



**IMT Atlantique**  
Bretagne-Pays de la Loire  
École Mines-Télécom

# Data-driven methods in geophysics

**Pierre Tandeo**  
**RIKEN visitor, June-July 2018**



# Outline

## I. Covariance estimation in data assimilation

- A. Nonlinear and Gaussian state-space model
- B. What are Q and R covariances?
- C. Timeline of estimation of Q and R
- D. Methods comparison: preliminary results
- E. Summary about this review paper

## II. A bunch of data-driven methods

- A. AnDA applied to spatial oceanography
- B. Deep learning on SAR images
- C. Predictability of rogue waves
- D. Machine learning for satellite data
- E. Machine learning for solar energy prediction



# Covariance estimation in data assimilation

Nonlinear and Gaussian state-space model

The most popular formulation in DA is:

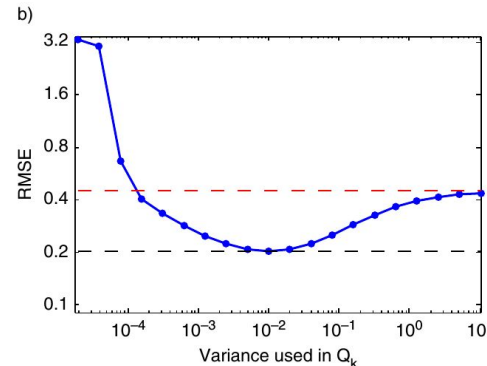
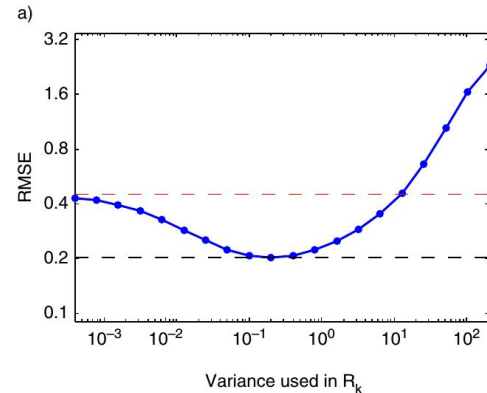
$$\begin{cases} \mathbf{x}(k) = \mathcal{M}(k-1, \mathbf{x}(k-1)) + \boldsymbol{\eta}(k), \\ \mathbf{y}(k) = \mathcal{H}(k, \mathbf{x}(k)) + \boldsymbol{\varepsilon}(k), \end{cases}$$

With important unknown covariance matrices  $\mathbf{Q}$  and  $\mathbf{R}$ :

$$\boldsymbol{\eta}(k) \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}(k))$$

$$\boldsymbol{\varepsilon}(k) \sim \mathcal{N}(\mathbf{0}, \mathbf{R}(k))$$

- Reconstruction of  $\mathbf{x}$  highly depends  $\mathbf{Q}$  and  $\mathbf{R}$
- Joint Estimation of  $\mathbf{Q}$  and  $\mathbf{R}$  is necessary
- Many authors worked on this topic but...

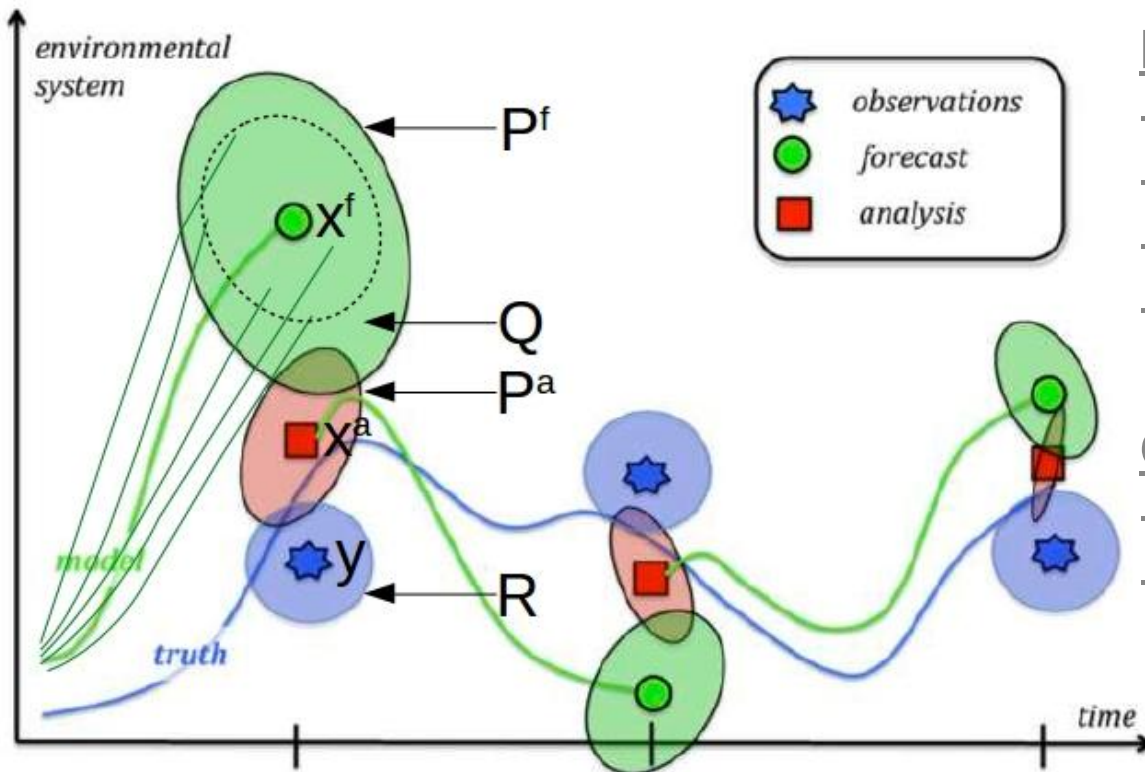


Simulation results on the L96  
Berry & Sauer 2013 [Tellus A]

# Covariance estimation in data assimilation

What are Q and R covariances?

Scheme of the sequential DA:



Model error  $Q$  represents:

- model deficiencies
- errors in the parameters
- unresolved scales
- errors in numerical schemes

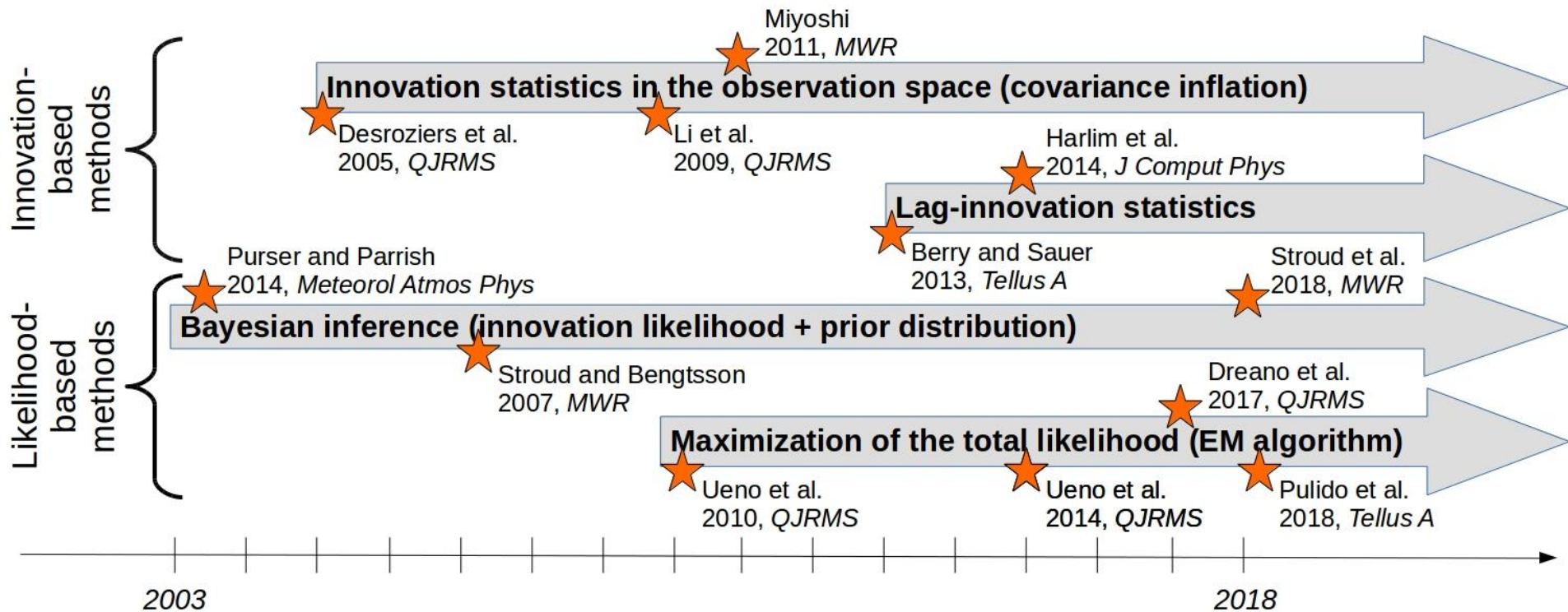
Observation error  $R$  represents:

- instrument noise
- representativeness error

# Covariance estimation in data assimilation

Timeline of estimation of Q and R

Research field initiated by Daley et al. 1992 [MWR] & Dee 1995 [MWR]



# Covariance estimation in data assimilation

Methods comparison: preliminary results

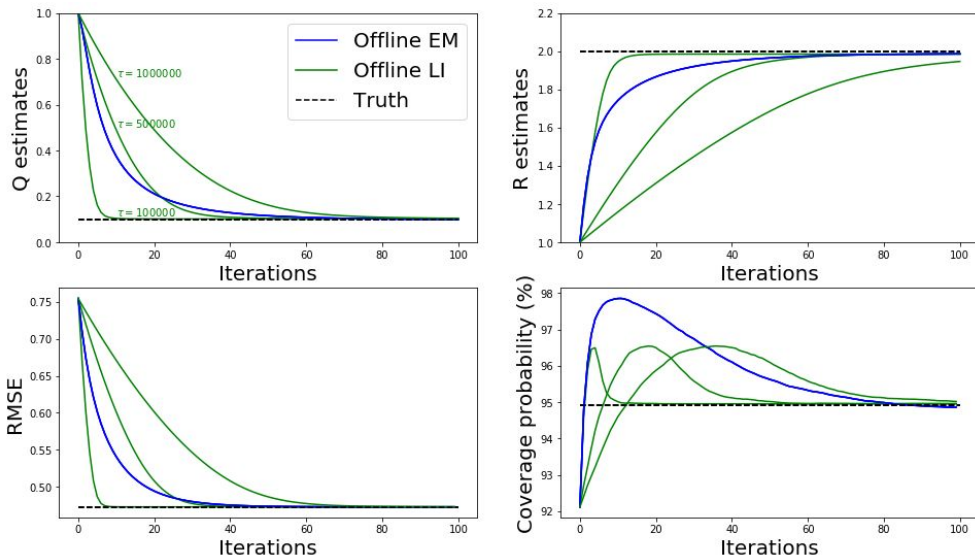
Focus on 2 methods:

- Lag-Innovation (LI) method
- Expectation-Maximization (EM) algorithm
- robust and accurate in practice

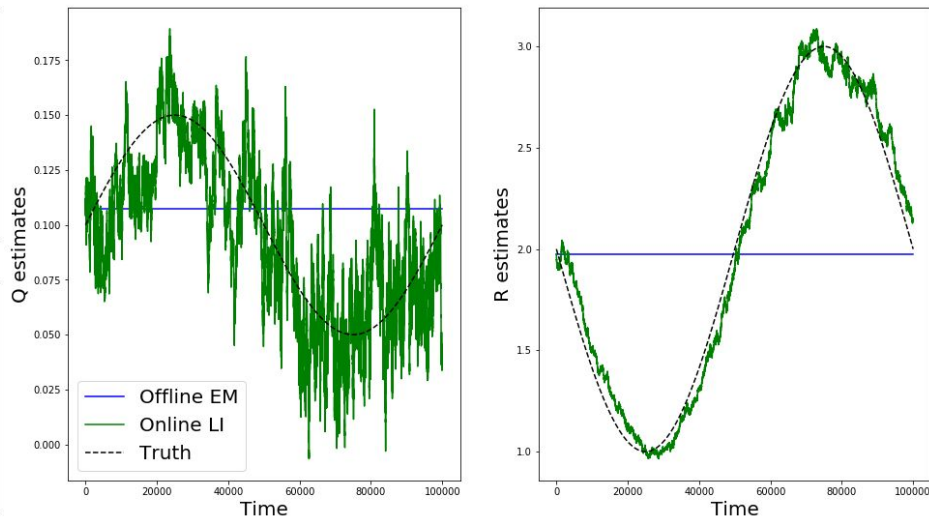
Numerical experiment:

- linear and Gaussian AR(1) model
- constant Q and R variances
- time varying Q and R variances

Offline estimation (constant Q & R):



Online estimation (varying Q & R):



# Covariance estimation in data assimilation

Summary about this review paper

## Schedule:

- draft available soon on arXiv
- accepted for submission in MWR
- ongoing simulation paper with L96 model & SPEEDY model

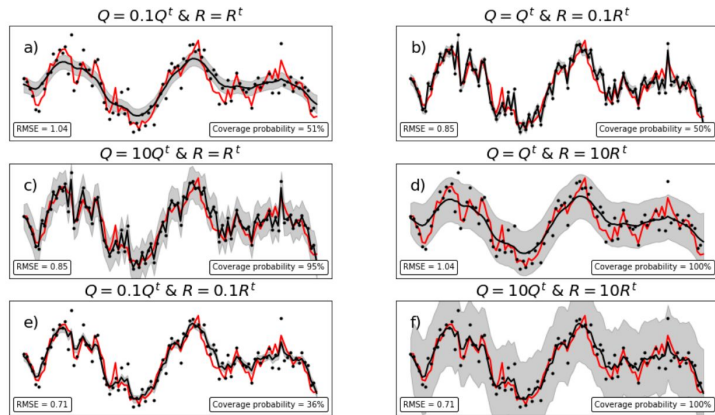


FIG. 1. Example of a univariate AR(1) process generated using Eq. (3) with  $Q^t = 1$  (red line), noisy observations using  $R^t = 1$  (black dots) and reconstructions using a Kalman smoother (black lines and gray 95% confidence interval) with different values of  $Q$  and  $R$ .

→ See my presentation at the UQ workshop in February 2018 for more details

## AMS Journals Welcome Review Articles

David M. Schultz

Chair, Subcommittee on Reviews, and Chief Editor, Monthly Weather Review

[See all authors & affiliations](#) ▾

<https://doi.org/10.1175/MWR-D-18-0114.1>

Published Online: 23 April 2018

## My feedbacks about such review paper:

- very long, lot of reading, need to be honest and exhaustive, sometimes boring...
- but I have now a global view of the methods
- nice to build collaborations
- I hope it will be useful!



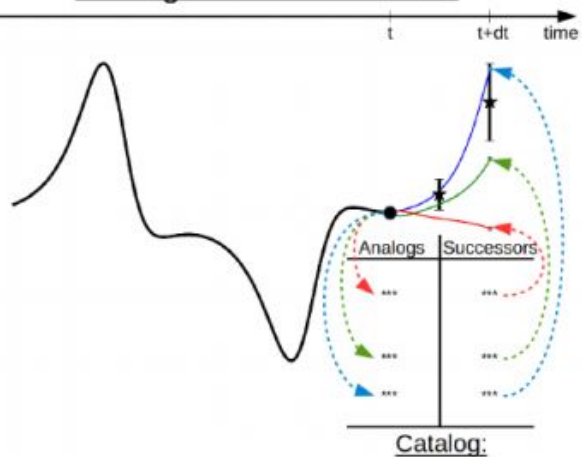
# A bunch of data-driven methods

AnDA applied to spatial oceanography (2018-2020, with IFREMER and Univ. Grenoble)

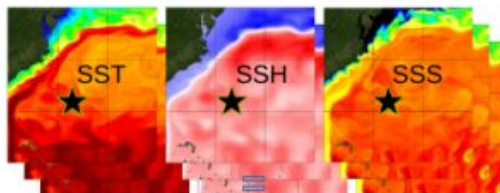
## Goal:

- adaptive spatio-temporal interpolator for spatial oceanography
- use an ensemble of numerical simulations (50 ensembles, 55 years)
- apply the Analog Data Assimilation (AnDA, Lguensat et al. 2017 [MWR])

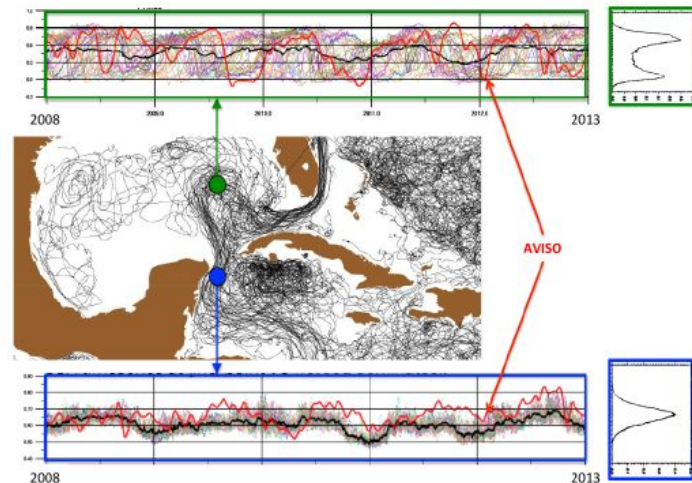
### Analog Data Assimilation:



### NEMO ensemble simulation:



Analogues ( $a_k$ ):	Successors ( $s_k$ ):
SST, SSH, SSS (time $t$ )	SST, SSH, SSS (time $t + dt$ )
(23.86, 0.71, 36.14)	(23.97, 0.73, 36.35)
(23.21, 0.43, 36.56)	(22.96, 0.41, 35.78)
...	...
(21.37, 0.15, 32.26)	(20.67, 0.14, 32.01)
(19.18, 0.09, 32.15)	(19.98, 0.11, 32.98)





# A bunch of data-driven methods

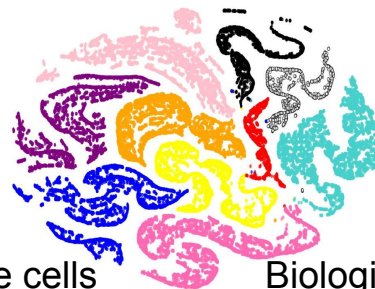
Deep learning on SAR images (2016-2019, with IFREMER and Univ. Seattle & New Hampshire)

## Goal:

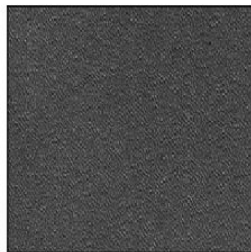
- use 20x20 km annotated SAR images (37,560)
- apply deep learning to classify natural phenomena

## Results:

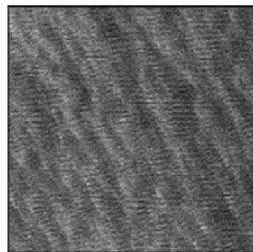
- 98% accuracy!
- lot of applications



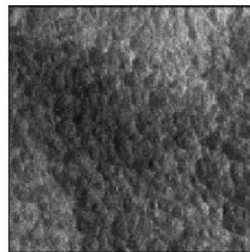
Ocean swell



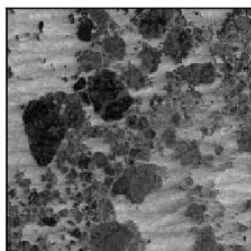
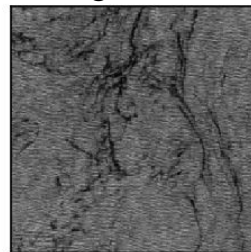
Wind streaks



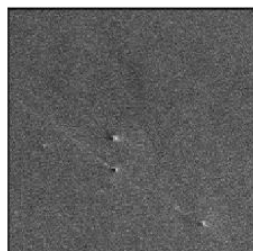
Convective cells



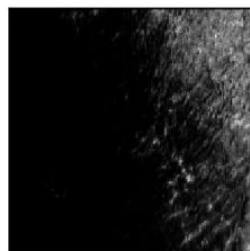
Biological slicks



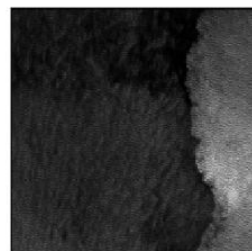
Sea ice



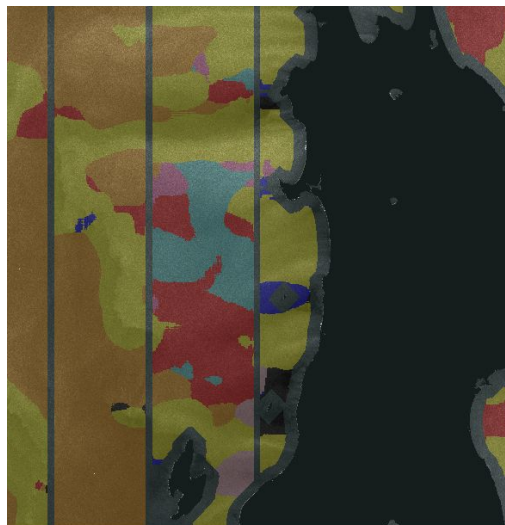
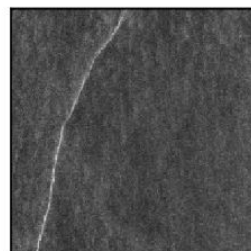
Icebergs



Oil sea



Atmospheric & oceanic fronts

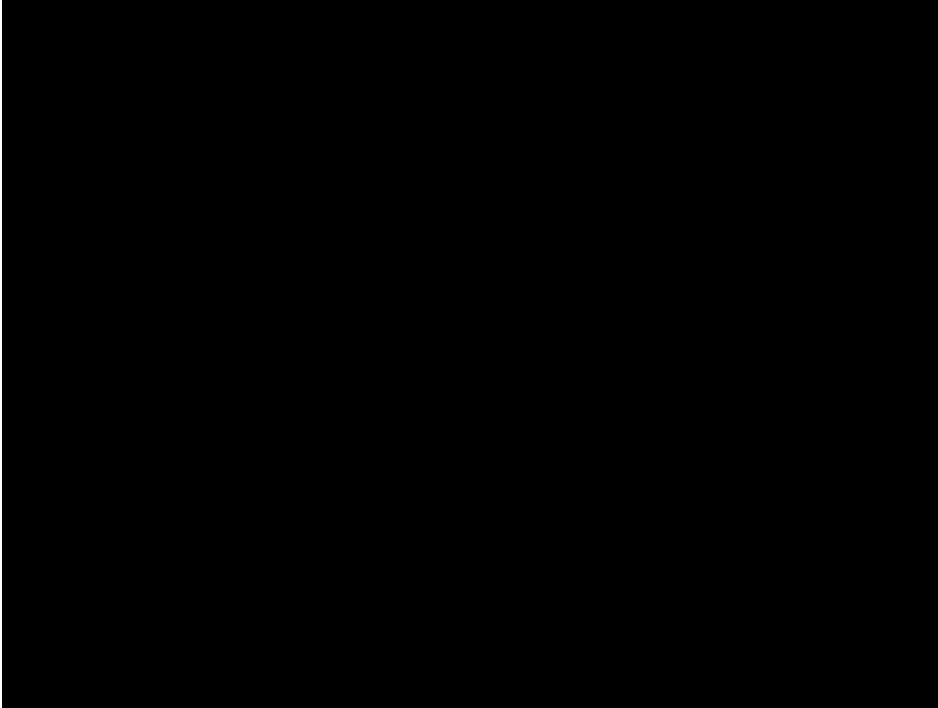


# A bunch of data-driven methods

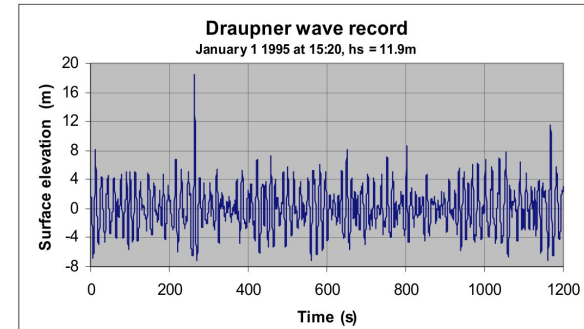
Predictability of rogue waves (2017-2019, with FEM and MIT)

## Goal:

- nowcasting of extreme wave events (up to 5 minutes)
- apply a mix of data-driven & model-driven approaches



Mitsuyasu (2009) [J OCEANOGR]



Famous Draupner rogue wave

# A bunch of data-driven methods

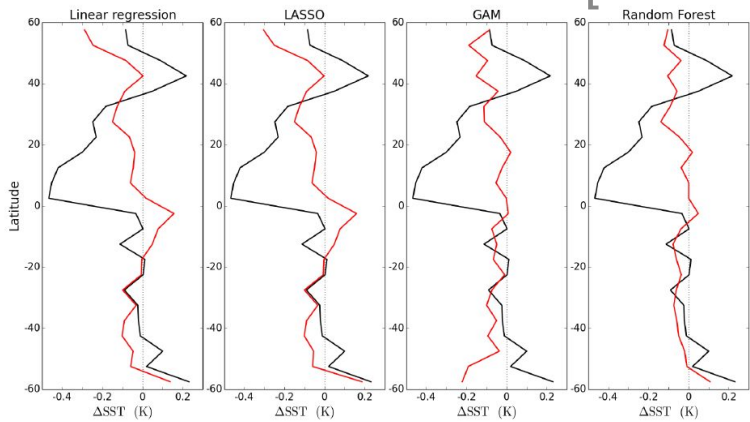
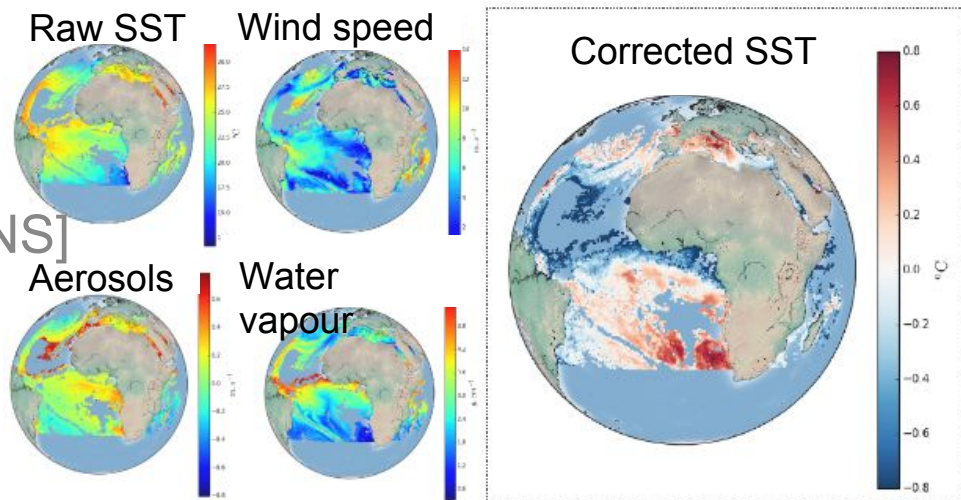
Machine learning for satellite data (with IFREMER and Météo-France)

## Goal:

- post-process satellite SST data using atmospheric information
- use geostationary data and *in situ* measurements (485,600 match-ups)
- apply machine learning regression algorithms

## Results:

- 31% of the variability is explained
- operationally applied at Météo-France
- Saux Picart et al. 2017 [REMOTE SENS]



- Raw bias
- Bias after correction

# A bunch of data-driven methods

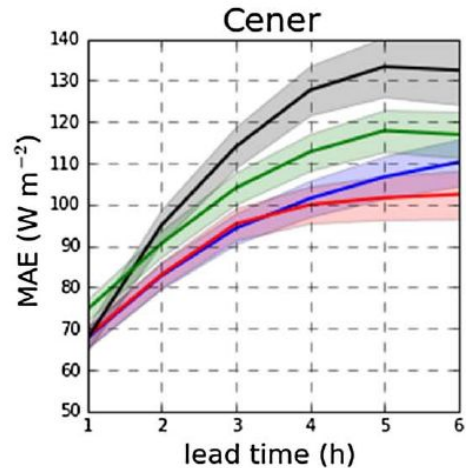
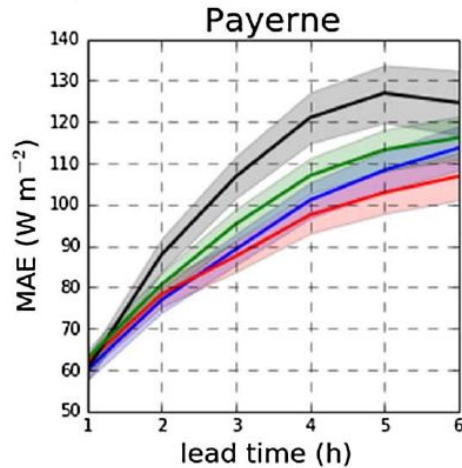
Machine learning for solar energy prediction (with Elum Energy, a French startup)

## Goal:

- predict solar irradiance 6h ahead for solar panels and energy saving
- use geostationary data (2011-2016, hourly data,  $0.05^\circ$ )
- apply analog forecasting and other statistical methods

## Results:

- method can be applied everywhere in Europe and Africa
- Ayet & Tandeo et al. 2018 [SOL ENERGY]



- Persistence
- VAR(1)
- Analog forecasting
- Analog forecasting (with post-processing)

