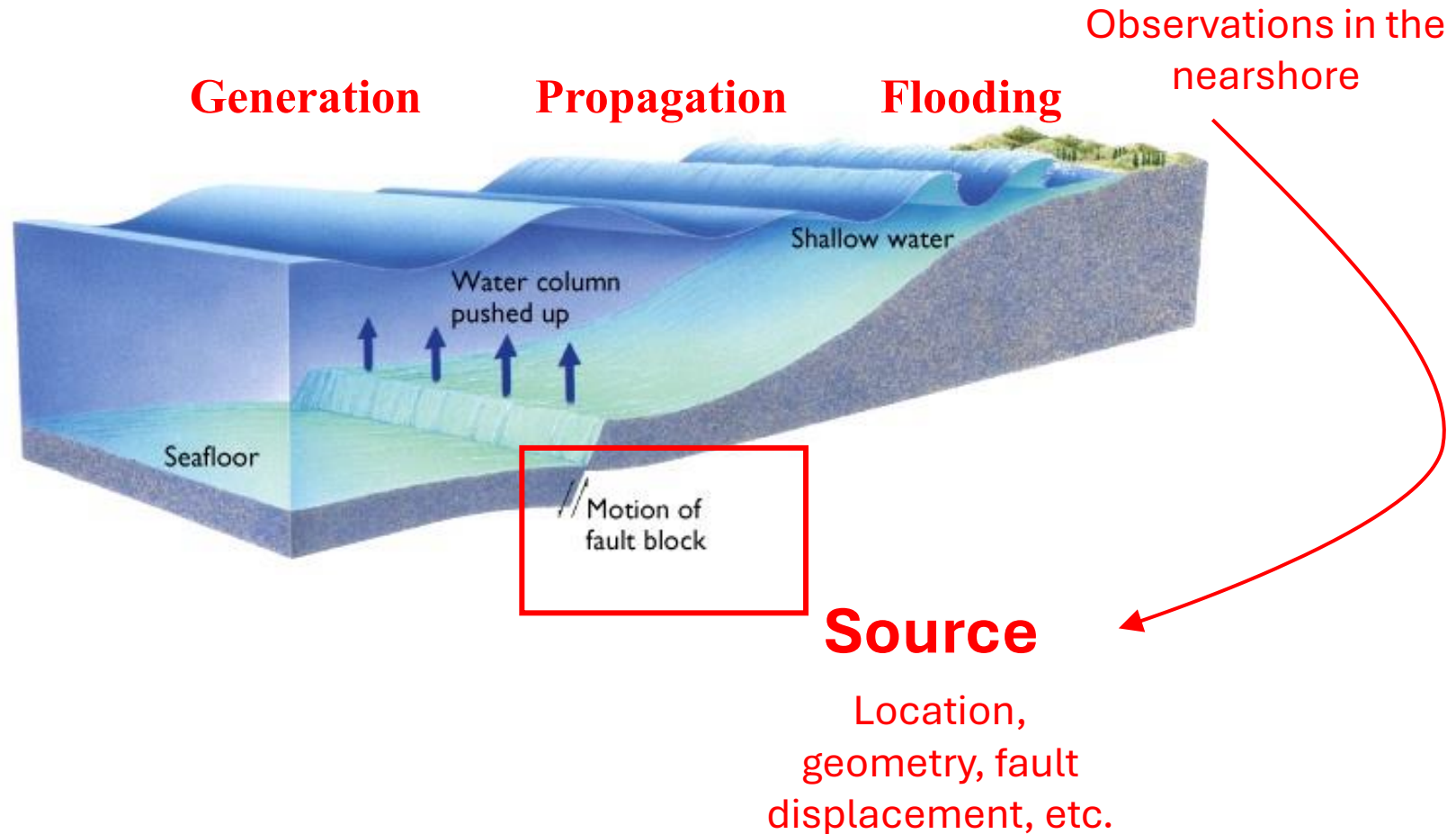


Bayesian inference for source characterisation of the Ligurian 1887 tsunami case: a surrogate-aided ABC setting



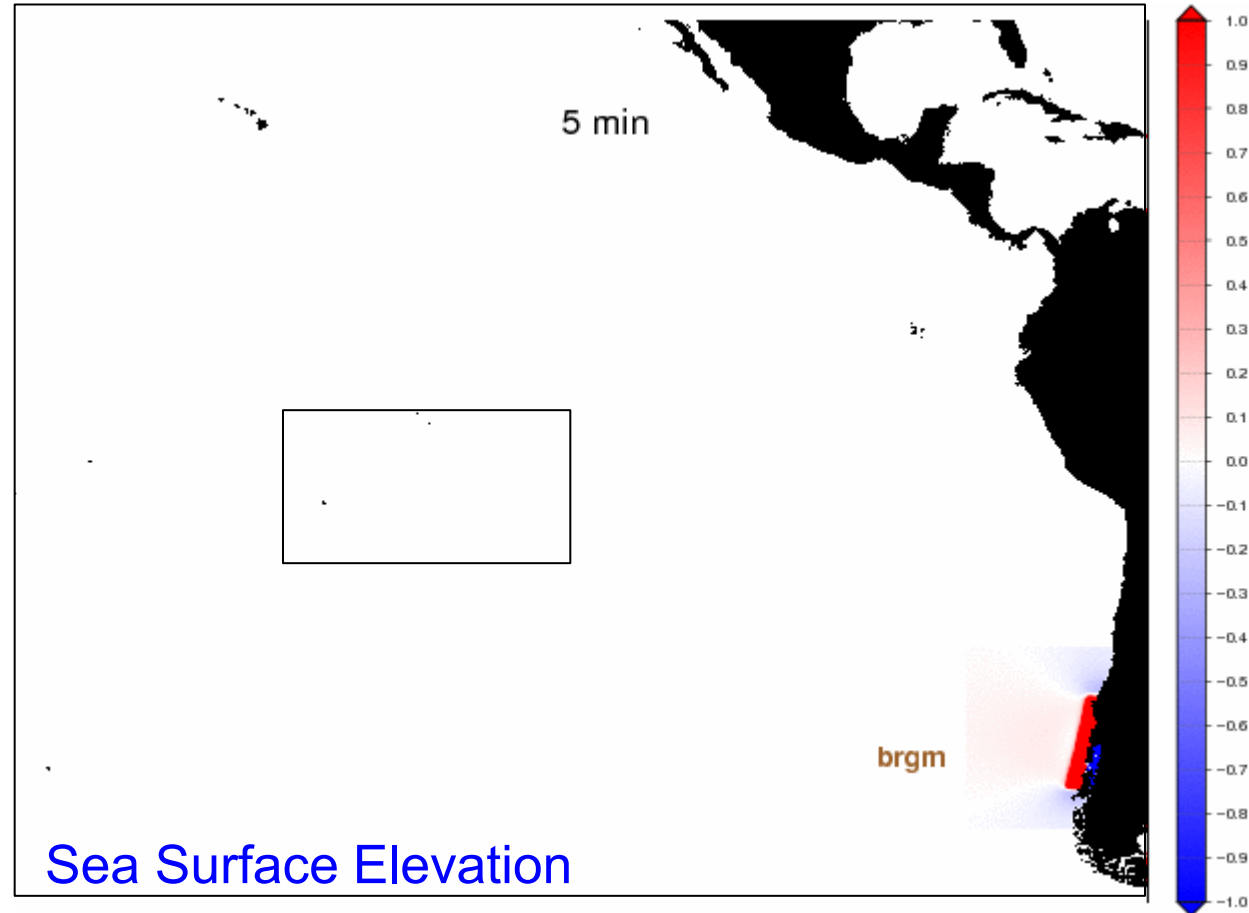
J. Rohmer (j.rohmer@brgm.fr), M. Rousseau, A. Lemoine,
J. Lambert, R. Pedreros, B. Aalae

Earthquake-induced tsunami



Simulation of the tsunami generated in Chili in 1960

Generation (Okada 1985) and propagation (Funwave-TVD) up to French Polynesia - **R. Pedreros (BRGM)**



Inversion for the 2011 Tohoku-Oki earthquake

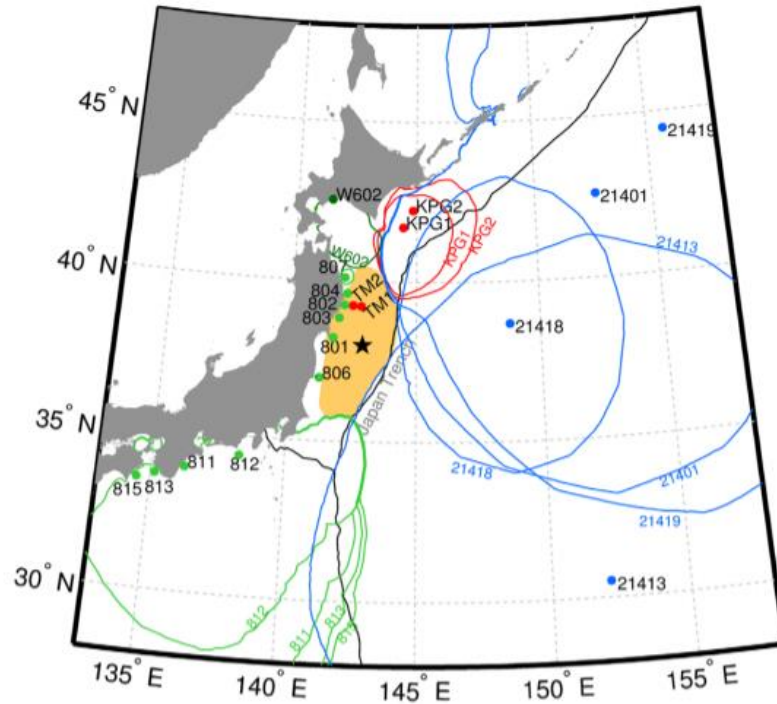


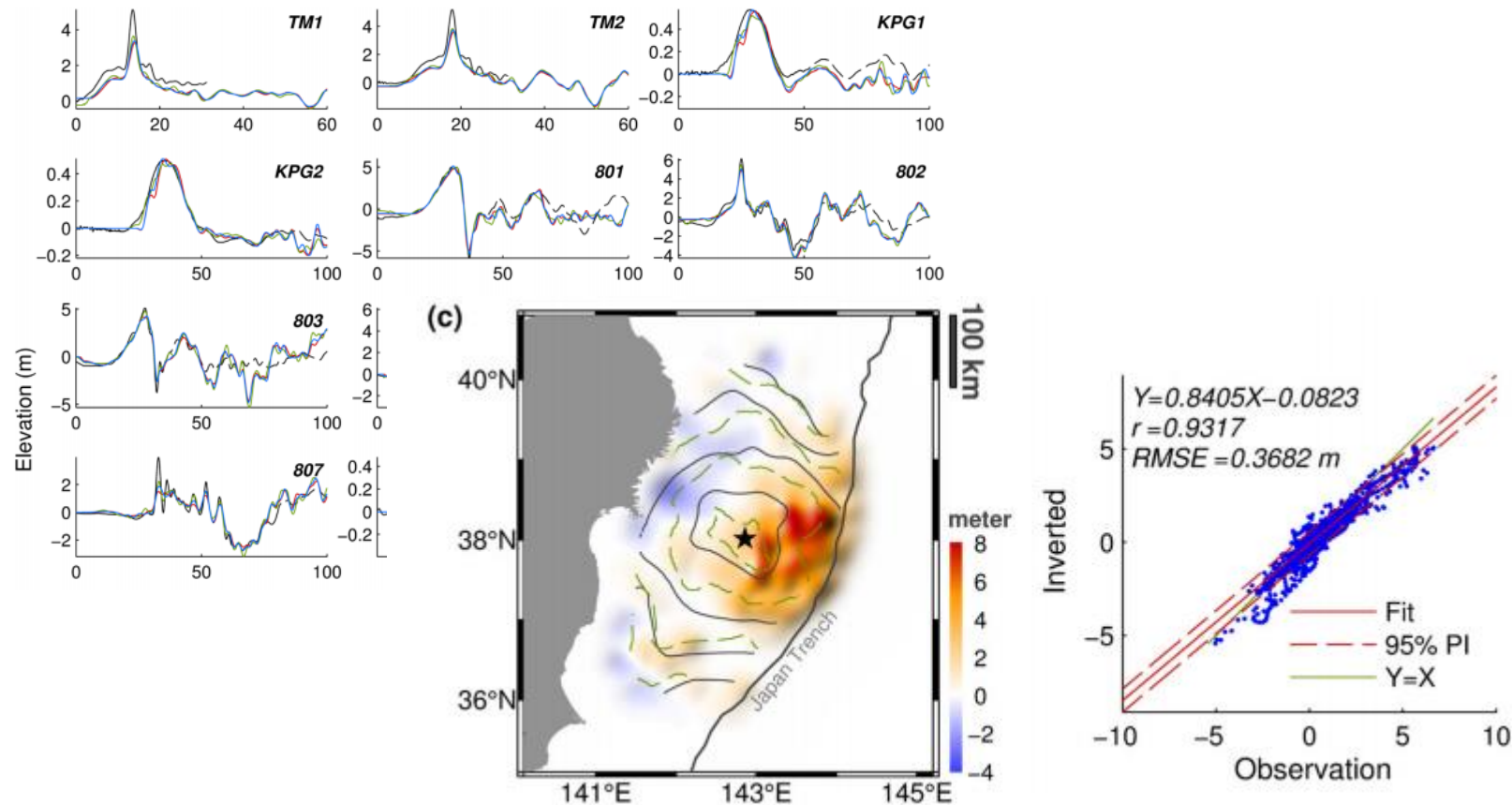
Figure 1. Model domain and source area (yellow). The black star indicates the location of the epicenter of the 2011 Tohoku-Oki earthquake. The contour lines are the backward propagated tsunami arrival times from their corresponding observation stations.

Available data

- From ocean-bottom pressure (OBP) gauges
- Global positioning system (GPS)
- Coastal tide/wave gauges
- **19 observation pts**

Mulia, I. E., and T. Asano (2016), Initial tsunami source estimation by inversion with an intelligent selection of model parameters and time delays, *J. Geophys. Res. Oceans*, 121, 441–456, doi:10.1002/2015JC010877.

Inversion for the 2011 Tohoku-Oki earthquake

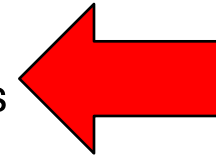


Mulia, I. E., and T. Asano (2016), Initial tsunami source estimation by inversion with an intelligent selection of model parameters and time delays, J. Geophys. Res. Oceans, 121, 441–456, doi:10.1002/2015JC010877.

Past tsunami cases....

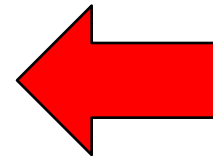
- Examples:
 - 1693 eastern Sicily
 - 1755 Lisbon
 - 1887 Liguria tsunami
 - ...
- Available data
 - Eyewitness accounts, Tide gauge if available
 - Often restricted to Sea Surface Elevation
 - Some indications of time arrivals
 - Wide variation of source parameters' values

**Scarcity &
imprecision
=> Uncertainty
in the inversion
results**



Past tsunami cases....

- Examples:
 - 1693 eastern Sicily
 - 1755 Lisbon
 - 1887 Liguria tsunami
 - ...
- Available data
 - Eyewitness accounts, Tide gauge if available
 - Often restricted to Sea Surface Elevation
 - Some indications of time arrivals
 - Wide variation of source parameters' values
- In nearshore coastal areas
 - Necessity to account for non-linear effects in the numerical simulations

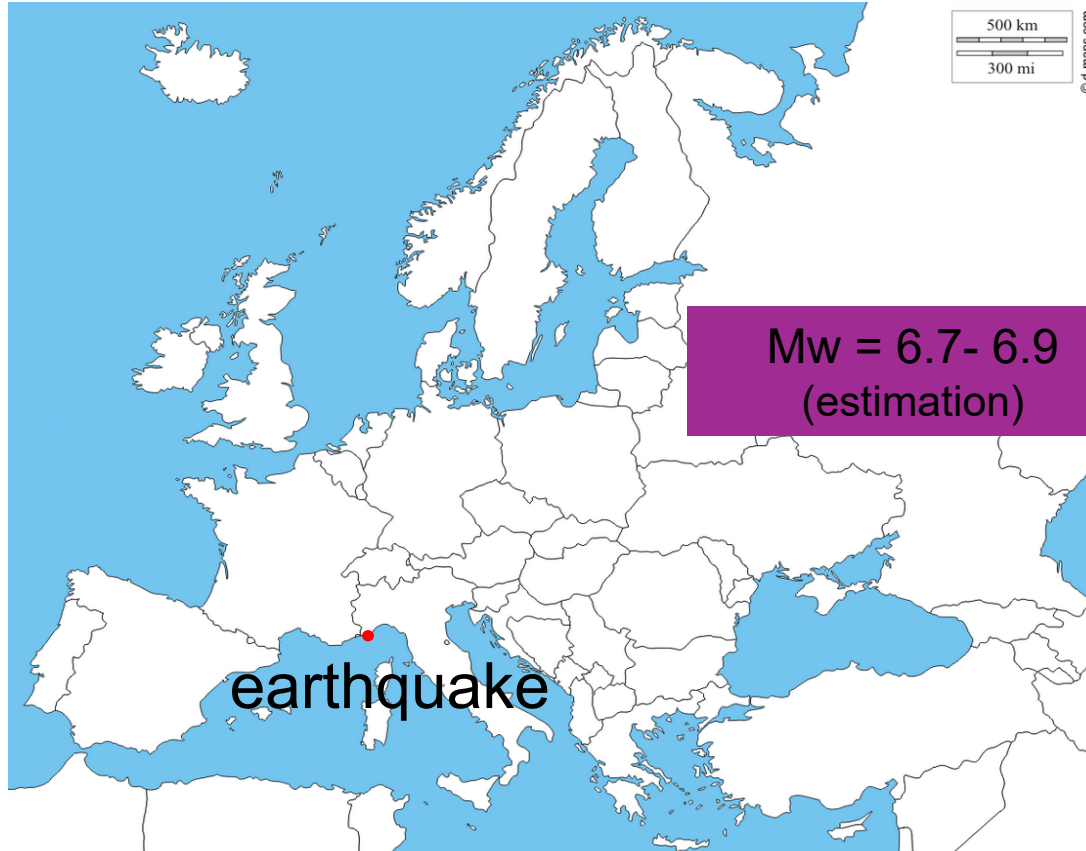


**Need for
accurate
modelling code
=> Computation
time cost** ↗↗↗

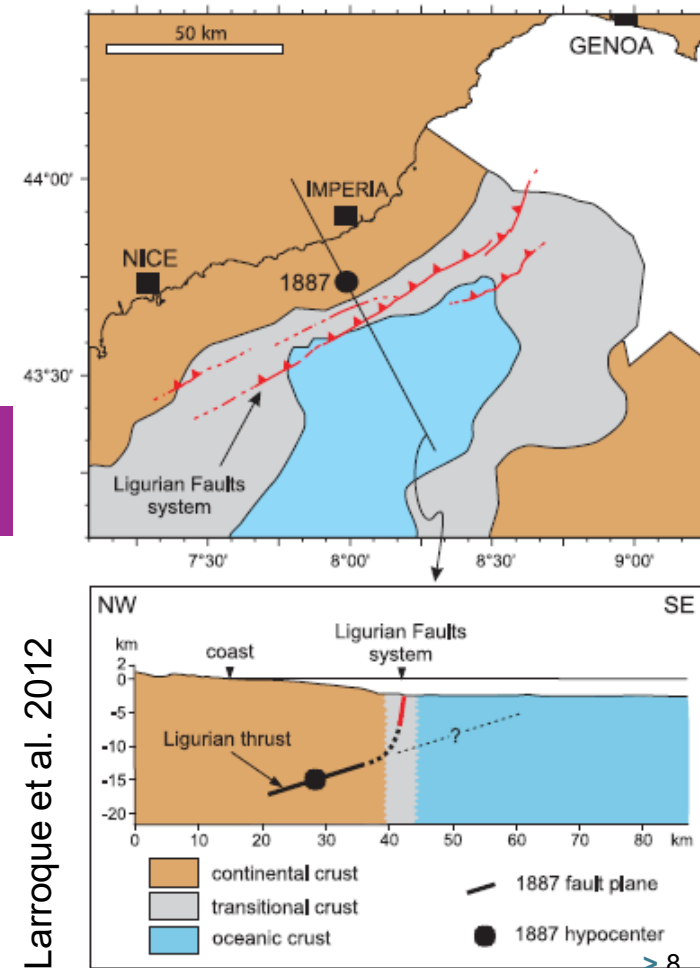


Motivating case study: The 1887 Ligurian event

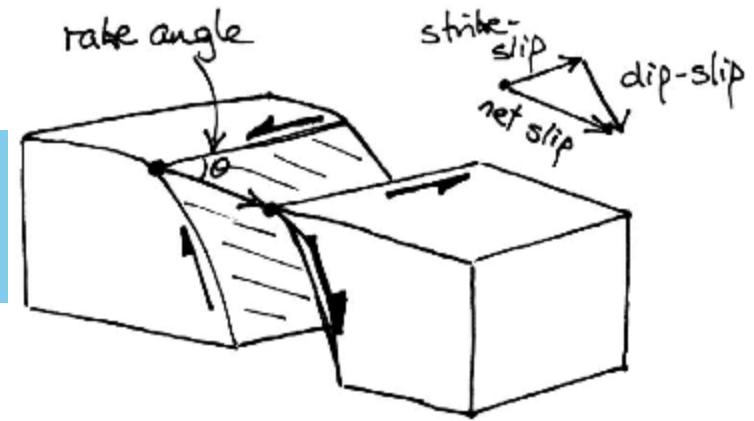
Damaging historical earthquake occurring at the junction
between the southern French-Italian Alps and Ligurian basin
induced tsunami



Larroque et al. 2012

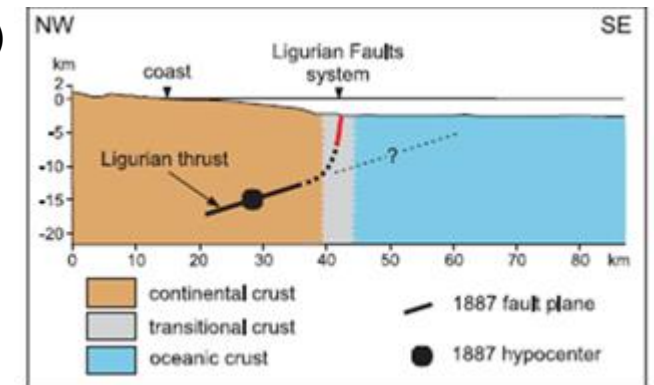


Uncertainty characterisation of the source



Location			orientation			geometry		
Lon (°)	Lat (°)	Depth Z (km)	Azim (°) 2 scenarios North (South) dipping	DIP (°)	Rake (°)	Average displacement D (m)	Length (m)	Width (km)
7.78	43.45	5	220 (40)	10	70	0,3	20	10
8.15	43.92	20	260 (80)	70	110	2	57	22

Based on Larroque et al. (2012) and Ioualalen et al. (2014)



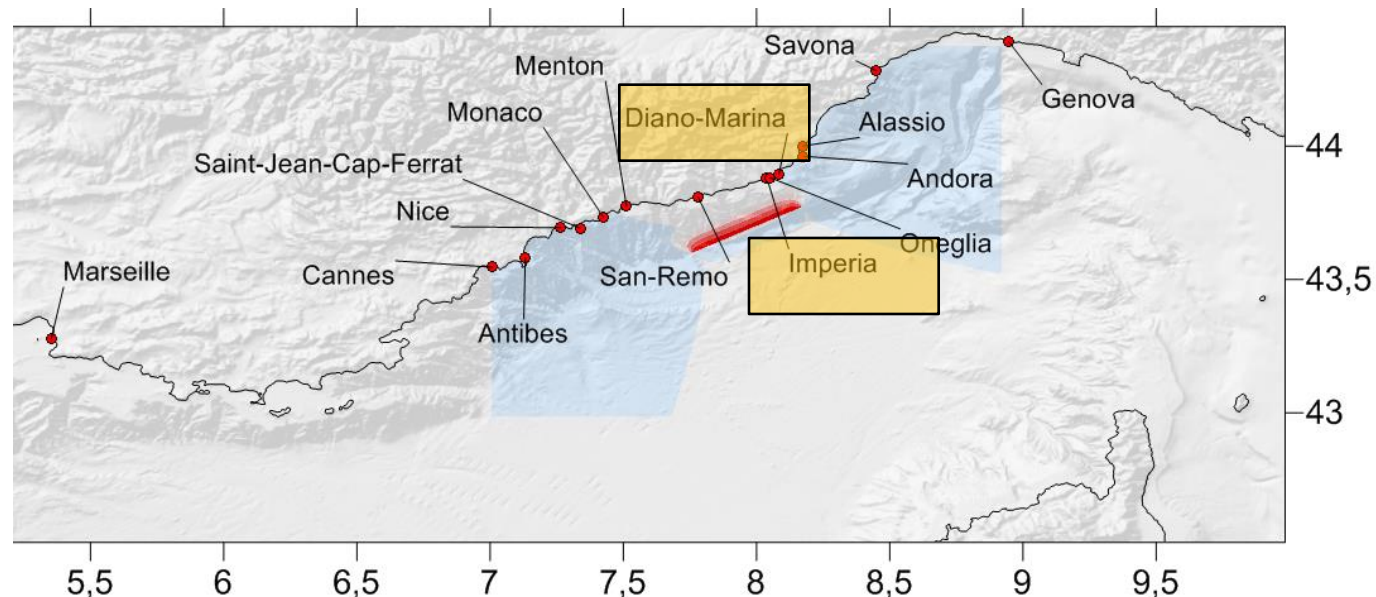
Historical observations in the near field



Confidence

Moderate

Location	Observation	Value	Confidence
Marseille	Tsunami intensity	0	High
Diano Marina	Maximum SSE	1 m	Moderate
Diano Marina	Minimum SSE	-1m	Moderate
Genova	Maximum SSE	0.07 m	High
Porto Maurizio (Imperia)	Minimum SSE	-1m	Moderate



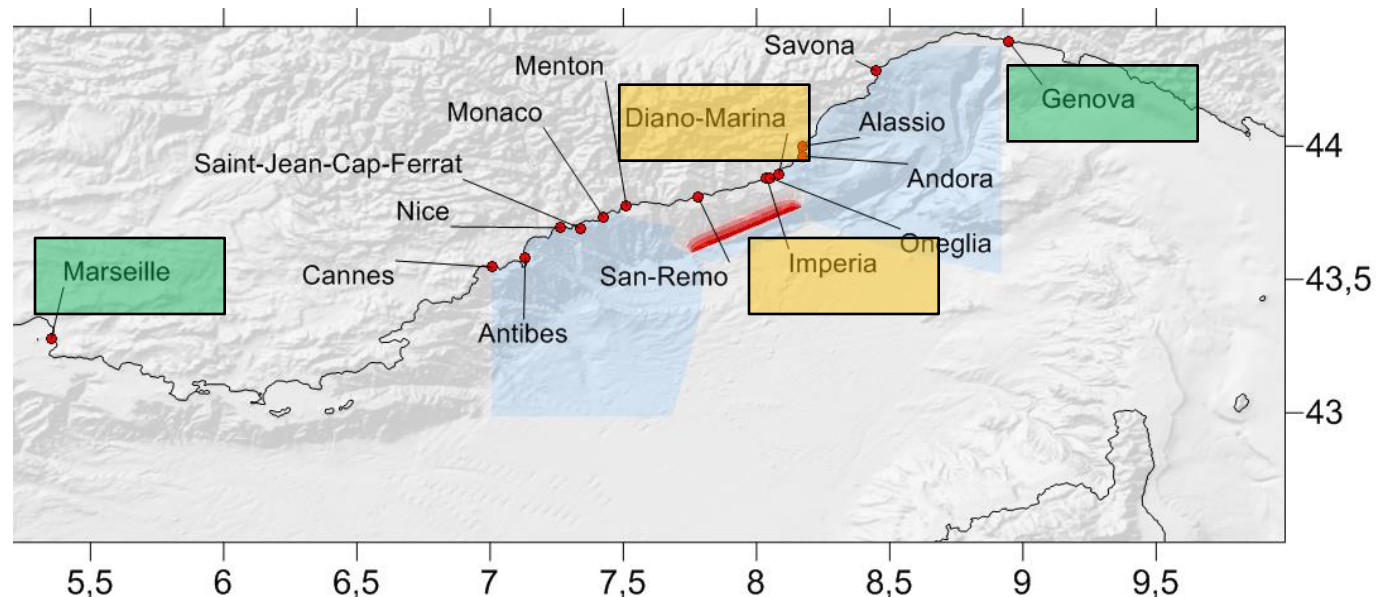
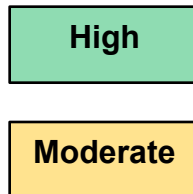
Historical observations in the far field



Location	Observation	Value	Confidence
Marseille	Tsunami intensity	0	High
Diano Marina	Maximum SSE	1 m	Moderate
Diano Marina	Minimum SSE	-1m	Moderate
Genova	Maximum SSE	0.07 m	High
Porto Maurizio (Imperia)	Minimum SSE	-1m	Moderate



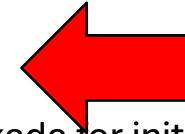
Confidence



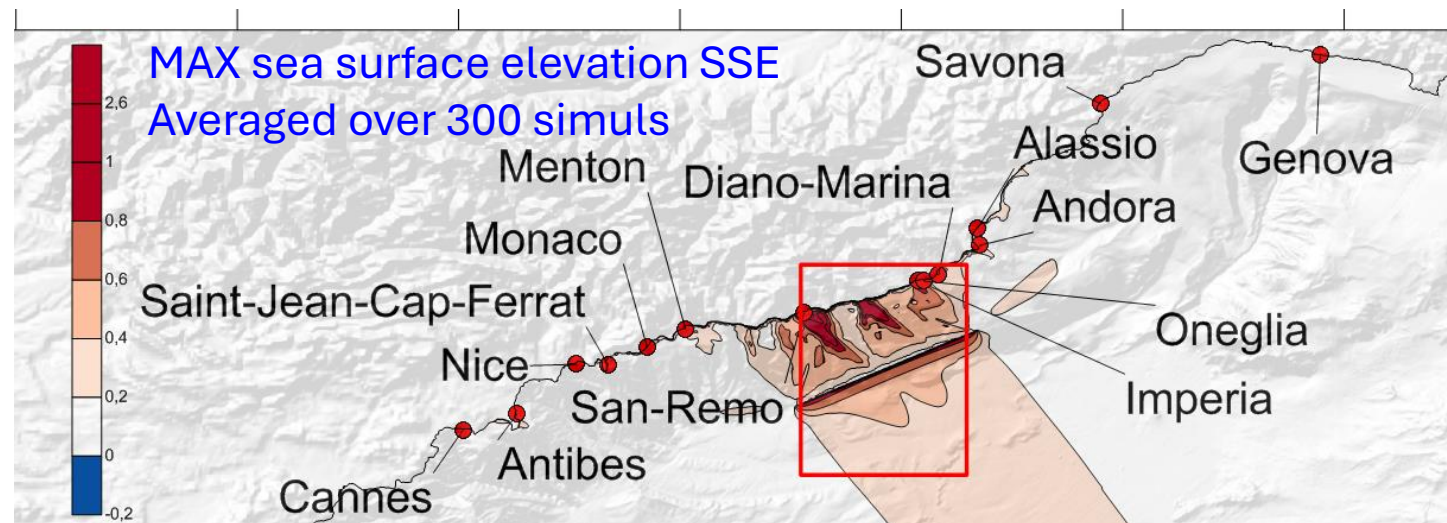
Ingredient 1: Numerical simulation

MODEL CHARACTERISTICS

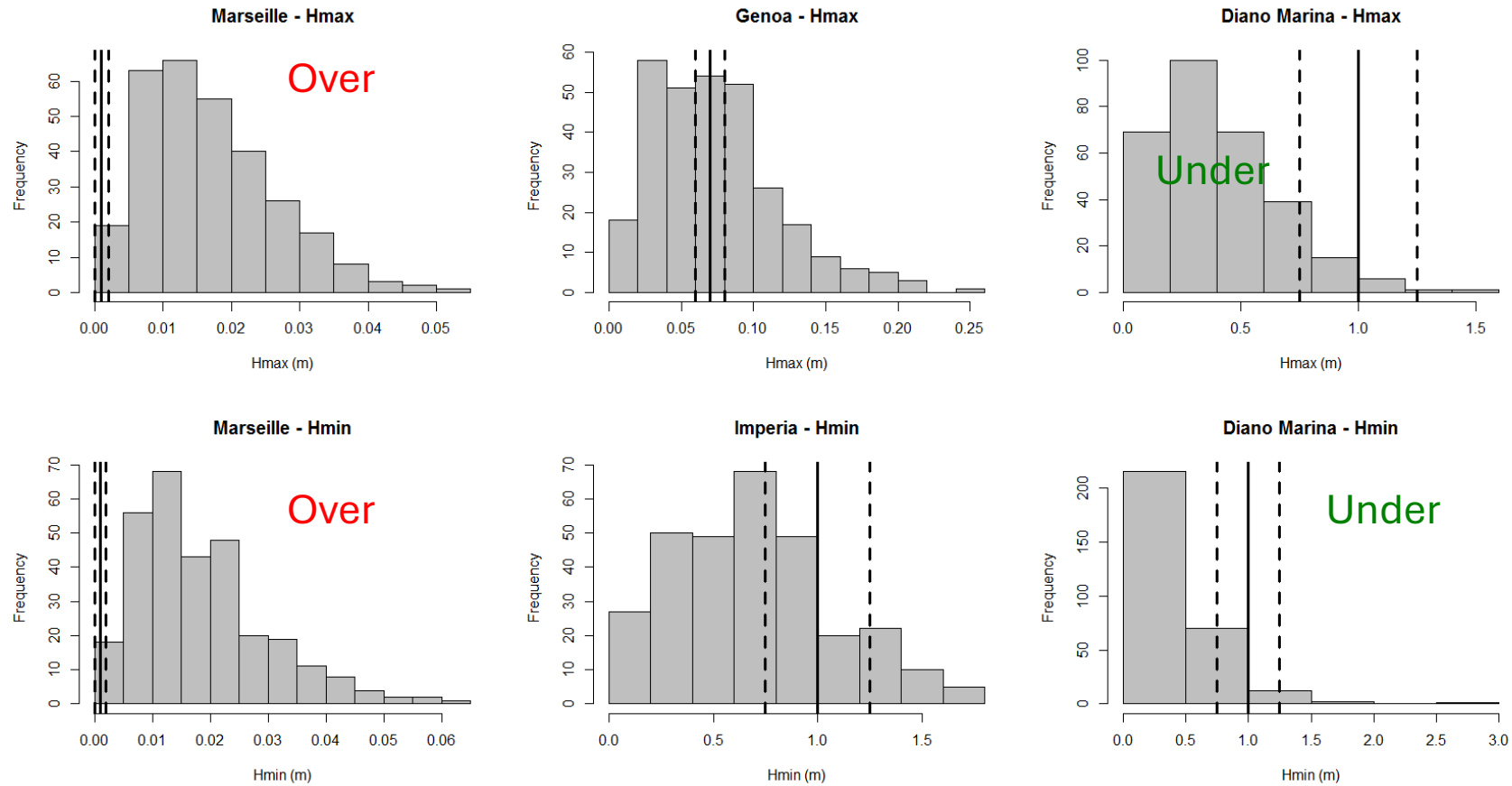
- 2,650,000 mesh cells
- CPU time of a single simulation **30-60 min** with **4*24 cores**
- Funwave_TVD Boussinesq ocean surface wave propagation + Okada for initial deformation



300 configurations were randomly generated (latin hypercube sampling and uniform distribution).



Simulation results (a priori)

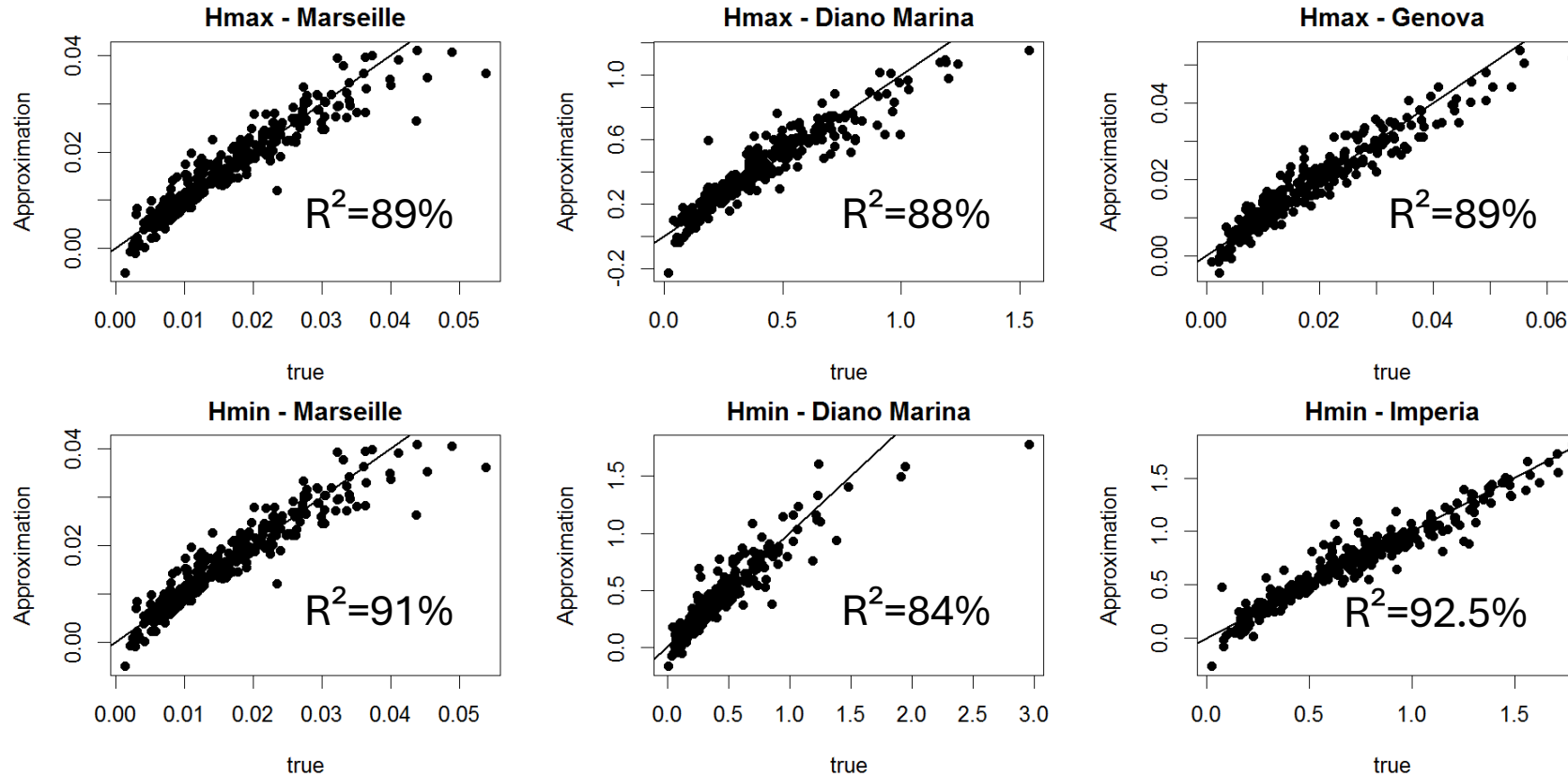


———— Observation
----- Assumed range of uncertainty

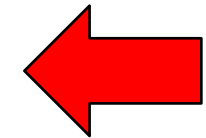
Ingredient 2: overcoming the computation time cost with kriging surrogate models

Tutorial on Friday!

training with 300 simulation results



Satisfactory approximation quality (typical threshold at 80%, see e.g., Marrel et al., (2009); Storlie et al. (2009))



Ingredient 3: inference within a Bayesian setting

$$(A1) \quad H_{observed} = H_{simulated} + \theta_{bias} \approx \hat{H}(\theta_{Source}) + \theta_{bias}$$

$$(A2) \quad p(\theta|H_{obs}) \propto p(\theta) \cdot p(H_{obs}|\theta)$$



**Probability
information
on θ after
observing H**



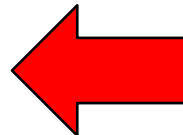
**Prior
knowledge**



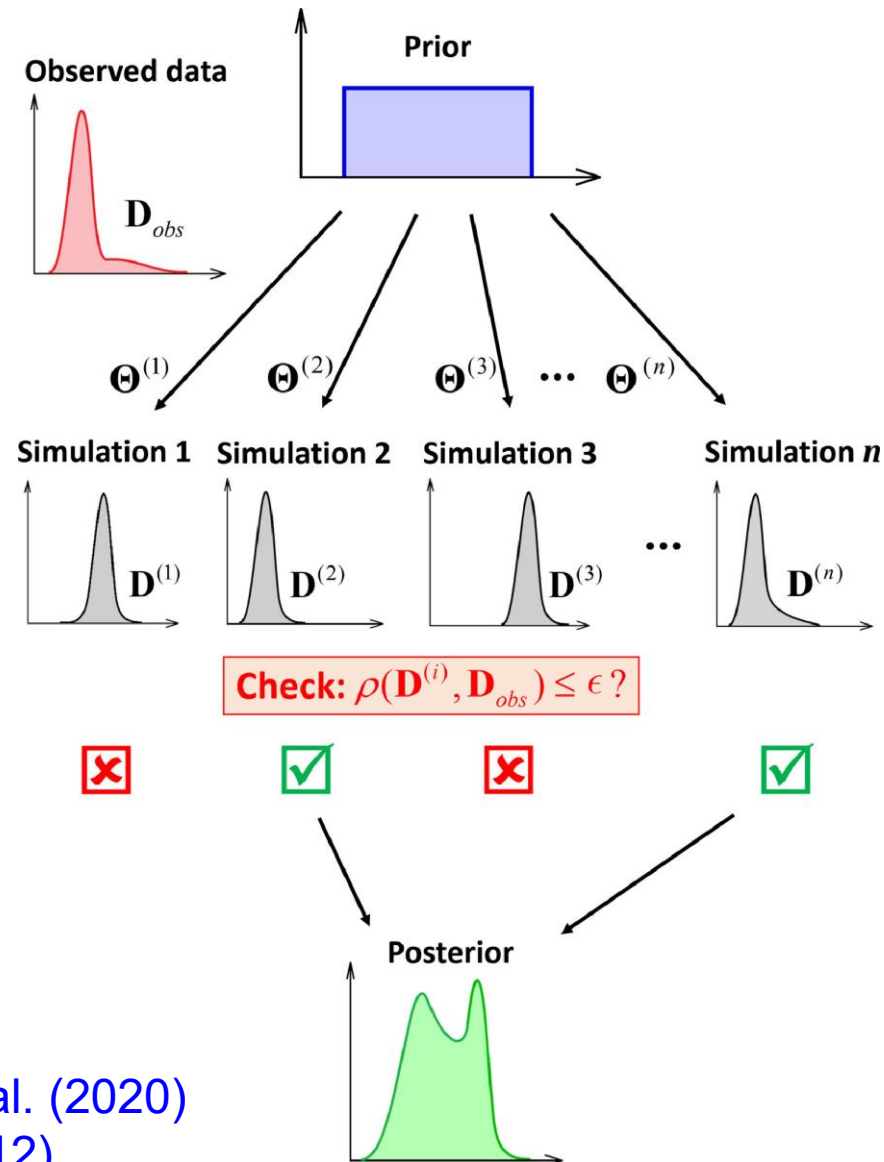
**Likelihood =
probability of
observing H
given θ**

Likelihood function usually hard to compute

Advanced techniques: MCMC, SMC (particle filters), etc.



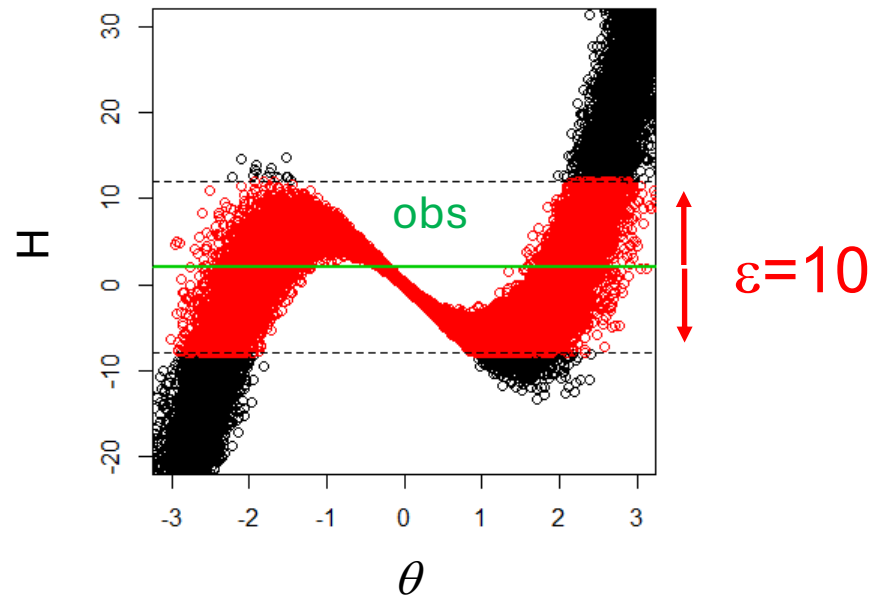
Approximate Bayesian Computation ABC



ρ Distance
 ϵ Tolerance

Extracted from Hazra et al. (2020)
See also Marin et al. (2012)

Toy example of ABC

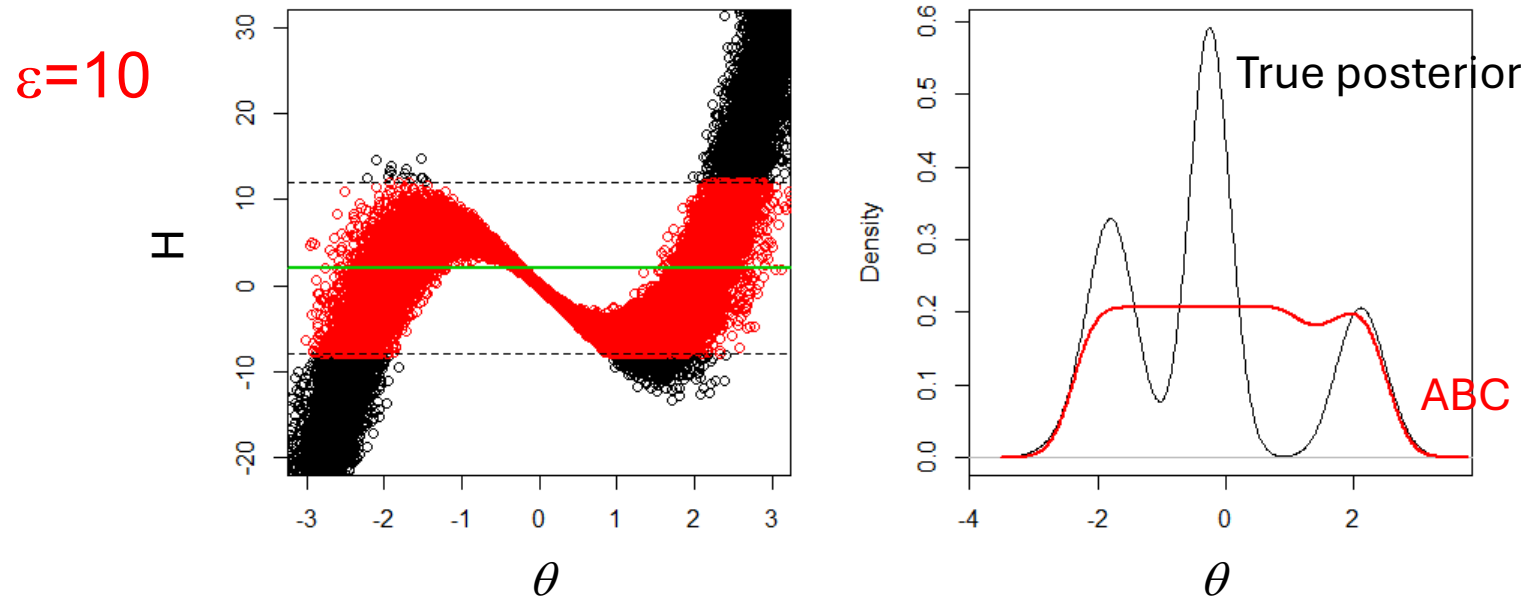


Prior: $\theta \sim U(-10, 10)$

$$p(H|\theta) = N(2(\theta + 2)\theta(\theta - 2), 0.1 - \theta^2)$$

$$\rho = |\text{obs} - \theta|, \text{obs} = 2$$

Toy example of ABC

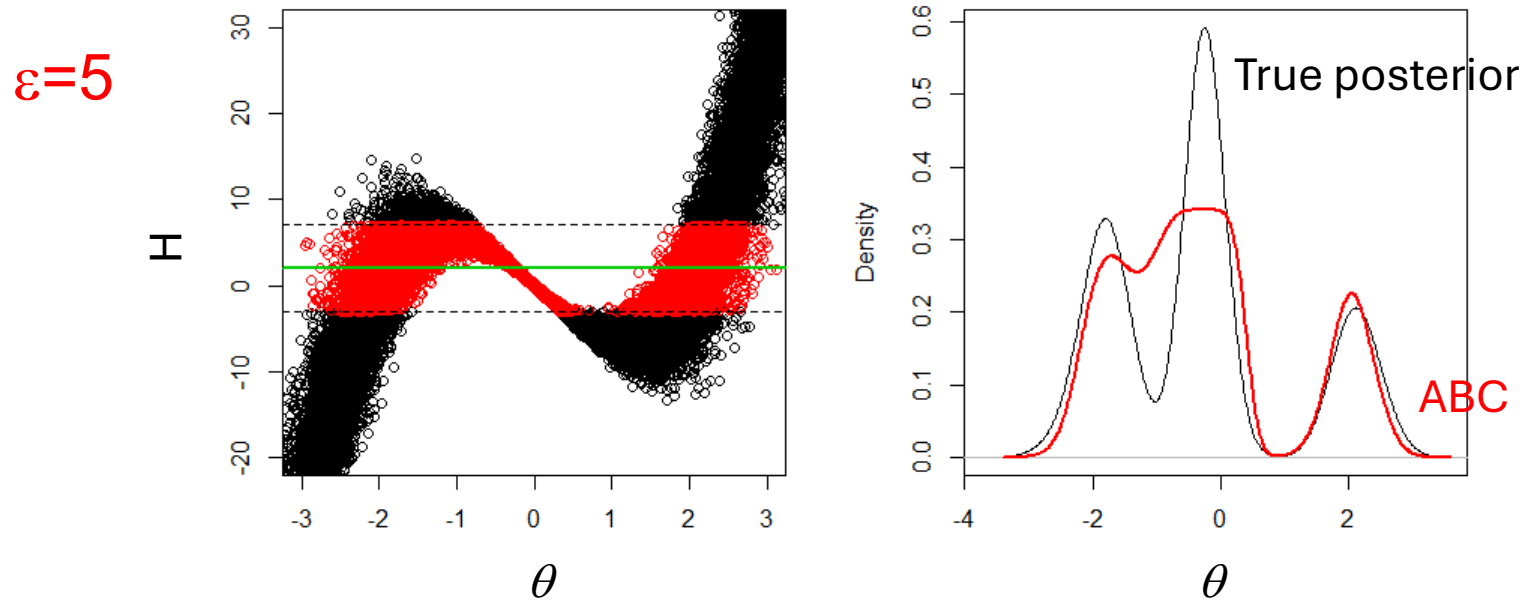


Prior: $\theta \sim U(-10, 10)$

$$p(H|\theta) = N(2(\theta + 2)\theta(\theta - 2), 0.1 - \theta^2)$$

$$\rho = |\text{obs} - \theta|, \text{obs} = 2$$

Toy example of ABC

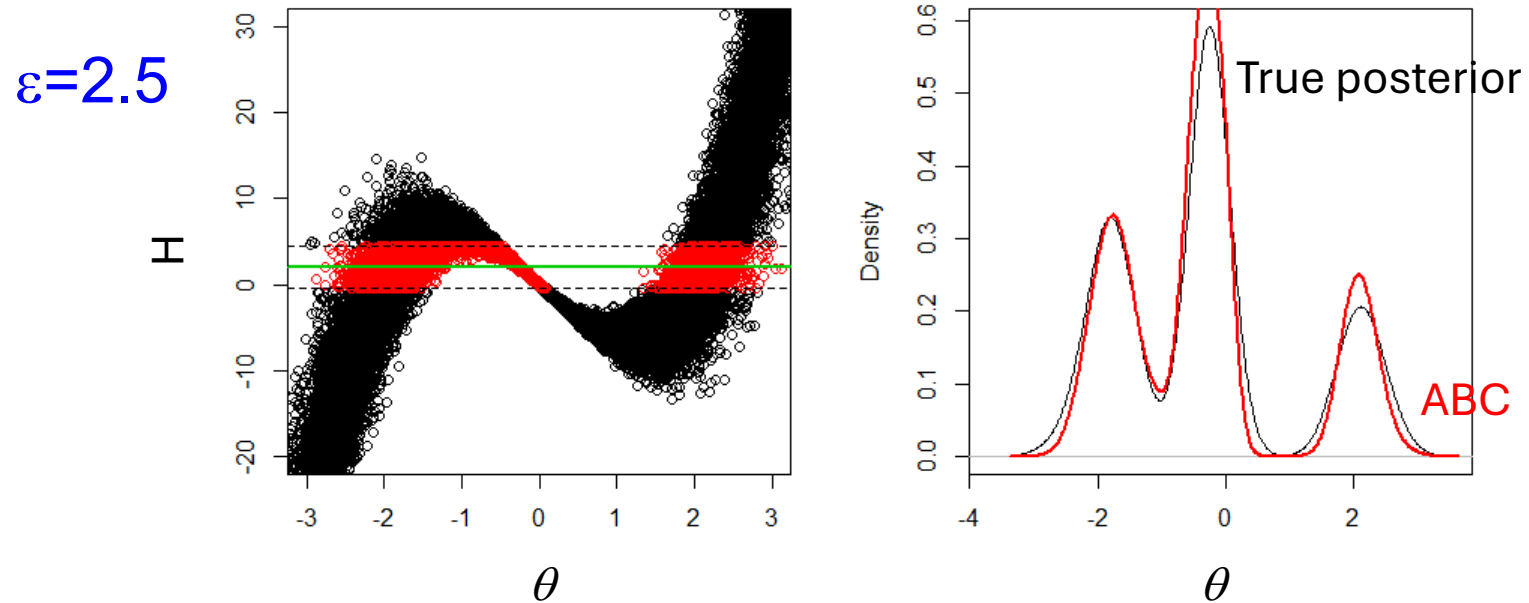


Prior: $\theta \sim U(-10, 10)$

$$p(H|\theta) = N(2(\theta + 2)\theta(\theta - 2), 0.1 - \theta^2)$$

$$\rho = |\text{obs} - \theta|, \text{obs} = 2$$

Toy example of ABC



Prior: $\theta \sim U(-10, 10)$

$$p(H|\theta) = N(2(\theta + 2)\theta(\theta - 2), 0.1 - \theta^2)$$

$$\rho = |\text{obs} - \theta|, \text{obs} = 2$$

How to choose ε ? = choosing the proportion of accepted samples

→ Test the **coverage property**

Let us assume that we know the true value θ_0

The **credible interval** I at level $\alpha\%$ (from the posterior) is defined as
 $P(\theta_0 \in I | \text{obs}) = \alpha\%$

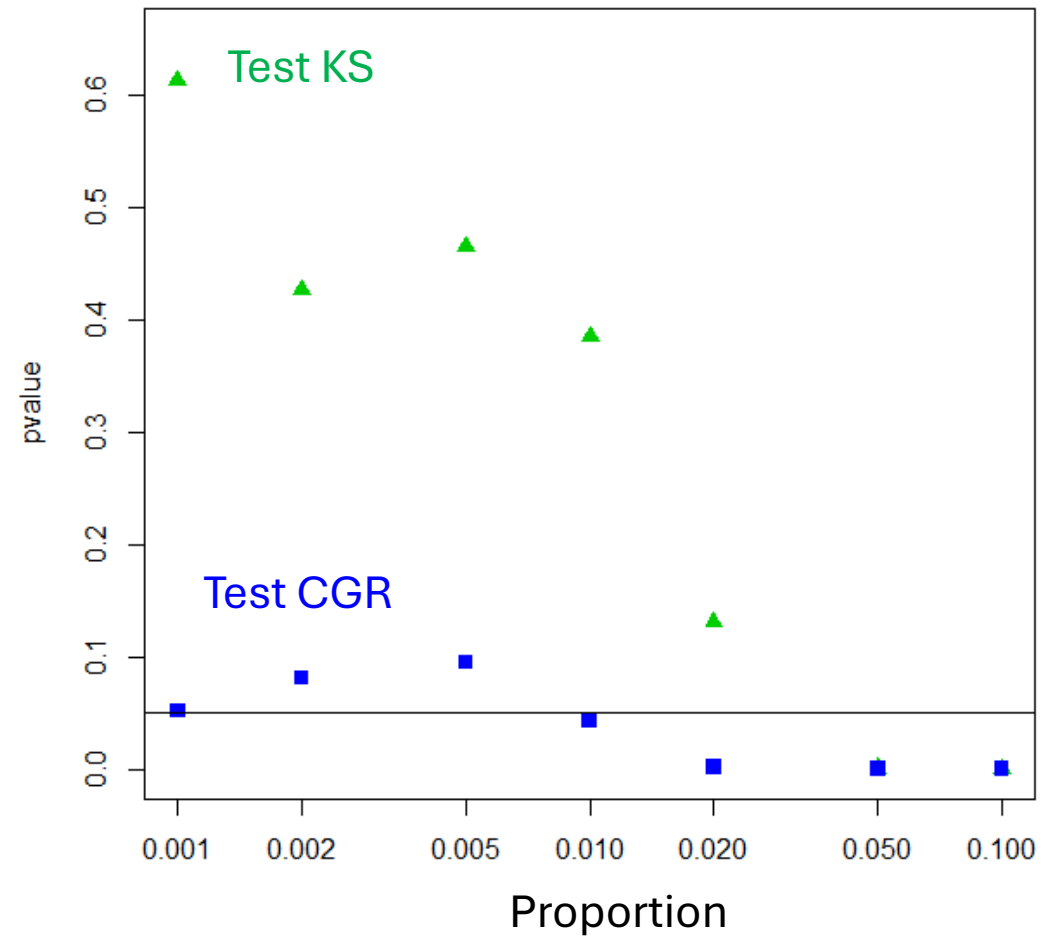
It is equivalent that the probability p_0 of observing $\theta_0 \leq \theta \sim U(0,1)$

→ Test the **uniformity** (KS test, CGR test, etc.)

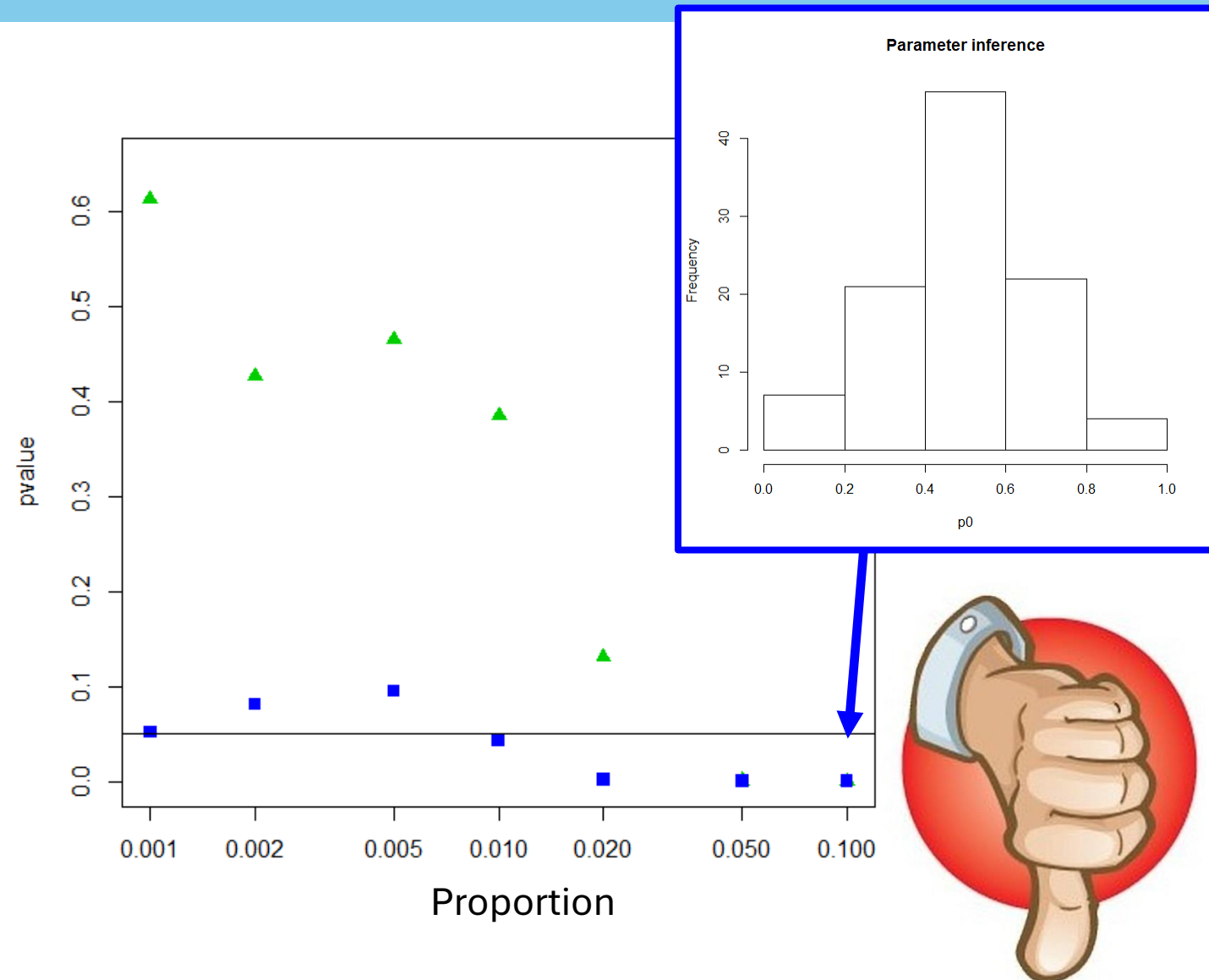
Implementation: we do not know *a priori* the true value θ_0

→ **Bootstrap random selection of** (θ_0, obs) repeated several times

Illustration

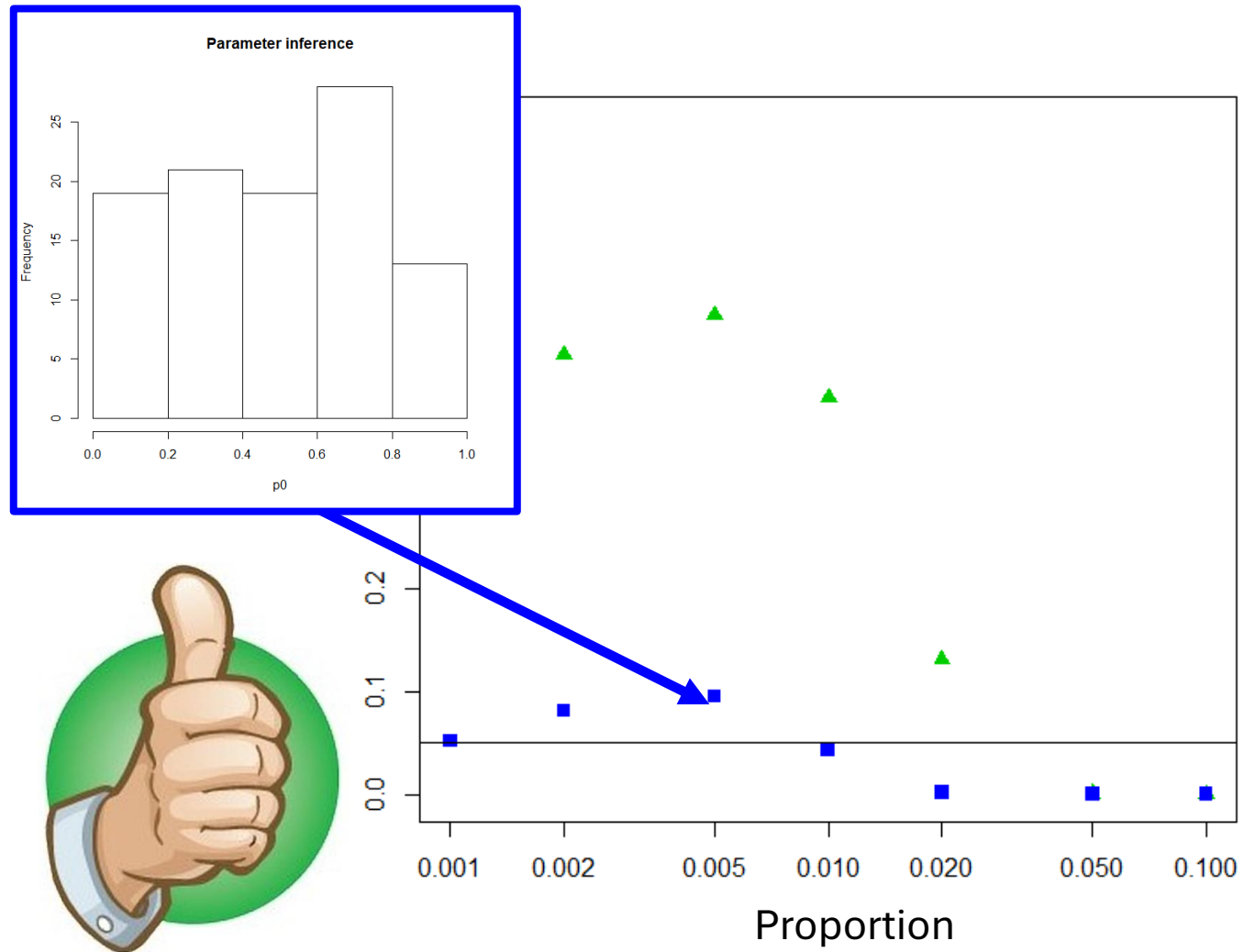


Illustration



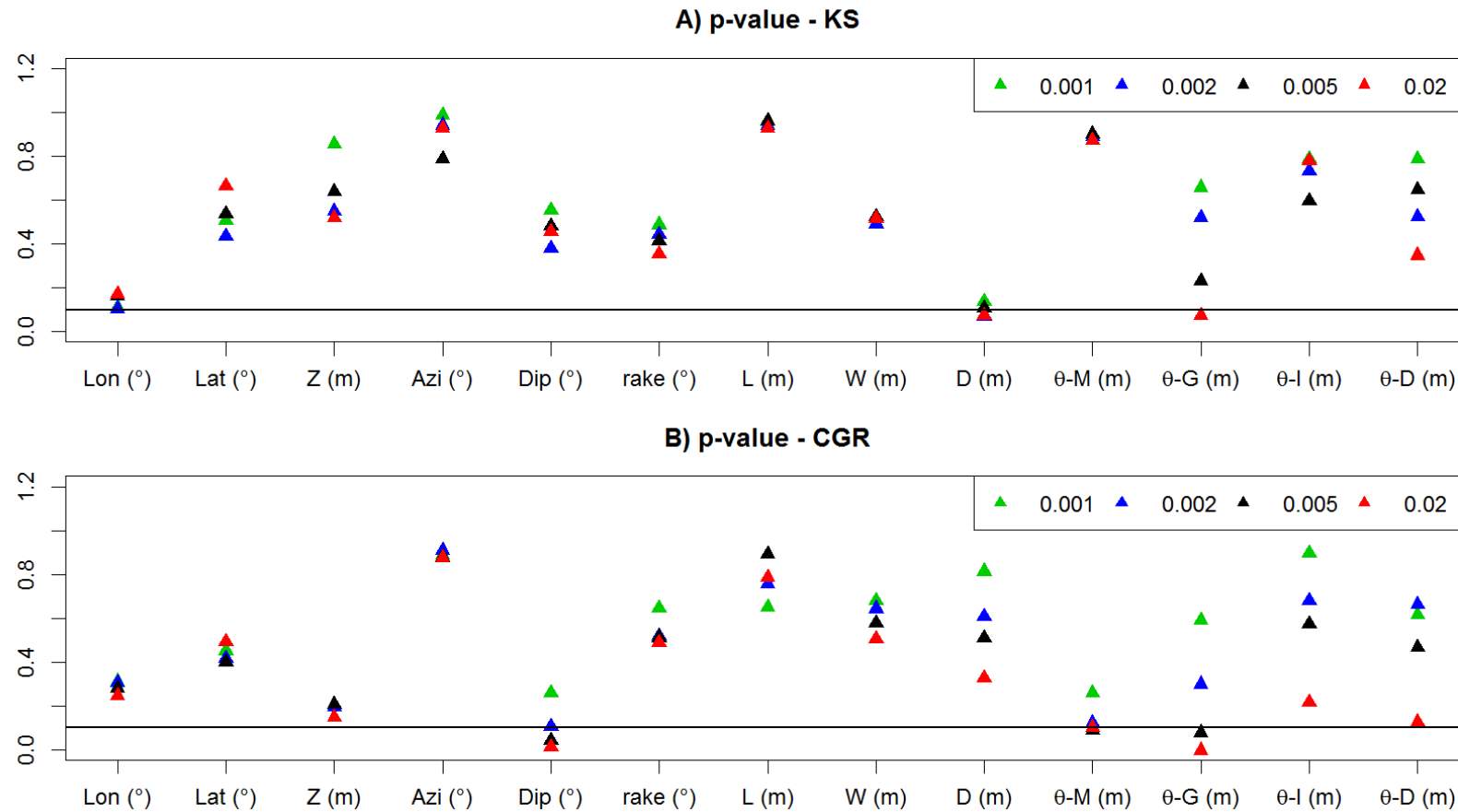
Weak p-value = strong evidence against the null hypothesis 'uniform distribution'

Illustration

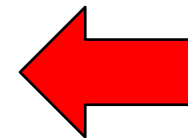


Choosing the proportion of accepted samples

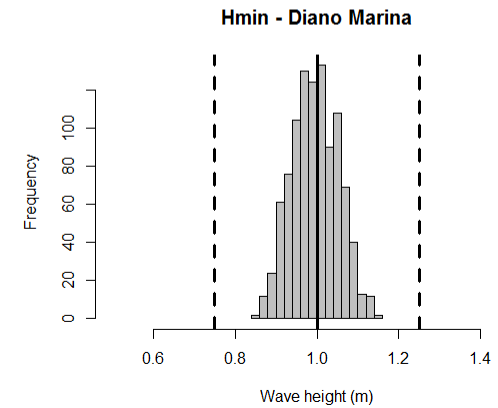
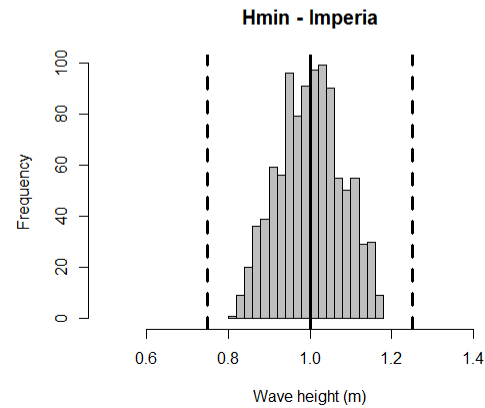
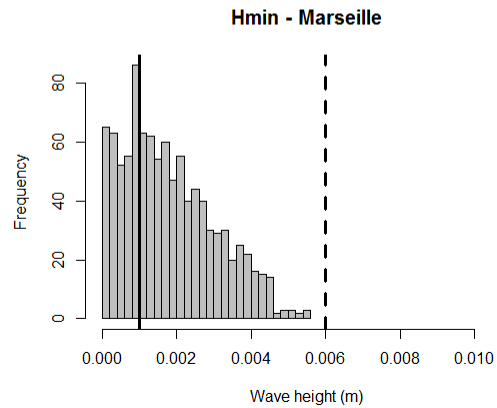
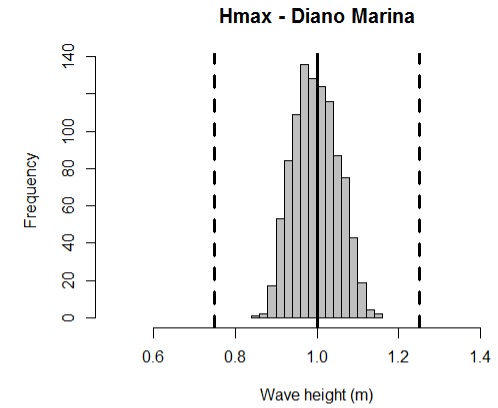
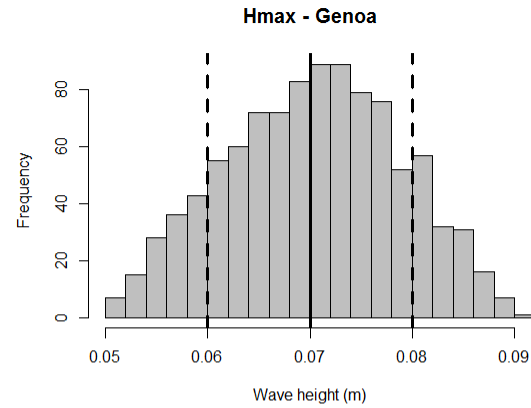
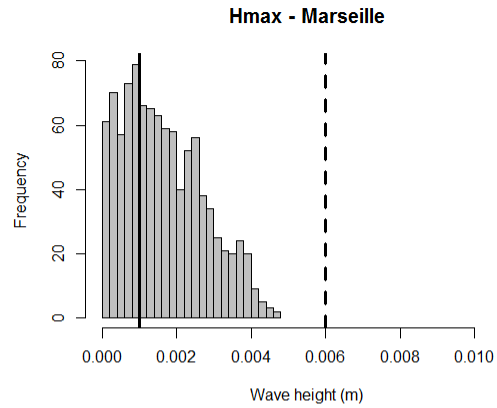
Initial number of random samples = 1 million (quasi random sequence of Sobol)



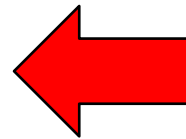
Verifying the coverage property (Prangle et al. 2014) with 250 bootstrap samples



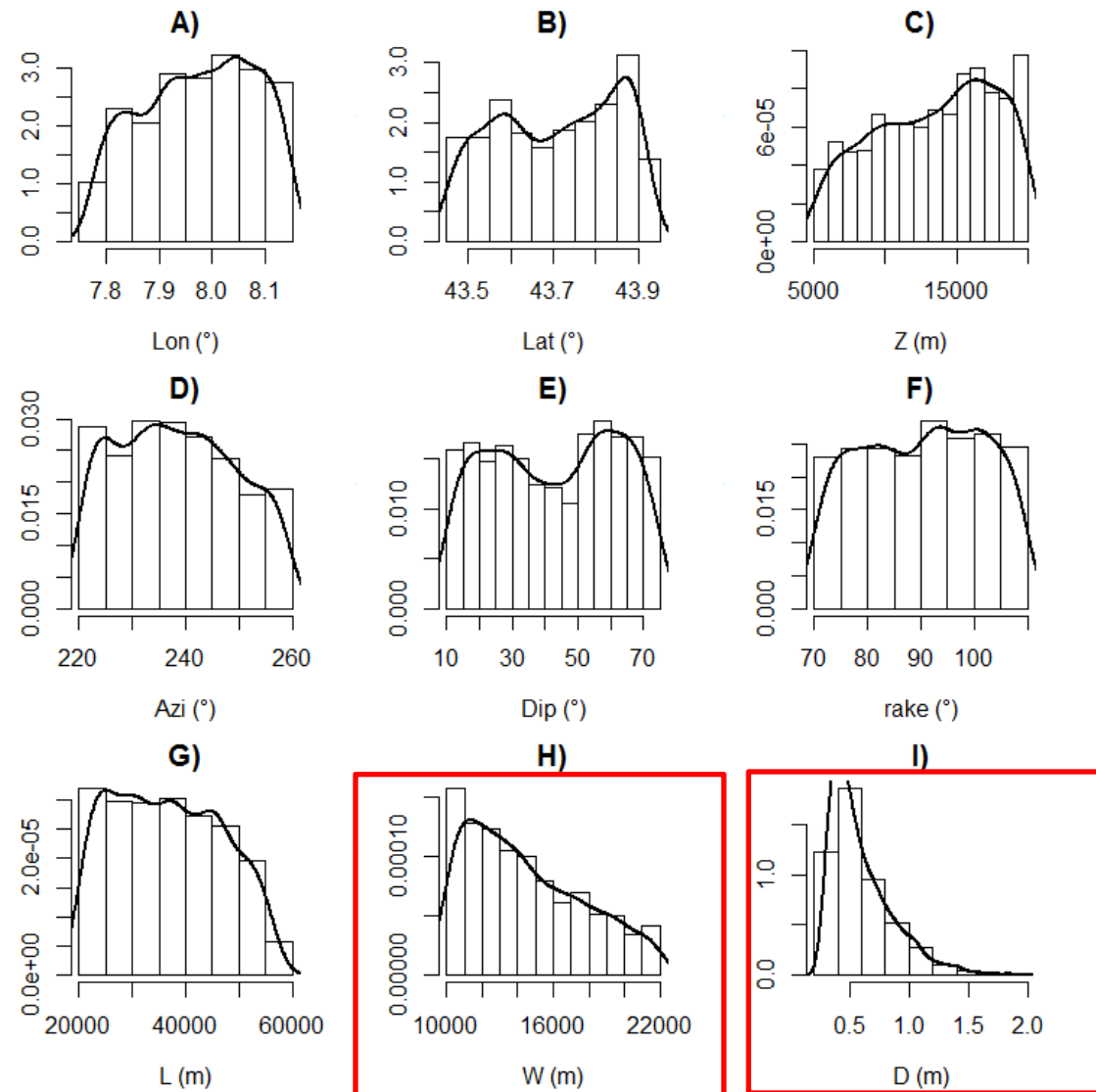
a posteriori distributions



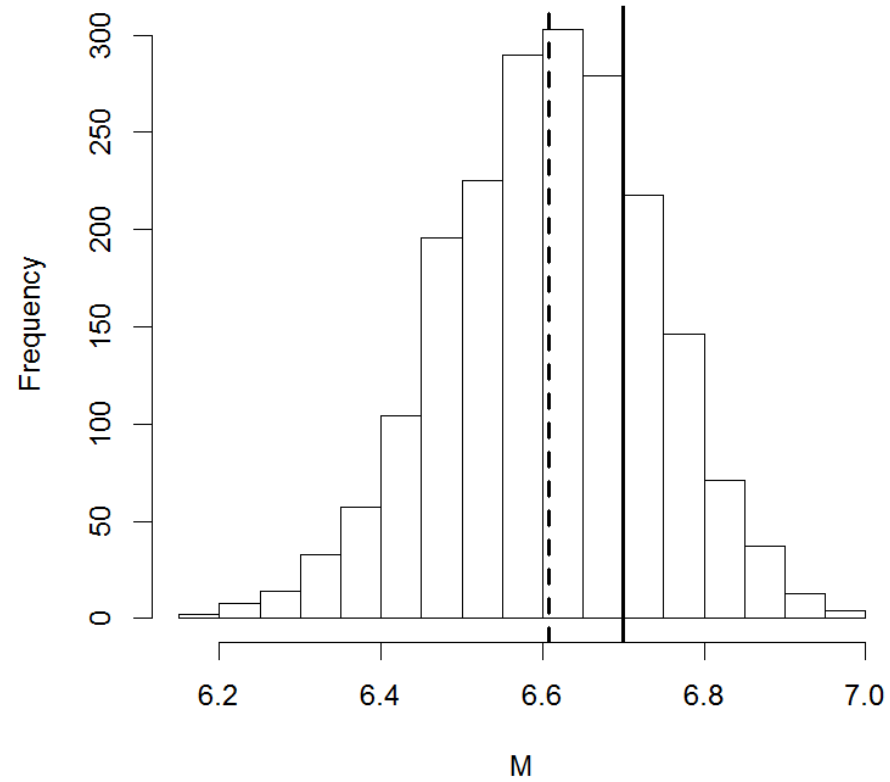
1,000 accepted random samples



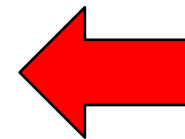
Inference of source parameters



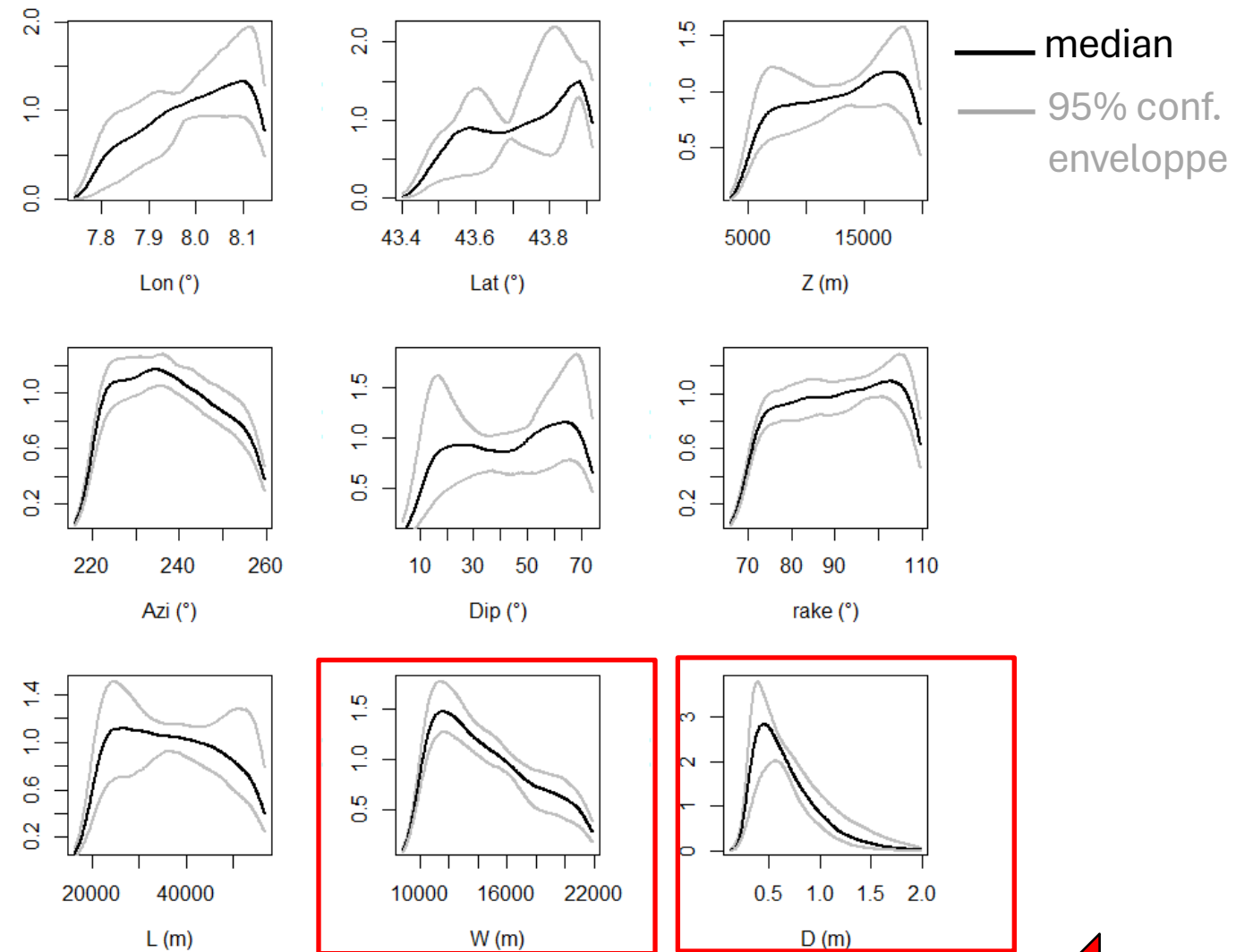
Inference of magnitude - North Dipping model



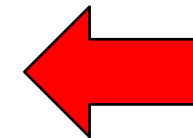
In agreement with recent studies: 6.8 (Larroque et al., 2026)



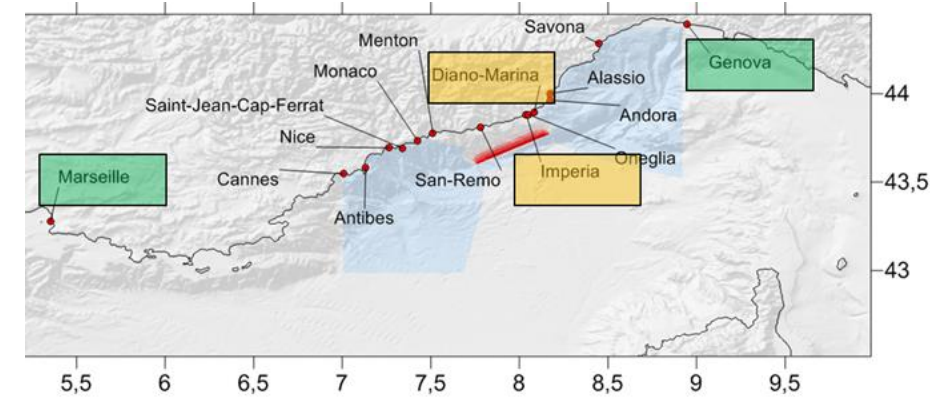
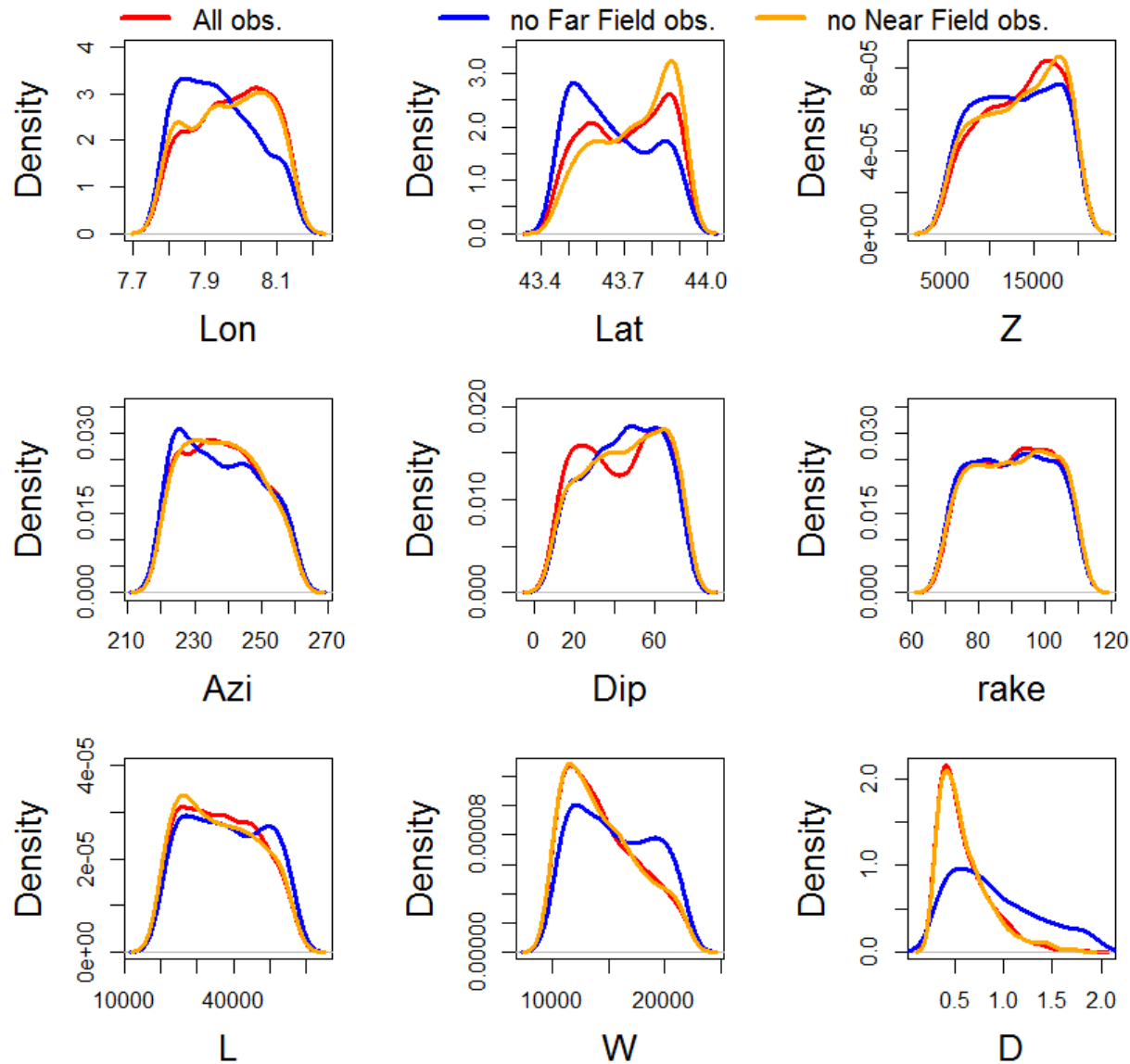
Impact of observation imprecision



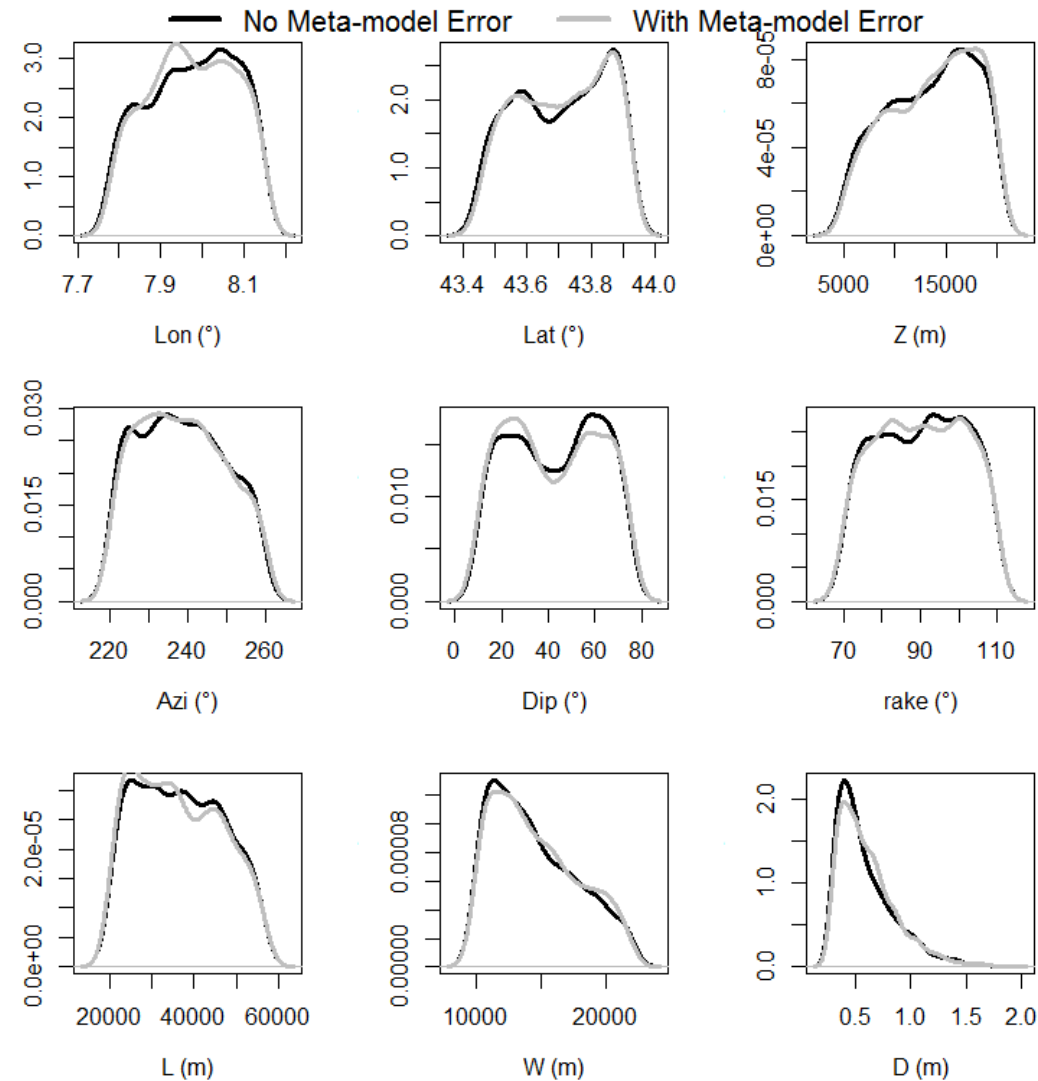
ABC-kriging procedure reconducted 1,000 times; observations are randomly varied



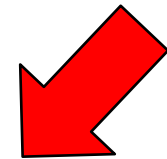
Impact of the type of observation



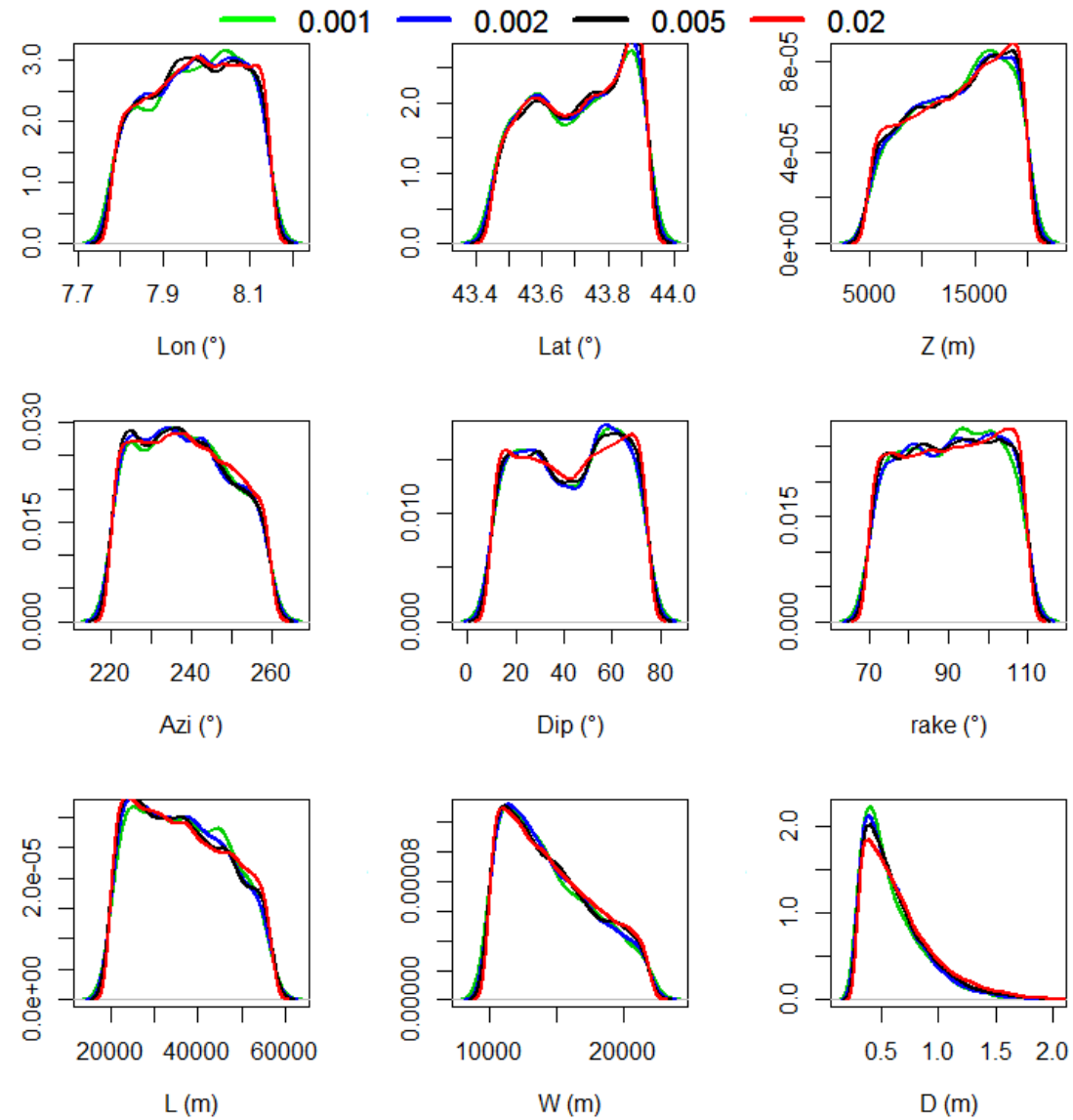
Influence of meta-model error



At each iteration of the random sampling a new kriging trajectory is randomly generated



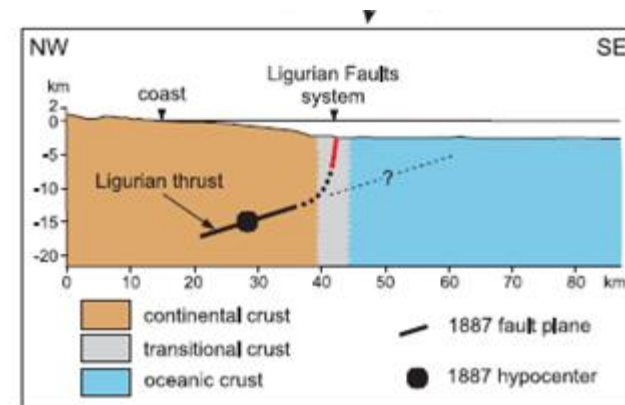
Influence of ABC tuning



Summary

- ABC-based framework for combining imprecise observations and numerical simulations
- Emulation of the long running numerical simulator (surrogate modelling)
- Further work
 - Inferring **geological scenarios** i.e. complex fault geometry
 - Variables are **spatio-temporal!**

Ioualalen et al. (2014)





Merci pour votre attention!



SCAN ME

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J. Lambert, R. Pedreros, B. Aalae