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# STOCHASTIC REDUCED ORDER MODEL FOR REAL-TIME UNSTEADY FLOW ESTIMATION

Valentin Resseguier,

Matheus Ladvig, Agustin M Picard

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# CONTENT

1. Context
2. Physics + data = reduced order model (ROM)
3. Simulation + measurements = data assimilation
4. Results



# **PART I**

# **CONTEXT**

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# SCALIAN

## Lab (~ 15 peoples)

Research, R&T, R&D

### Expertise:

- Geophysical fluid dyn.
- Signal, data assimilation
- Machine Learning
- Multi-agents systems
- Drones

## CEN « Simulation » (~ 70 people)

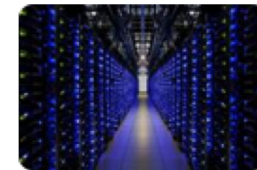
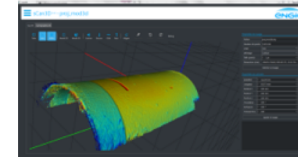
R&D and engineering

### Expertise:

- Radar, optronics, sonar
- Geophysical fluid dyn.
- Mechanical and thermal

### Business:

- Scientific softwares
- Simulations, HPC
- VR & AR

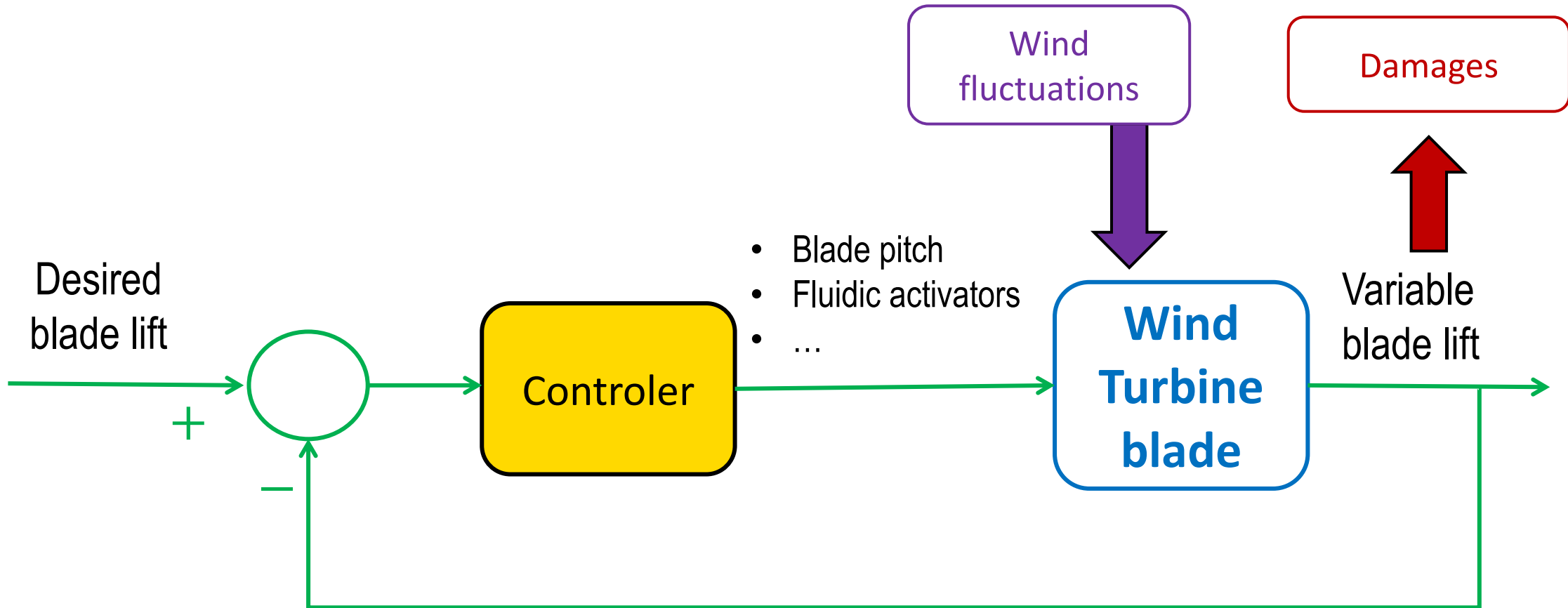


## Other Business Units

~ 2400 people



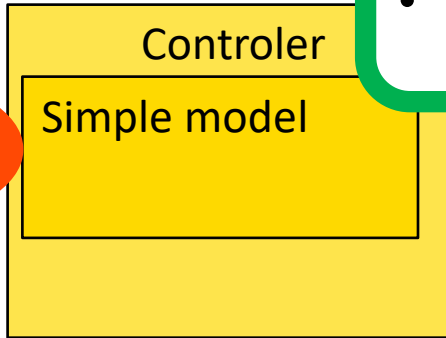
# BLADE LIFT CONTROL



# OBSERVEUR & CONTROL

Estimation and prediction:

- Flow
- ...



- Which simple model?
- How to combine model & measurements?

- Blade pitch
- Fluidic activators
- ...

Wind turbine blade

Observer

Simple model

Incomplete measurements :

- TrimControl
- LIDAR
- ...



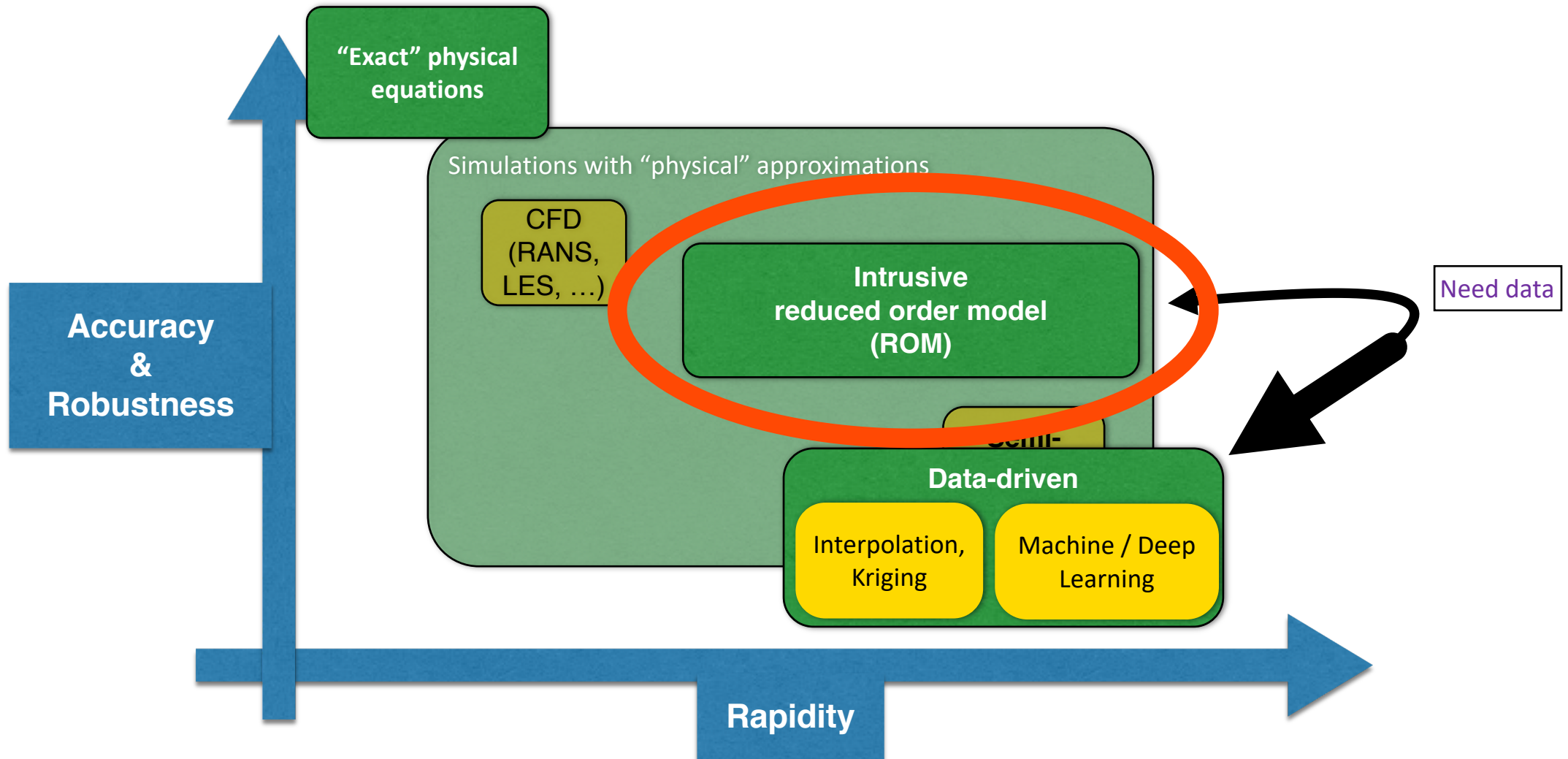


**PART II**  
**PHYSICS + DATA**  
**= REDUCED ORDER MODEL**

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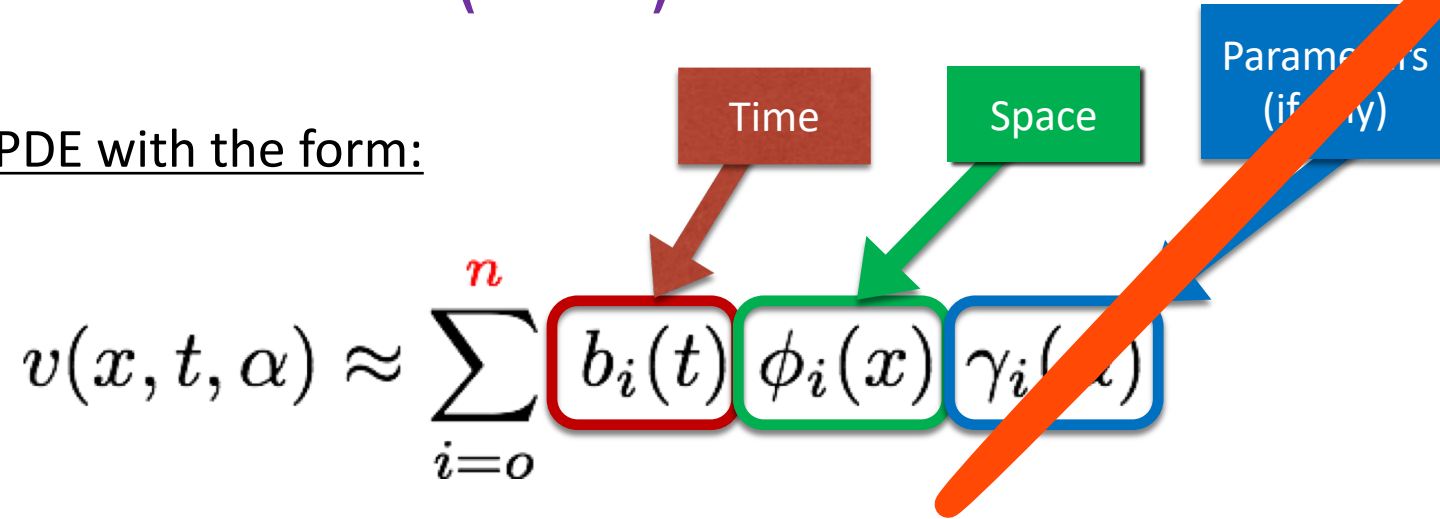


# TRADEOFF ACCURACY / RAPIDITY



# REDUCED ORDER MODEL (ROM)

Solution of an PDE with the form:

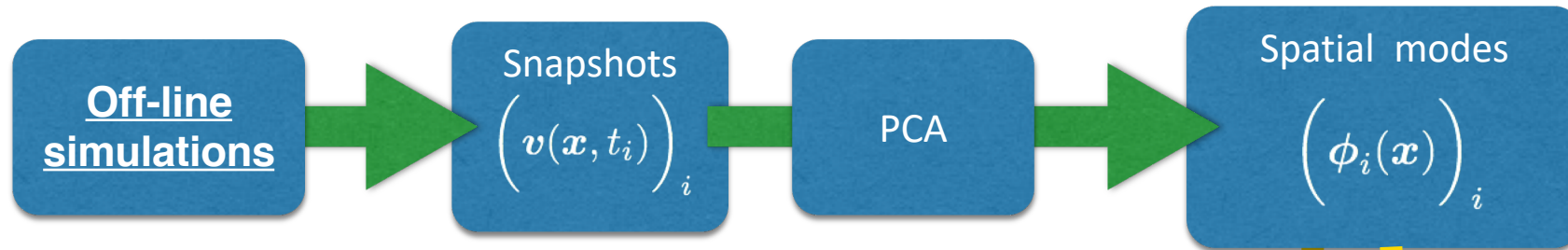


Order of magnitude examples in CFD

	Full space	Reduced space
Solution coordinates	$v_q(x_i, t)_{qi}$	$(b_i(t))_i$
Dimension	$M \times d \sim 10^7$	$n \sim 10 - 100$

# POD (PROPER ORTHOGONAL DECOMPOSITION)

- Principal Component Analysis (PCA) on a *dataset* to reduce the dimensionality:



- Approximation:

$$v(x, t) \approx \sum_{i=0}^n b_i(t) \phi_i(x)$$

Resolved modes

- Projection of the “physics” onto the spatial modes :

$$\int_{\Omega} dx \phi_i(x) \cdot (\text{Physical equation (e.g. Navier-Stokes)})$$

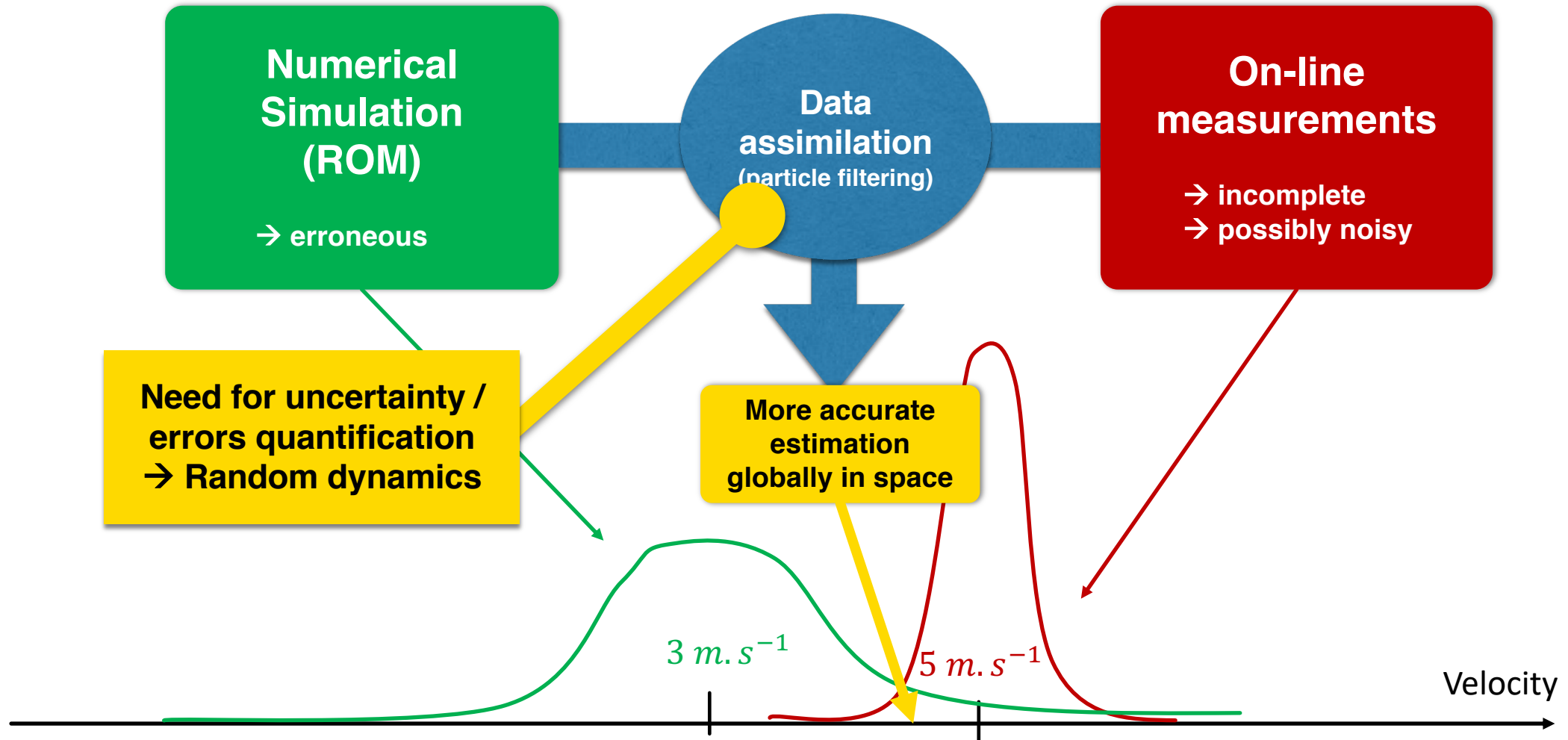
→ ROM for very fast simulation of temporal modes



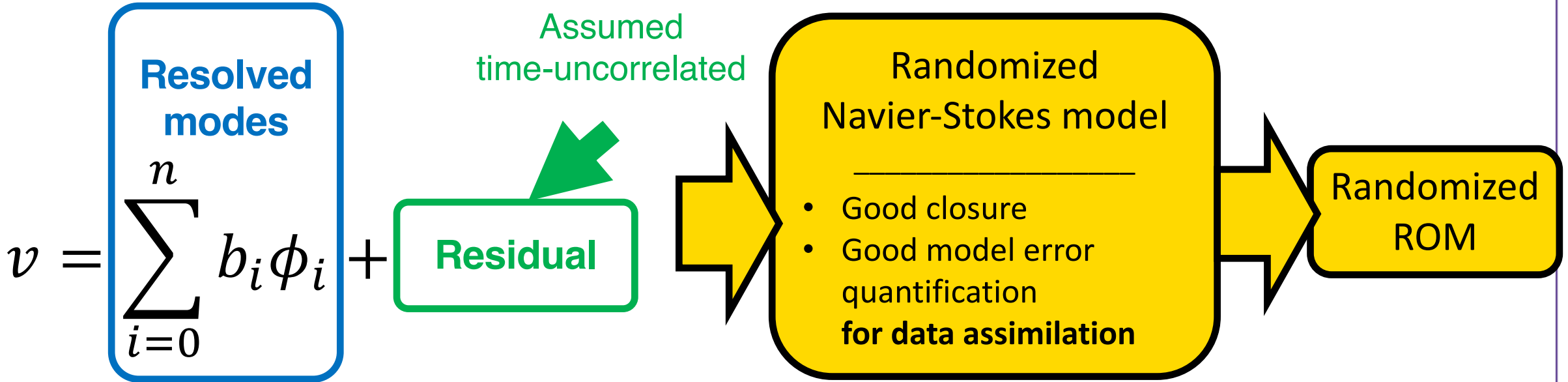
**PART III**  
**SIMULATION + MEASUREMENTS**  
**= DATA ASSIMILATION**

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# COMBINING SIMULATIONS AND MEASUREMENTS



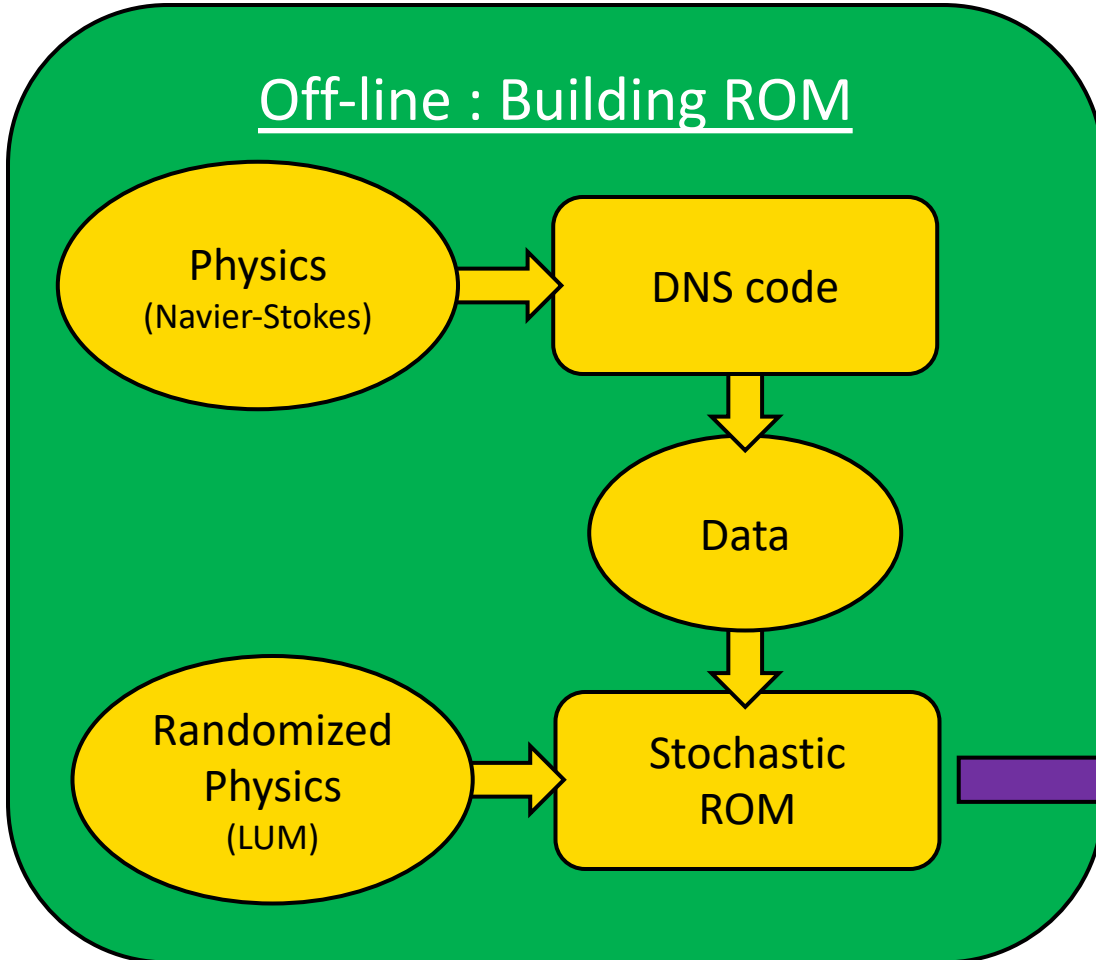
# LOCATION UNCERTAINTY MODELS (LUM)



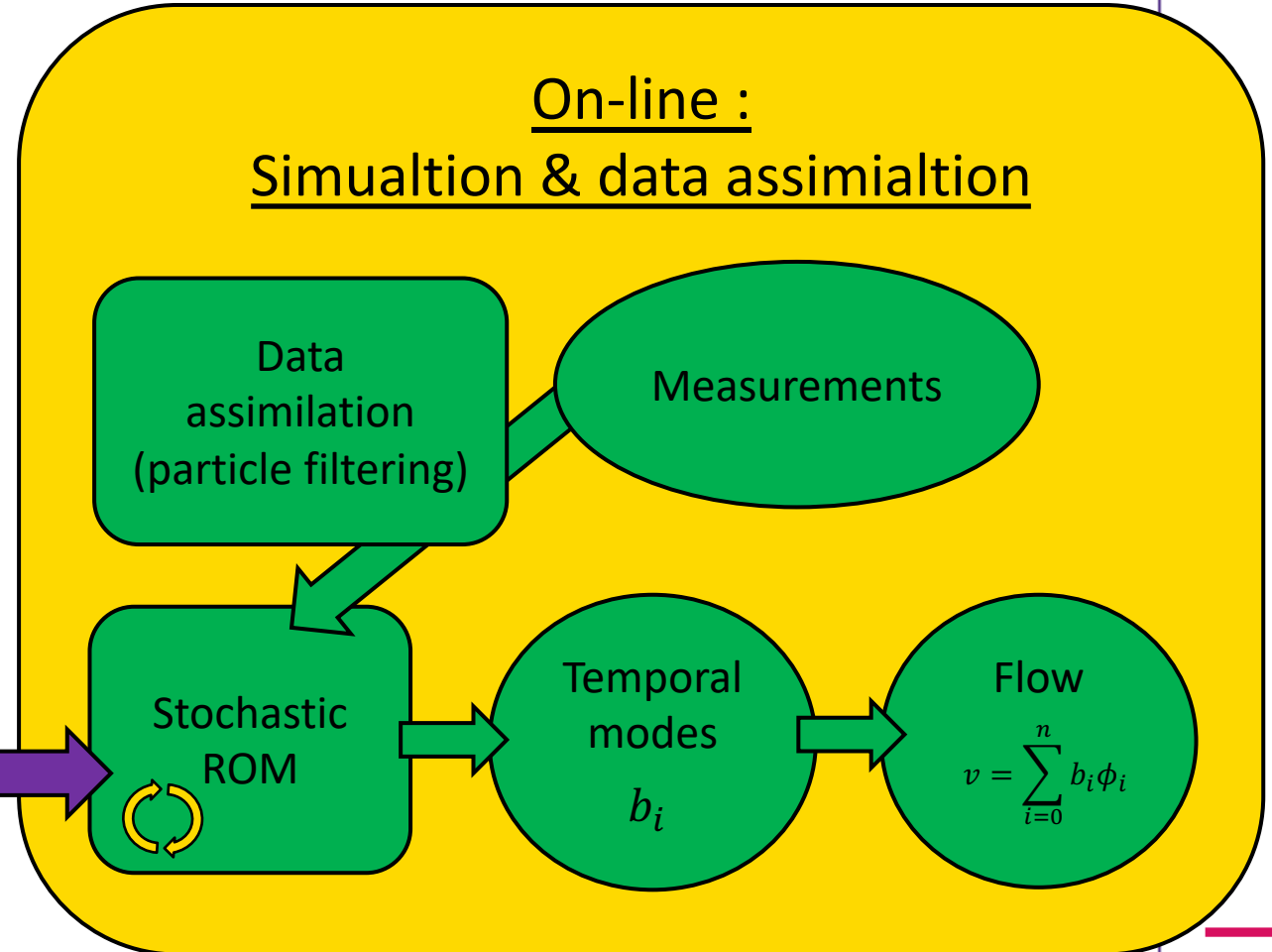
	LUM	SALT
References :	Memin, 2014 Resseguier et al. 2017 a, b, c, d Cai et al. 2017 Chapron et al. 2018 Yang & Memin 2019	Holm, 2015 Holm and Tyranowski, 2016 Arnaudon et al. 2017 Crisan et al., 2017 Gay-Balmaz & Holm 2017 Cotter and al. 2018 a, b Cotter and al. 2019
	Cotter and al. 2017 Resseguier et al. 2019 a, b	

# SUMMARY

## Off-line : Building ROM



## On-line : Simulation & data assimilation





**PART IV**  
**RESULTS :**  
**FAST OBSERVER OF THE FLOW**

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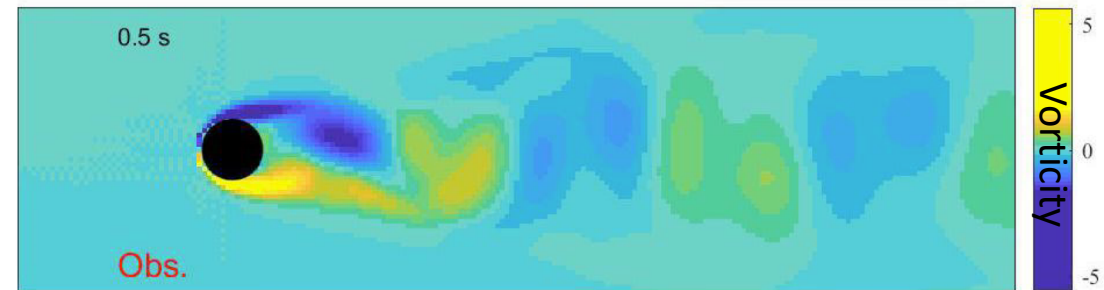
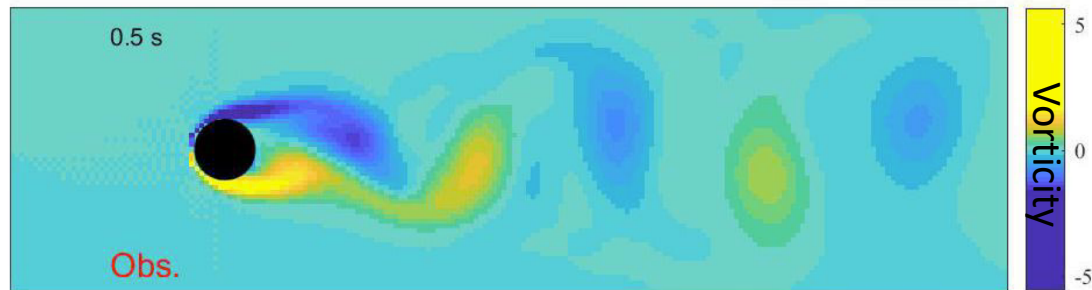
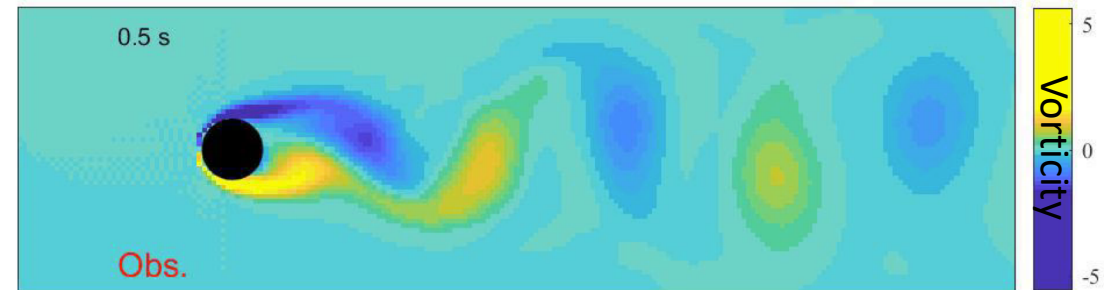
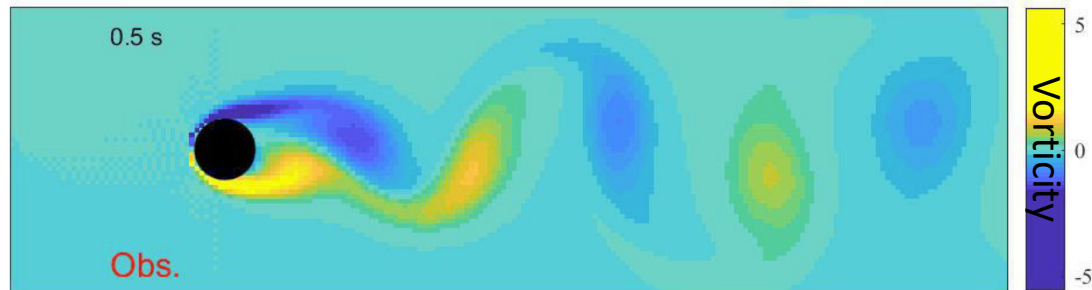


# 1<sup>ST</sup> RESULTS: WAKE AT RE 100

Reduced order models with  $n = 6$   
and 2dB-SNR obs. assimilated every 5 sec

Reference  
(DNS)  
 $10^4$  degrees of freedom

Theoretical bound  
(Optimal from 6-d.o.f. linear decomposition)  
6 degrees of freedom



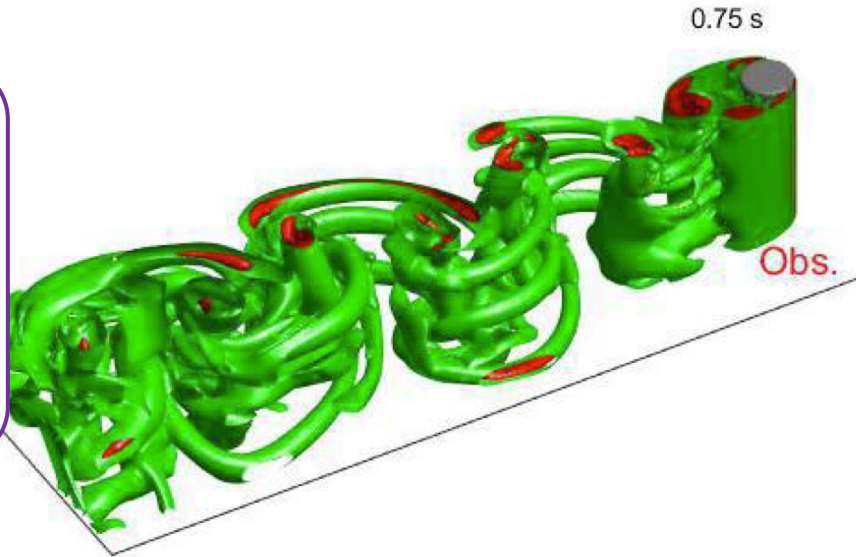
**Our method**  
(Red-LUM-based data-assimilation)  
6 degrees of freedom

Benchmark  
(POD-ROM (with eddy viscosity) + init. by obs.)  
6 degrees of freedom

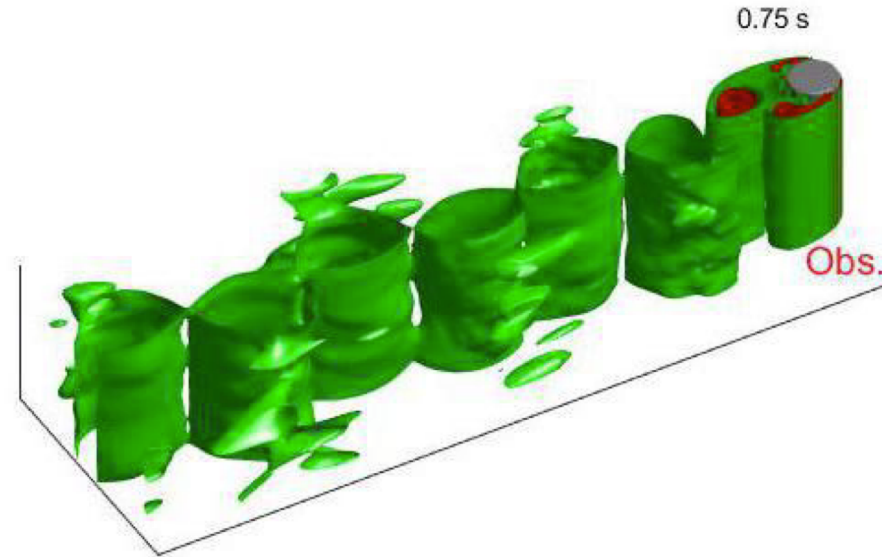
# 1<sup>ST</sup> RESULTS: WAKE AT RE 300

Reduced order models with  $n = 6$   
and 2dB-SNR obs. assimilated every 5 sec

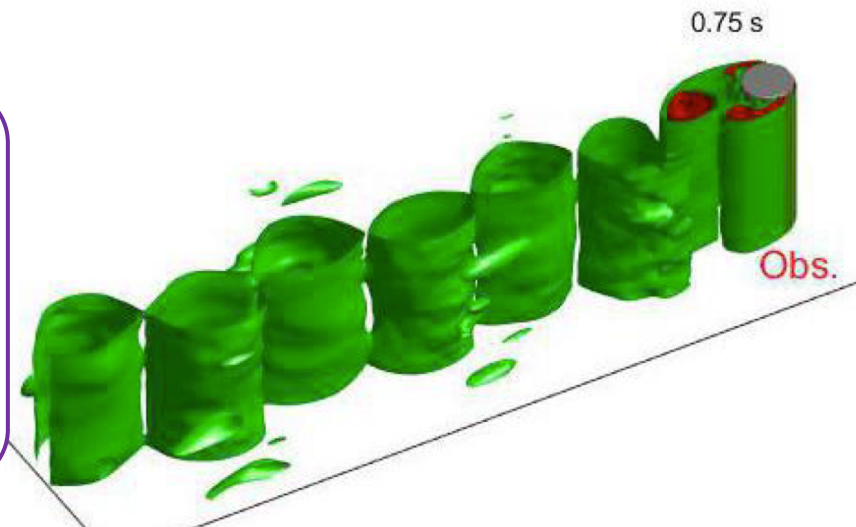
Reference  
(DNS)  
 $10^7$  degrees of freedom



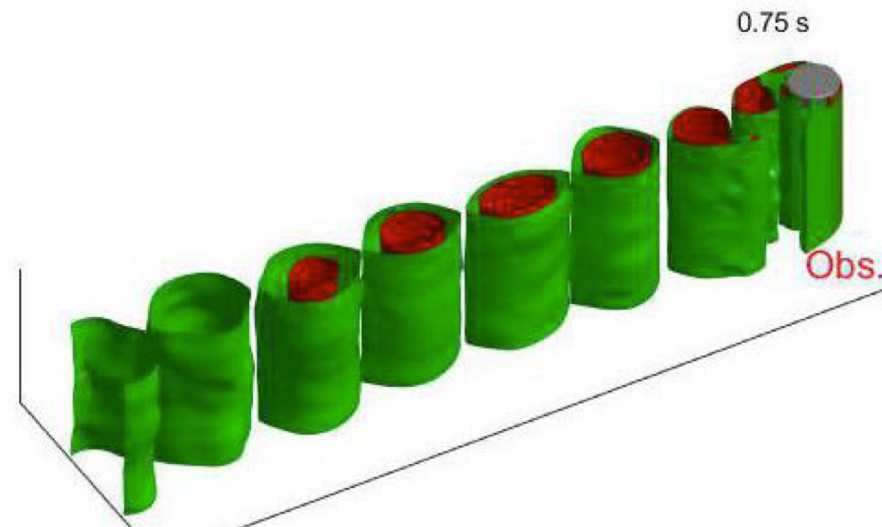
Theoretical bound  
(optimal from  
6-d.o.f. linear  
decomposition)  
6 degrees of freedom



Our method  
(Red-LUM-  
based data-  
assimilation)  
6 degrees of freedom



Benchmark  
(POD-ROM  
(with eddy  
viscosity) +  
init. by obs.)  
6 degrees of freedom





# CONCLUSION

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## CONCLUSION

- ▶ Reduced order model (ROM) : for very fast and robust CFD ( $10^7 \rightarrow 6$  degrees of freedom.)
  - Combine data & physics (built off-line)
  - Closure problem handled by LUM
- ▶ Data assimilation : to correct the fast simulation on-line by incomplete/noisy measurements
  - Model error quantification handled by LUM
- ▶ First results
  - Optimal unsteady flow estimation/prediction in the whole spatial domain (large-scale structures)
  - Robust far outside the learning period

## NEXT STEPS

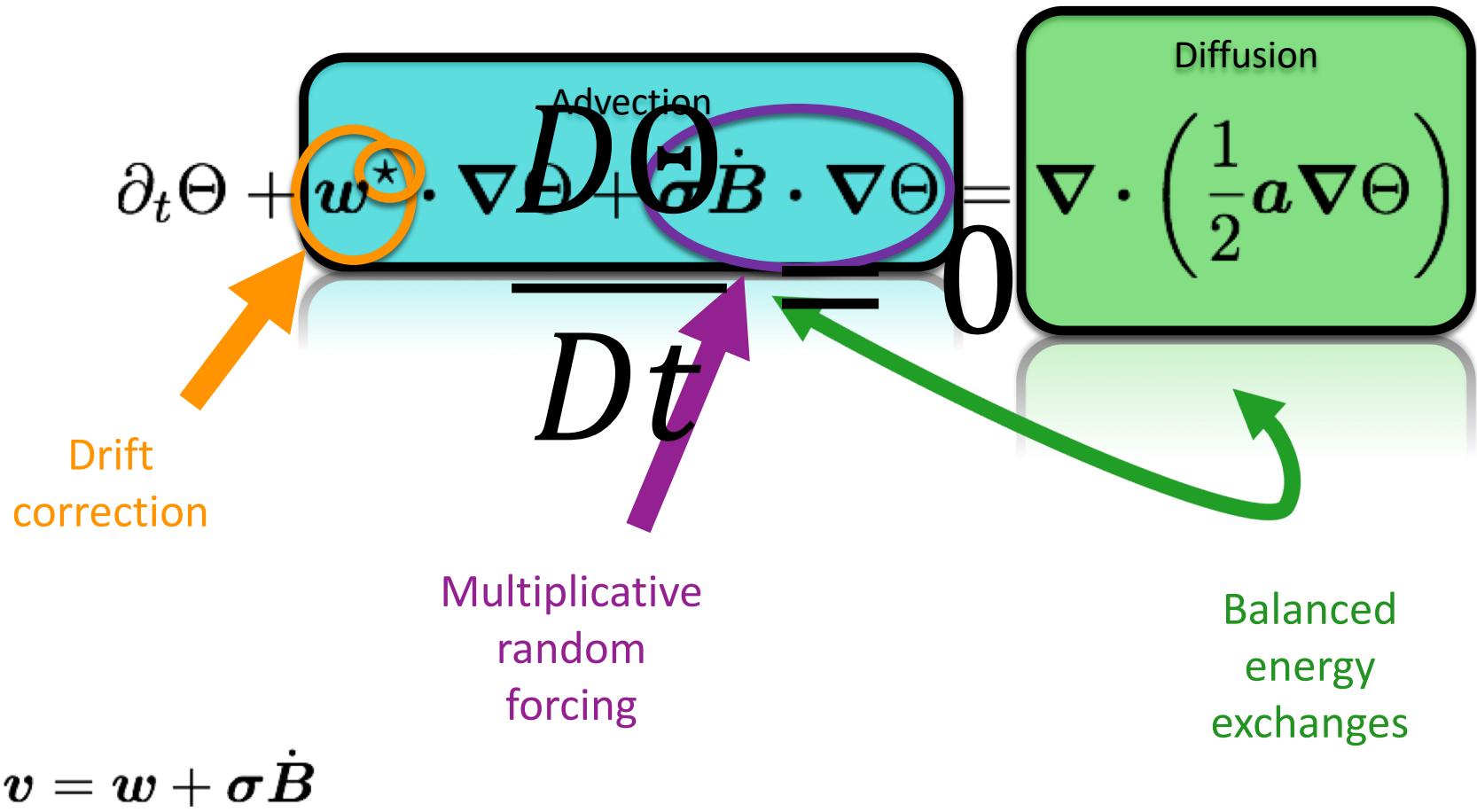
- ▶ Real measurements (PIV, TrimControl, ...)
- ▶ Increasing the degrees of freedom ( $n$ )
- ▶ Increasing Reynolds (reduced DNS  $\rightarrow$  reduced LES)
- ▶ Blade geometry



# BONUS SLIDES

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# LUM: ADVECTION OF TRACER $\Theta$



# GALERKIN PROJECTION GIVES SDES FOR RESOLVED MODES

$$\int_{\Omega} \phi_i \cdot (\text{stochastic Navier-Stokes})$$



$$db_i = \boxed{F_i(\mathbf{b})} dt + \underbrace{\left( \overset{n \times M}{\alpha_{\bullet i \bullet}} \overset{M \times 1}{dB_t} \right)^T \overset{n \times 1}{\mathbf{b}}}_{\text{multiplicative noise}} + \underbrace{\left( \overset{1 \times M}{\theta_i \bullet} \overset{M \times 1}{dB_t} \right)}_{\text{additive noise}}$$

**Correlations to estimate**

2<sup>nd</sup> order polynomial:  
coefficients given by physics,

and  $(\phi_j)_j$        $a(\mathbf{x}, \mathbf{x}) = \frac{1}{t} \langle (\boldsymbol{\sigma}(\mathbf{x})\mathbf{B})_{obs}, (\boldsymbol{\sigma}(\mathbf{x})\mathbf{B})_{obs}^T \rangle_t$