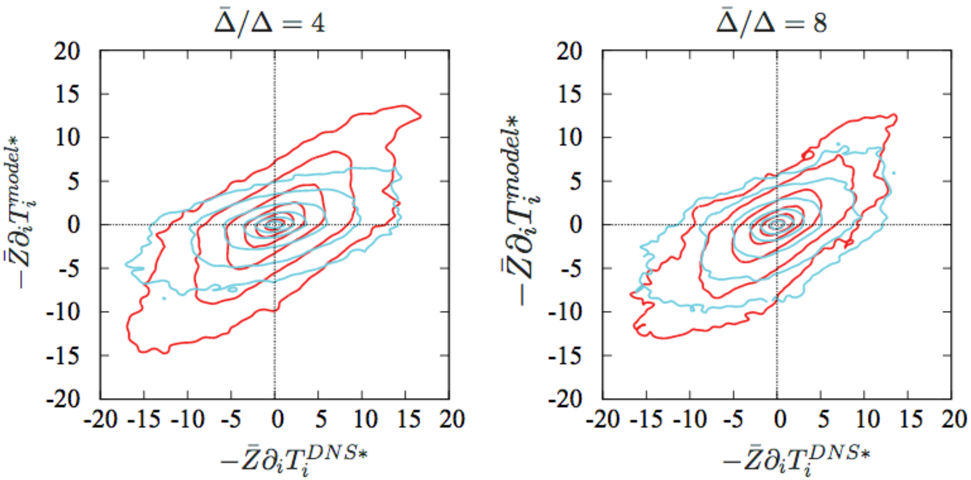

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- some cloud micro-physics closures have already been designed from LES simulations using data-driven approaches.
- There has been several attempts for designing SGS closures for ocean models with data-driven approaches, so far unsuccesfully.

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$$\langle u'_j, c' \rangle = -K_{jj} \frac{\partial \langle c \rangle}{\partial x_j}$$

Consider the **eddy diffusivity** closure

- central to several of our closures
- actually a statistical fit
- with a weak first principle basis…

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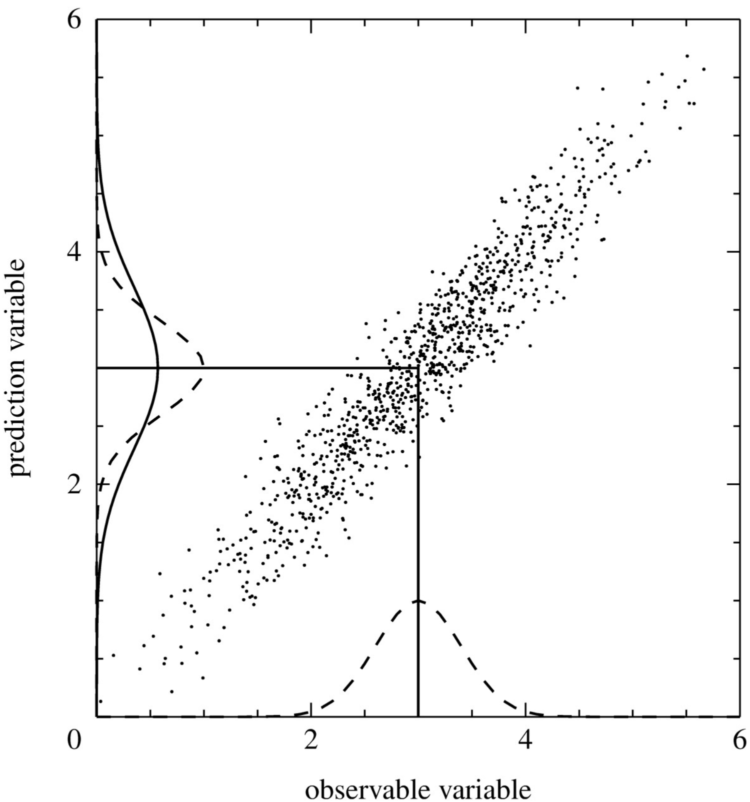

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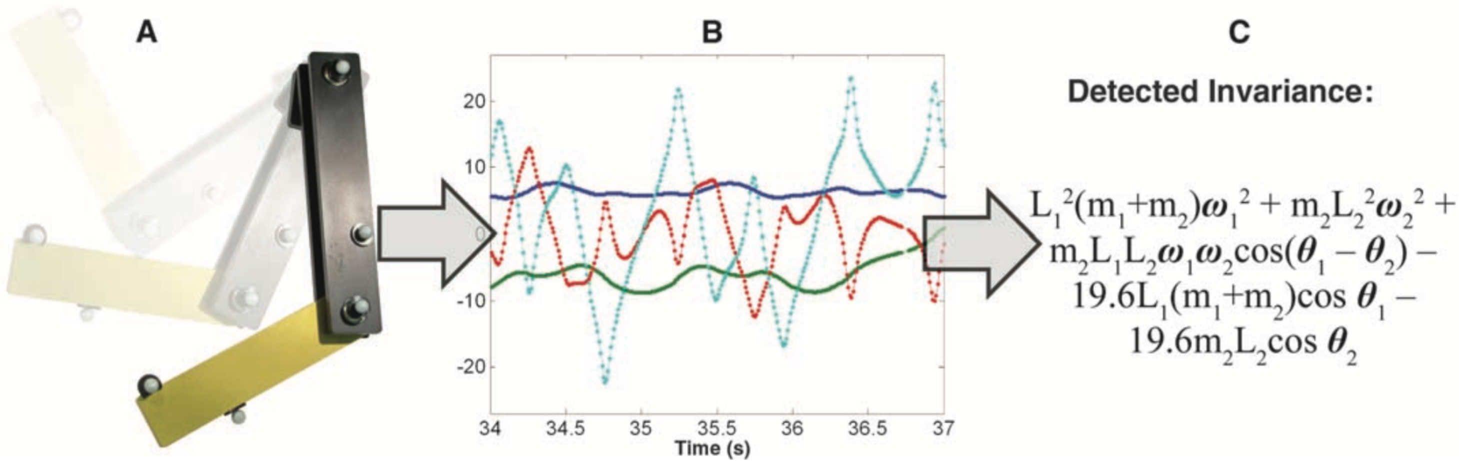

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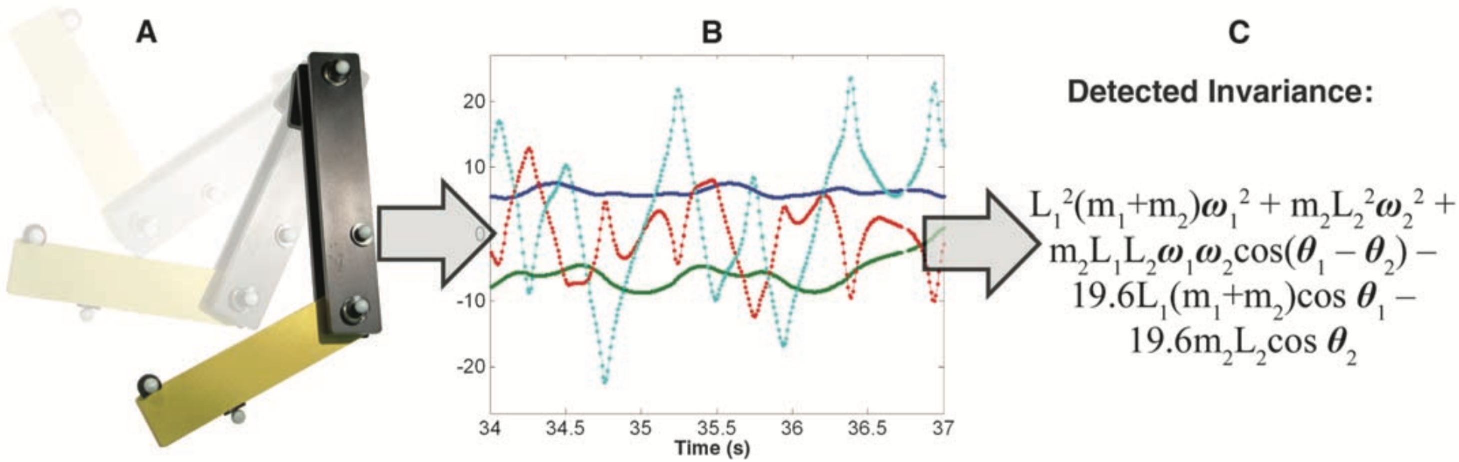

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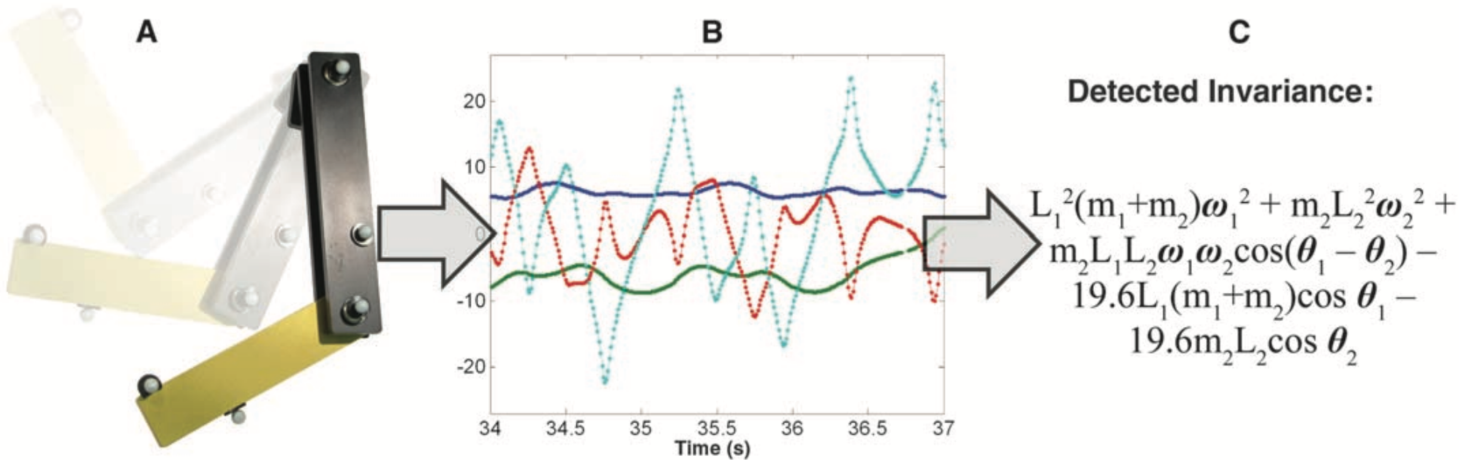

- data-driven techniques have be used for recovering the evolution equation of simple dynamical systems
- applied successsfully so far to low dimensional systems with perfect observations (Lipson 2009)
- how / when would those techniques be applicable to high dimensional / imperfectly observed dyamical systems ?

Wrapping-up Lecture #3

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Towards data-driven, probabilistics ocean circulation models

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- advocated that the **Bayesian framework** allows to consider ocean circulation models for what they actually are, namely **probabilistic models of possible states of the ocean**.

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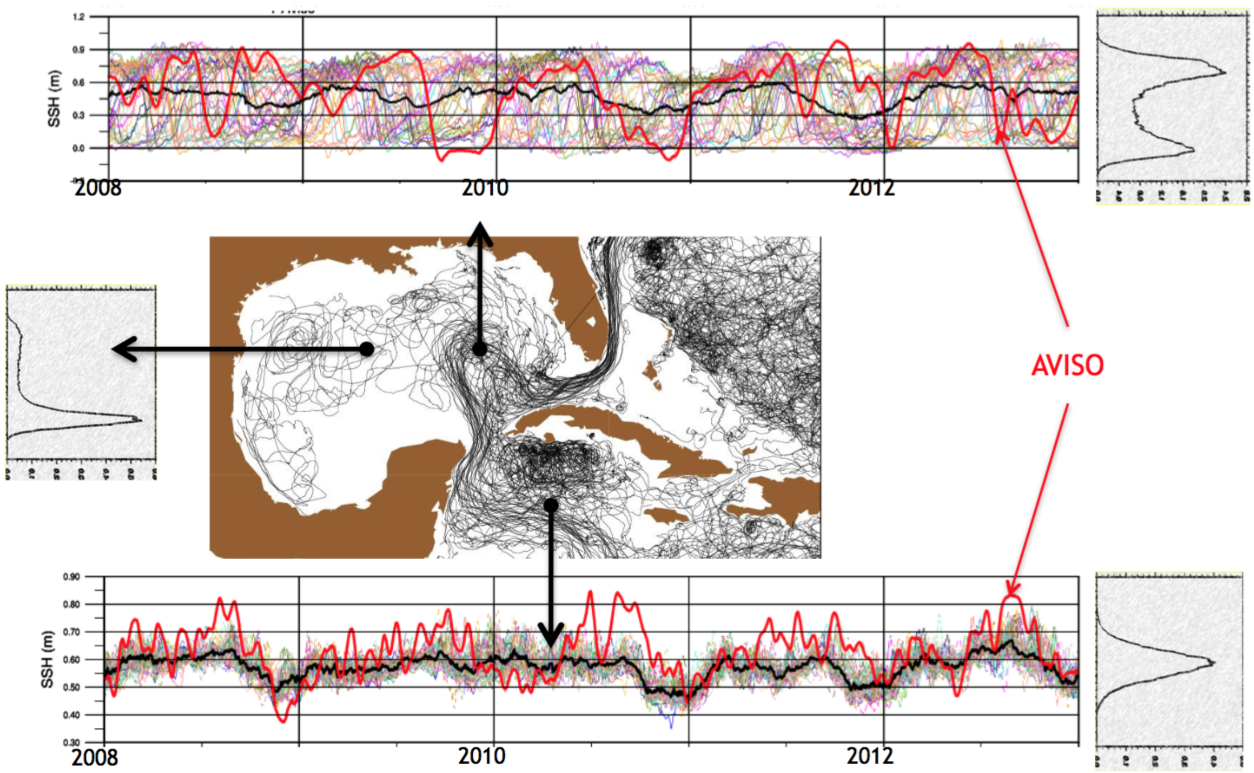
- discussed how ensemble simulations can help **understanding the drivers of low frequency oceanic variability**
- advocated that the **Bayesian framework** allows to consider ocean circulation models for what they actually are, namely **probabilistic models of possible states of the ocean**.
- asked whether **ocean circulation model development** will be more **data-driven** in the future.

Additional material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