SANGOMA: Stochastic Assimilation for the Next Generation Ocean Model Applications EU FP7 SPACE-2011-1 project 283580

Deliverable 6.4: Ph.D workshop 1 report

Due date: 31/10/2013 Delivery date: 30/04/2014 Delivery type: Report, Public



J.-M. Beckers A. Barth Y. Yan M. Canter University of Liège, BELGIUM

P.-J. Van Leeuwen S. Vetra-Carvalho University of Reading, UK

L. Nerger P. Kirchgessner Alfred-Wegener-Institut, GERMANY

A. Heemink N. van Velzen M. Verlaan U. Altaf Delft University of Technology, NETHERLANDS

P. Brasseur J.-M. Brankart G. Candille S. Metref CNRS-LEGI, FRANCE

P. de Mey CNRS-LEGOS, FRANCE

L. Bertino F. Counillon NERSC, NORWAY



Deliverable 6.4



Chapter 1 Content

To be completed. In annex presentations and summary.



Work Package 6 Outreach

on the MoorSPICE cruise March 2014

Annual SANGOMA Meeting, April 2014

MoorSPICE cruise, 2014

Program : SPICE international programLocation : Salomon seaResearch Vessel : T.G. Thompson



Main objectives :

- Understand air-sea fluxes and oceanic currents in Salomon Sea
- Describe local and global effects of water mass transformations
- Estimate impacts of water redistribution from the subtropics to the equator and the Southern Ocean (e.g. ENSO modulations)

Workshop participants

Participants are specialized in *in situ* observations. This workshop is an introduction to data assimilation and SANGOMA's work.

Participants :

- 2 chief scientists (SCRIPS, San Diego; IRD, Nouméa)
- **9 students** (University of Fiji ; University of Papua-New Guinea ; IRD, Nouméa ; SCRIPS, San Diego ; LEGOS, Toulouse ; MEOM, Grenoble)
- 5 engineers (CNRS-INSU, Brest; SCRIPS, San Diego; IRD, Nouméa)
- 6 marine technicians (University of Washington)

SANGOMA Workshop Between observations and modelization

Workshop part I :

Sammy Metref



Introduction to data assimilation

- Introduction and challenges in DA
- SANGOMA presentation
- Training (SANGOMA demo webpage)



SANGOMA Workshop Between observations and modelization

Workshop part II :

Florent Garnier



Toward data assimilation :

The use of stochastic parametrizations

- Presentation of ensemble simulations
- Basics on stochastic parametrizations
- Results on large benchmark



	Classical approaches	New challenges O	What about me? 0000

Workshop SANGOMA - Part I Between observations and modelization Introduction to data assimilation

Sammy Metref, Florent Garnier

MEOM Team - LGGE, Grenoble, France European project : SANGOMA





MoorSPICE cruise Noumea, March, 2014



596

э

What is DA ?	Estimation problem	New challenges 0	SANGOMA o	

1 What is DA?

- 2 Estimation problem
- Classical approaches
- 4 New challenges
- **5** SANGOMA
- 6 What about me?

What is DA ? ●00	Estimation problem	Classical approaches	New challenges 0	SANGOMA o	What about me? 0000
What is	data assim	ilation (DA)	?		

Methods estimating a set of unknowns in a system by optimally combining different sources of information :

model equations

- observations, data
- background, prior information
- uncertainties (statistics)

What is DA ? 0●0	Estimation problem	Classical approaches	New challenges 0	SANGOMA o	What about me? 0000
The obs	servations				



- Satellites
- Scientific cruises
- Voluntary merchant
- Moored buoys
- Surface drifters
- Argo profiling floats

э

- Gliders
- Tide gauges
- Sea mammals
- Airplanes

What is DA ? 0●0	Estimation problem	Classical approaches	New challenges 0	SANGOMA o	What about me? 0000
The obs	servations				



- Satellites
- Scientific cruises
- Voluntary merchant
- Moored buoys
- Surface drifters
- Argo profiling floats

- Gliders
- Tide gauges
- Sea mammals
- Airplanes

 \Rightarrow Observation errors = Measurement errors + Representation errors

What is DA ? 00●	Estimation problem	Classical approaches	New challenges O	SANGOMA o	What about me? 0000
The mo	dels (SST,	1/36th model [N	l. Djath])		



Characteristics of a model :

- Fluid dynamic
- Thermodynamic
- Geochemistry
- Biology
- Numerical schemes

Error sources :

- Approx. in model equations
- Parameters
- Forcings
- Initial conditions
- Numerical discretization

▲□▶ ▲圖▶ ▲臣▶ ▲臣▶ ―臣 … のへで

What is DA ? 000	Estimation problem	Classical approaches	New challenges 0	SANGOMA o	What about me? 0000

1 What is DA?

- 2 Estimation problem
- Classical approaches
- 4 New challenges
- **5** SANGOMA
- 6 What about me?

What is DA?	Estimation problem	Classical approaches	New challenges	SANGOMA	What about me?
000	●○	0000	O	o	0000
What is	DA for?				

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

Historically : meteorology. Later, oceanography.

Today, many other fields :

- glaciology,
- seismology,
- nuclear fusion,
- medicine,
- agronomy,
- etc

What is DA ?	Estimation problem	Classical approaches	New challenges	SANGOMA	What about me?
000	○●		O	o	0000
What a	re the goals	of DA?			

Historically : initial state estimation, for weather forecasting.

Today, many other applications :

- initial conditions for predictions,
- calibration and validation,
- observing system design, monitoring and assessment,
- reanalysis,
- better understanding (model errors, data errors, physical process interactions, parameters, etc),

• etc

What is DA ? 000	Estimation problem	Classical approaches	New challenges O	SANGOMA o	What about me? 0000

1 What is DA?

- 2 Estimation problem
- 3 Classical approaches
- 4 New challenges
- 5 SANGOMA
- 6 What about me?

What is DA?	Estimation problem	Classical approaches	New challenges	SANGOMA	What about me?
		0000			0000

Two main approaches : Stochastic or Variational

• Stochastic approach (e.g. EnKF) :

- \rightarrow Optimal stochastic estimation theory
- \rightarrow Sequential correction of the model state (at each observed time)
- \rightarrow Minimizes the uncertainty of the estimated solution (in the least-squares sens)

 \rightarrow Knowledge of the observation and background errors is needed

• Variational approach (e.g. 4D-var) :

- \rightarrow Optimal control theory.
- \rightarrow Minimization of a cost function J

 \rightarrow J measures the quadratic distance between a set of ata and a trajectory of the model.

 \rightarrow J can be controled by initial conditions, boundary conditions, model parameters ...

What is DA ?	Estimation problem	Classical approaches	New challenges	SANGOMA	What about me?
000		○●○○	O	o	0000
Stochas	stic scheme				



◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 臣 のへぐ

What is DA ? 000	Estimation problem	Classical approaches	New challenges O	SANGOMA o	What about me? 0000
Stochas	tic scheme				



Drawbacks of classical sequential stochastic DA :

• Observation and background errors are assumed Gaussian

• Model and observation operator are assumed linear

What is DA ?	Estimation problem	Classical approaches	New challenges	SANGOMA	What about me?
000		○○●○	O	o	0000

Variational scheme



◆□ ▶ < 圖 ▶ < 圖 ▶ < 圖 ▶ < 圖 • 의 Q @</p>



Variational scheme



Drawbacks of classical variational DA :

• Observation and background errors are assumed Gaussian

▲ロト ▲帰ト ▲ヨト ▲ヨト - ヨ - の々ぐ

• Model needs to be linearized during minimization

Estimation problem	Classical approaches ○00●		What about me?

SANGOMA : Data Assimilation Demo

A word on twin experiments : A methodological tool

- A simulation of reference = Truth \rightarrow Diagnose the exact performance of the assimilation
- Creating observations from the truth
 - \rightarrow Controle the spat/temp repartition + observation error

- Creating background from the truth
 - \rightarrow Controle the background error

What is DA ? 000	Estimation problem	Classical approaches	SANGOMA o	What about me? 0000

1 What is DA?

- 2 Estimation problem
- 3 Classical approaches
- 4 New challenges

5 SANGOMA

6 What about me?

What is DA ? 000	Estimation problem	Classical approaches	New challenges ●	SANGOMA o	What about me? 0000
DA new	concerns				

Data assimilation techniques are now used for a range of geophysical state estimation problems (e.g. land surface, ocean, atmospheric constituents)

and are applied to the atmosphere on scales from global to convective.

Coupling between the state components (e.g. ocean and atmosphere) has also become an important area of research.

Foreword and Symposium Summary 6th WMO data assimilation symposium

What is DA ? 000	Estimation problem	Classical approaches	New challenges ●	SANGOMA o	What about me? 0000
DA new	concerns				

Data assimilation techniques are now used for a range of geophysical state estimation problems (e.g. land surface, ocean, atmospheric constituents)

 \Rightarrow Nonlinear and non-Gaussian problems

and are applied to the atmosphere on scales from global to convective.

⇒ Parameter estimation, Multiscale DA, Adaptative grids ... Coupling between the state components (e.g. ocean and atmosphere) has also become an important area of research. ⇒ Coupling DA

Foreword and Symposium Summary 6th WMO data assimilation symposium

What is DA ? 000	Estimation problem		SANGOMA o	What about me? 0000

1 What is DA?

- 2 Estimation problem
- 3 Classical approaches
- 4 New challenges



6 What about me?



What is DA ? 000	Estimation problem	Classical approaches 0000	New challenges O	SANGOMA •	What about me?
SANGC	MA Project	:			

Stochastic Assimilation for the Next Generation Ocean Model Applications



A European project providing new developments in data assimilation for future operational forecasting and monitoring systems.

э

SANGOMA is a collaboration of 7 expert groups in data assimilation from 6 countries (Fr/Be/Ge/Nor/Ne/UK).

Composed of several benchmarks :

- Small Lorenz96 (40 variables),
- Medium NEMO SeaBASS (square ocean config.),
- Large NEMO North Atlantic (realistic 1/4° config.)

Objective : Develop and compare DA methods on each benchmark

What is DA ? 000	Estimation problem 00	Classical approaches	New challenges O	SANGOMA o	What about me?

1 What is DA?

- 2 Estimation problem
- 3 Classical approaches
- 4 New challenges
- **5** SANGOMA
- 6 What about me?

What is DA ? 000	Estimation problem	Classical approaches	New challenges O	SANGOMA o	What about me? ●000
NA //					

What about me? - My interests

Data assimilation in a non-Gaussian context : Methodology and applications to marine bio-geochemistery.

Objectives :

- Define and caracterize non-linearity and non-gaussianity
- Diagnose non-linearity and non-gaussianity in a system
- Methodologically compare DA methods
- Define/Caracterize/Diagnose/Compare on an experimental marine bio-geochemistery 1D model

What is DA?	Estimation problem		What about me? ⊙●○○

What about me? - Methodological investigation

S. Metref, E. Cosme, C. Snyder, P.Brasseur

Creation of a new method with no Gaussian hypothesis!

The Rank Histogram Filter (Anderson, 2010) :



Idea \Rightarrow Develop this concept to multidimensional problems : MRHF [Metref et al., in revision]

What is DA?	Estimation problem	Classical approaches	New challenges	SANGOMA	What about me?
					0000

What about me? - Biogeochemical adventures

S. Metref, P. Brasseur, E. Cosme, J.-M. Brankart, S. Grégorio

MODECOGel : 1D vertical marine biogeochemistery model (5 dyn. + 12 bio.)

- Experiment period : 2006/2007 (spinup+DA)
- Ensemble creation : Perturbation on wind intensity forcing
- Observations : T/S/Phyto/Ni profilers, ocean color, SST/SSS
- Control variables : T and S
- DA methods : EnKF, ETKF, RHF, MRHF, PF ...



🖹 ୬ବ୍ଚ

o oo		es New challenge O	es SANGOMA o	What about me? 000●
------	--	-----------------------	-----------------	------------------------

Thank you !

Sammy Metref

LGGE/CNRS/SANGOMA







Workshop SANGOMA-Part II Between observations and modelization

Towards data assimilation in a realistic configuration: the use of stochastic parametrizations

Florent Garnier, Sammy Metref, P.Brasseur, J-M.Brankart, J.Verron

MEOM Team-LGGE, GRENOBLE

Moor SPICE campaign March 2014



Laboratoire de Glaciologie et Géophysique de l'Environnement



PLAN



Introduction : Quick overview of data assimilation in oceanography

- Why?
- Where ?
- Main objectives of the presentation
- 2 Toward a probabilistic system : presentation of stochastic parametrization concepts
 - Basic ideas
 - One exemple : Impacts of unresolved scales uncertainties
 - Definition of the system

3 My work : Stochastic parametrizations of biogeochemical uncertainties

- The coupled Physical-biogeochemical model
- Stochastic parametrizations of unresolved processes
 - Formulations
 - Some results




Introduction : Quick overview of data assimilation in oceanography

- 2 Toward a probabilistic system : presentation of stochastic parametrization concepts
- 3 My work : Stochastic parametrizations of biogeochemical uncertainties
- 4 Conclusions



As already introduced in the previous presentation data assimilation in Oceanography is mainly used for :

- The reconstruction of the past dynamics (Reanalysis)
 - ► Better Understand the Physical/Biogeochemical processes
 - Improving climatological studies
- The forecast :
 - Identification of initial conditions
- 2 Approaches :
 - Stochastic approach
 - Variational approach



Where?

Scientific research

- Assimilation methods development for a 3D turbulent "green and blue" ocean
 - Strongly non linear and non gaussian
 - With various scales phenomena

Operationnal developpment

- Export new oceanographic tools and data
- Match operationnal R&D needs

Long term

- Contribute to the comprehension of the earth system component evolutions in the climate perspective ↔ observations
 - Satellite data (altimetry : Jason,SARAL/altika, ocean colour : SeaWIFS, Meris)
 - In situ data



Main objectives of the presentation

The more probable is the message, the less information it gives. Cliches, for example, are less illuminating than great poems... Norbert Wiener (1894-1964)

The use of **stochastic parametrizations** (i.e the inclusion of randomness in a model) bring some **statistical informations** on the distribution of the model **uncertainties** able to :

- Consider a system as probabilistic instead of deterministic
 ⇒ Work with ensemble simulations
- Improve the efficiency of data assimilation

Introduction : Quick overview of data assimilation in oceanography

2 Toward a probabilistic system : presentation of stochastic parametrization concepts

3 My work : Stochastic parametrizations of biogeochemical uncertainties

4 Conclusions



Basic ideas

Stochastic parametrization must simulate processes not resolved $\rightarrow We$ must identify the main sources of uncertainties



- Even if the dynamic of **U** can be assumed deterministic, the system **A** alone cannot be assumed **deterministic**
- To consider A as deterministic we assume that :
 - **B** is know (e.g atmospheric forcing)
 - ► the effects of B can be parameterized (e.g effects of unresolved scales)

\Rightarrow B is the main source of uncertainty in the model



Basic ideas

Due to the huge **complexity** of geophysical climatic systems, considering a system as **deterministic** will always be an **approximation** !! (*That could be entirely justified*)

 \Rightarrow The solution is to consider the system as probabilistic

Stochastic parameterizations

I believe that the ultimate climate models (...) will be stochastic, i.e. random numbers will appear somewhere in the time derivatives. Edward Lorenz (1975)



Exemple of unresolved scales uncertainty : the computation of the density

In the model, the large scale density is computed from large scale temperature and salinity, using the sea-water equation of state $\rho(T, S, p)$



Averaging T and S on the equation systematically overestimates the density. Know in reality as the cabella effect

Because of the nonlinearity of the equation of state, unresolved scales produce an average effect on density

Exemple of unresolved scales uncertainty : the computation of the density

From a T&S reananlysis data at $1/4^{\circ}$ we use an averaging operator to downscale data to 2° resolution



The figure (Brankart et al, 2013) present the density misfit ($\delta \rho$) between applying the averaging operator before and after the equation of state.

$$\delta \rho = \rho(T, S) - \rho(T, S)$$

A This unresolved scale uncertainty is only **mathematical** issued from the non linearity of the equation.

 \rightarrow The stochastic solution is to consider $\rho(\overline{T} + \delta \overline{T}, \overline{S} + \delta \overline{S})$



Definition of the system

Objective : Transform a deterministic model into a probabilistic model



Method : explicitely simulate model uncertainties using random numbers





• With this stochastic methods, the prior error covariance matrix $(P^a(t = t_0))$ in the previous presentation) is directly related to **the model formulations** instead of the only sensivity of initial conditions

● We expect a more consistent evaluation of model uncertainties ⇒ improve data assimilation



🧿 Introduction : Quick overview of data assimilation in oceanography

- 2 Toward a probabilistic system : presentation of stochastic parametrization concepts
- My work : Stochastic parametrizations of biogeochemical uncertainties
- 4 Conclusions



General idea about some of my work

The Idea is to implement **stochastic** parametrization in the **NEMO/PISCES** configuration to simulate some of the main biological unresolved processes. The results of this simulations would allow to perform assimilation of ocean colour data (SeaWifs)

I focused on 2 main points :

- The non linearity of biological equations (small scale effects)
- The uncertainty of biological formulations (diversity of species, biological adaptation)



As one simulation including random numbers can only represent one possible state of the system we perform ensemble simulations.



The Physical-Biogeochemical coupling

• The configuration used for the study is the 1/4° NEMO/PISCES coupled model



- The biogeochemical variables are tracers forced on-line by the physical model
- There is no biological feedback on the physics

Sources-Puits



The PISCES model

The PISCES model (Pelagic Interaction Scheme for Carbon and Ecosystem Studies)



- 24 state variables
 - ► 4 living species
 - 2 Phytoplanktons
 - 2 Zooplanktons
 - ▶ 5 limiting nutrients
 - NH4, NO3, Fe, SI, PO4
 - 3 non living compartments
 - semilabile DOM
 - 2 organic particles



Stochastic parametrizations of unresolved processes : formulation

Fluxes perturbation :

$$\begin{aligned} \frac{\partial C}{\partial t} \to SMS(C, u, p, t) &= \sum_{i=1}^{\alpha} F_i(C, u, p, t) \\ &\equiv \sum_{i=1}^{\alpha-n} F_i(C, u, p, t) + \sum_{i=\alpha-n}^{\alpha} F_i(C, u, p, t) \cdot \xi_i(t) \end{aligned}$$

Unresolved scales perturbations :

$$SMS(\overline{C}) \neq \overline{SMS(C)} \Rightarrow \frac{\partial C}{\partial t} = \frac{1}{m} \sum_{i=1}^{m} SMS(\overline{C} + \delta \overline{C_i}, u, p, t)$$
 with
 $\delta C \to \xi(t).C$ and $\sum_{i=1}^{m} \delta C_i = 0$

Stochastic parametrizations of unresolved processes : Some results





Stochastic parametrizations of unresolved processes : Some results



Surface chlorophyll standard deviation of the ensemble, 15 May 2005



Surface anomaly between the SeaWiFS data and the ensemble mean, 15 May $2005\,$

Strong spatial **coherence** between the patterns of higher anomalies and the maximum of standard deviations

 \Rightarrow Dispersion is higher where anomalies are stronger



Conclusions

- I hope i convinced you that people in modelling don't think their model are the perfect truth and that they might also be interested by the observations (at least for data assimilation).....
- Taking into account the uncertainties (even with random numbers) allows to bring informations and then to improve model representations.
- There is a strong link between the knowledge of model uncertainties and the efficiency of data assimilation →Stochastic parametrizations are a relevant tool for this
- The future of oceanography (for modellers) is probably with ensemble simulations and high resolution simulations !!





Thanks for your attention Any questions?









