



# Model error representation in AROME-EPS

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# AROME-EPS

Horizontal resolution: 2.5km

Vertical levels: 90

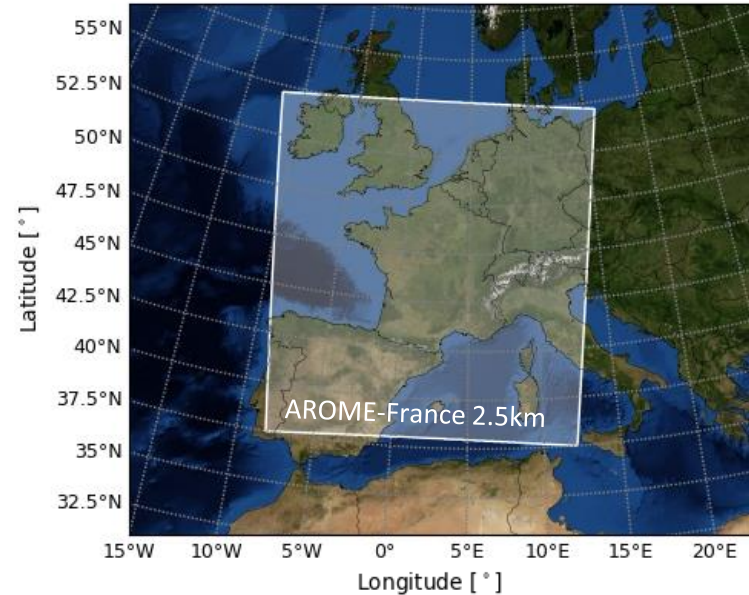
Members: 12 (16 members since July 2019)

Initial state: EDA

Lateral boundary coupling: ARPEGE-EPS (clustering)

Surface error: random surface parameters

Model error: SPPT



Implement other model error representations using parameters perturbation

# Implementation steps of Parameters Perturbation methods

1 Determine parameters to perturb

Radiation

Microphysic

Turbulence

Diffusion

Surface

Convection

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Microphysic

Turbulence

Diffusion

Surface

Convection

RSWINHF

RLWINHF

RCRIAUTI

RCRIAUTC

VSIGQSAT

XLINI

XCTD

XCTP

XCED

XCEP

XCET

XPHI\_LIM

SLHDEPSH

SLHDKMIN

SLHDKMAX

XRIMAX

XFRACZO

XCMF

XABUO

XBDETR

XENTR\_DRY

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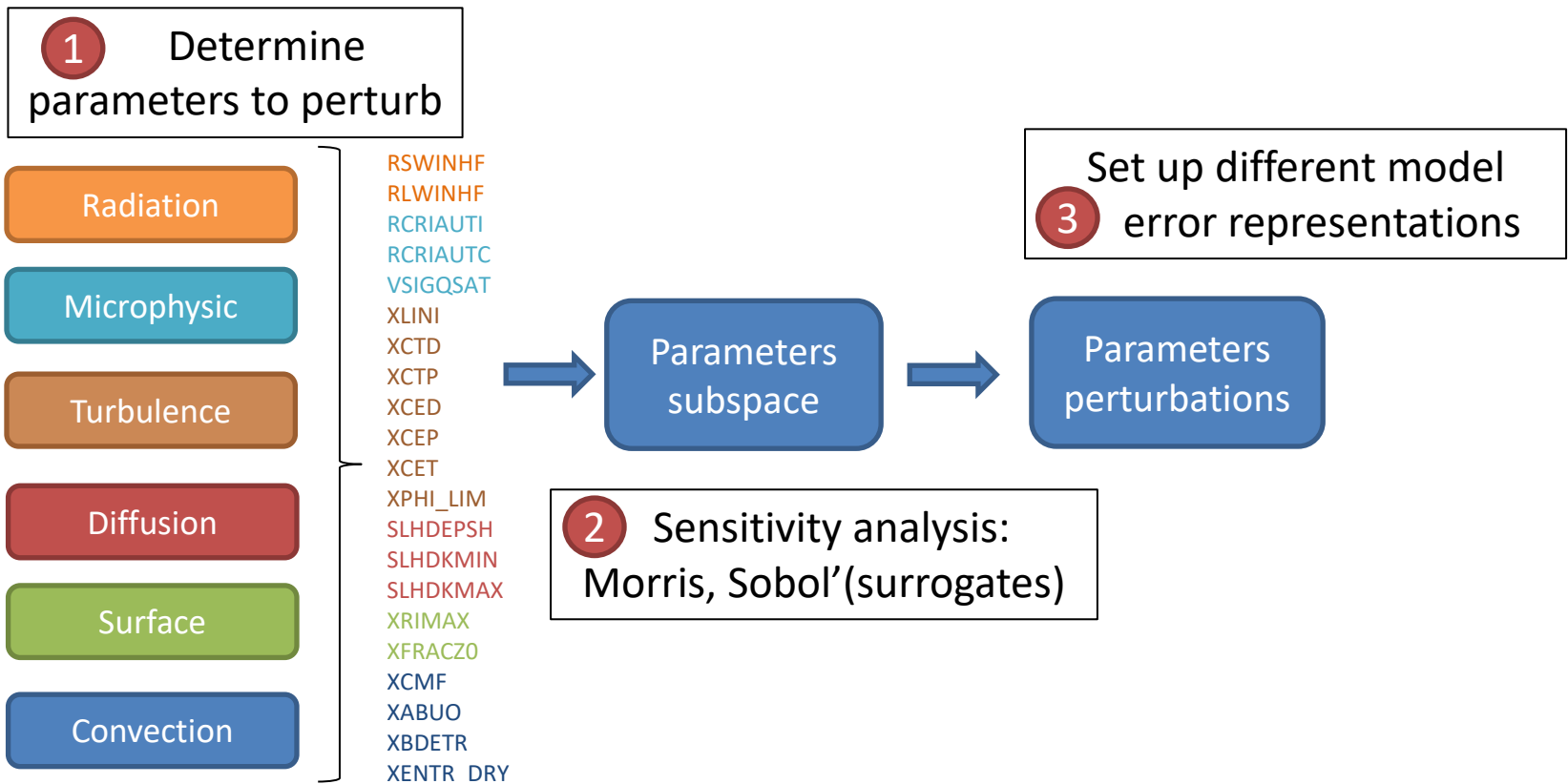
RSWINHF  
RLWINHF  
RCRIAUTI  
RCRIAUTC  
VSIQSAT  
XLINI  
XCTD  
XCTP  
XCED  
XCEP  
XCET  
XPHI\_LIM  
SLHDEPSH  
SLHDKMIN  
SLHDKMAX  
XRIMAX  
XFRACZO  
XCMF  
XABUO  
XBDETR  
XENTR\_DRY



Parameters subspace

2 Sensitivity analysis:  
Morris, Sobol'(surrogates)

# Implementation steps of Parameters Perturbation methods



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Parameters subspace



Parameters perturbations

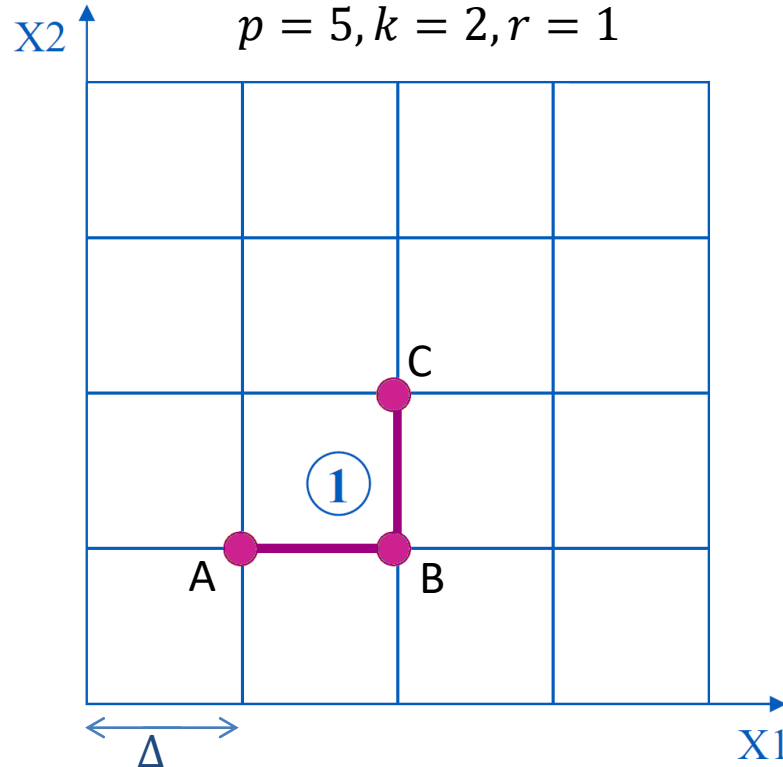


Evaluation with probabilistic scores

**3** Set up different model error representations

**2** Sensitivity analysis: Morris, Sobol'(surrogates)

# Morris Sensitivity Analysis: Theory



Modification of one parameter after another  
 -> One-At-a-Time design

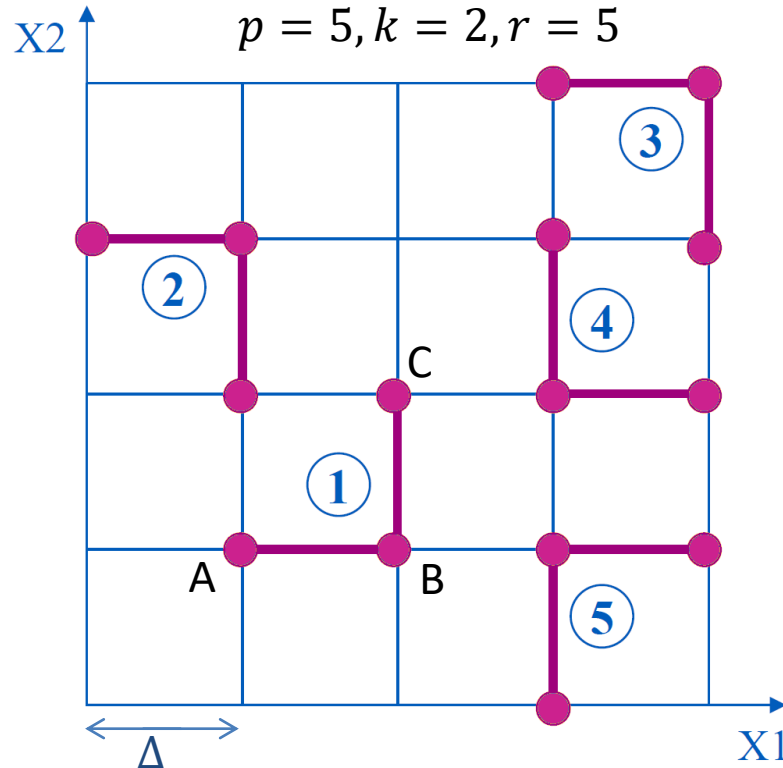
Parameters:  $X_1, X_2$  ( $k = 2$ )

Elementary effect for each parameter:

$$EE_1 = \frac{f(B) - f(A)}{\Delta} \quad EE_2 = \frac{f(C) - f(B)}{\Delta}$$



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Repeat:  $r$  times  $\longrightarrow r(k + 1)$  simulations

Mean of  $|EE|$ :

$$\mu_i^* = E(|EE_i|)$$

Standard deviation of  $EE$ :

$$\sigma_i = \text{std}(EE_i)$$

$$\sqrt{\mu^{*2} + \sigma^2}$$

# Morris Sensitivity Analysis: Applications to AROME-EPS

For 3 seasons (31 days):

- Summer 2018:  
01/05/2018 -> 30/07/2018: every 3 days
- Fall 2018:  
01/10/2018 -> 30/11/2018: every 2 days
- Winter 2018-2019:  
01/12/2018 -> 30/01/2019: every 2 days

Morris parameters:  $r = 12, k = 21, p = 8$

$$\begin{aligned} r(k + 1) &= 12 \times (21 + 1) \\ &= 264 \text{ simulations} \\ &\quad (\times 3 \text{ seasons} \times 31 \text{ days}) \\ &= 24\,552 \text{ forecasts} \end{aligned}$$

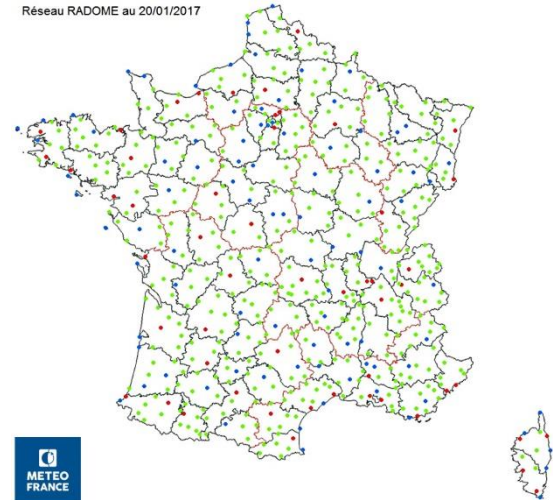
Reduce calculation cost:  
Non-hydrostatic -> Hydrostatic  
delete Predictor/Corrector Scheme

# Morris Sensitivity Analysis: Applications to AROME-EPS

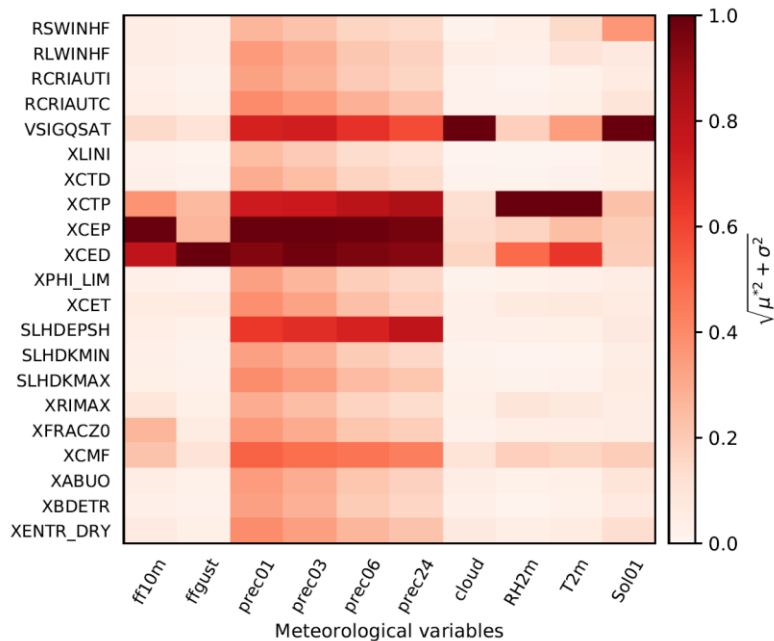
## Which scalar outputs ?

- **Mean meteorological field**
- **Deterministic Scores:** Mean Bias, RMSE, MAE  
-> RADOME & SYNOP observations

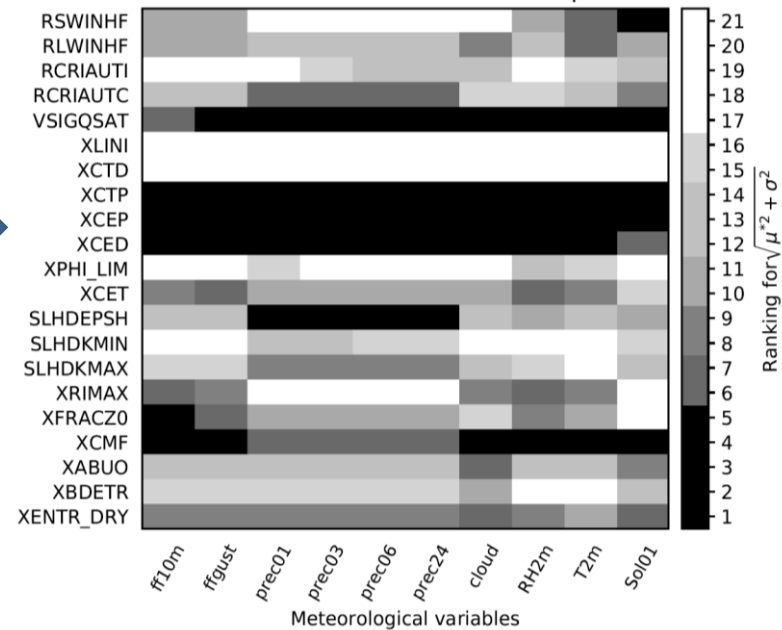
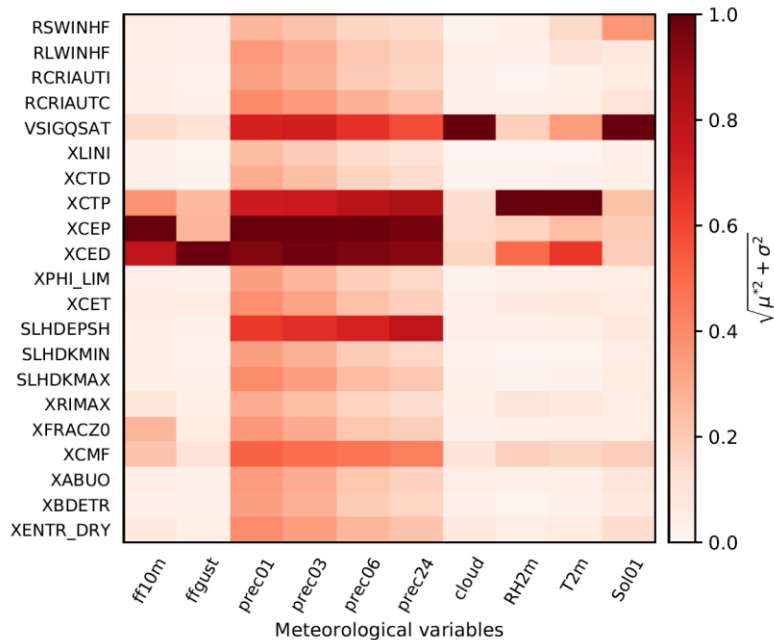
ff10m, ffgust, prec01, prec03, prec06,  
prec24, tcc, RH2m, T2m, Solar01



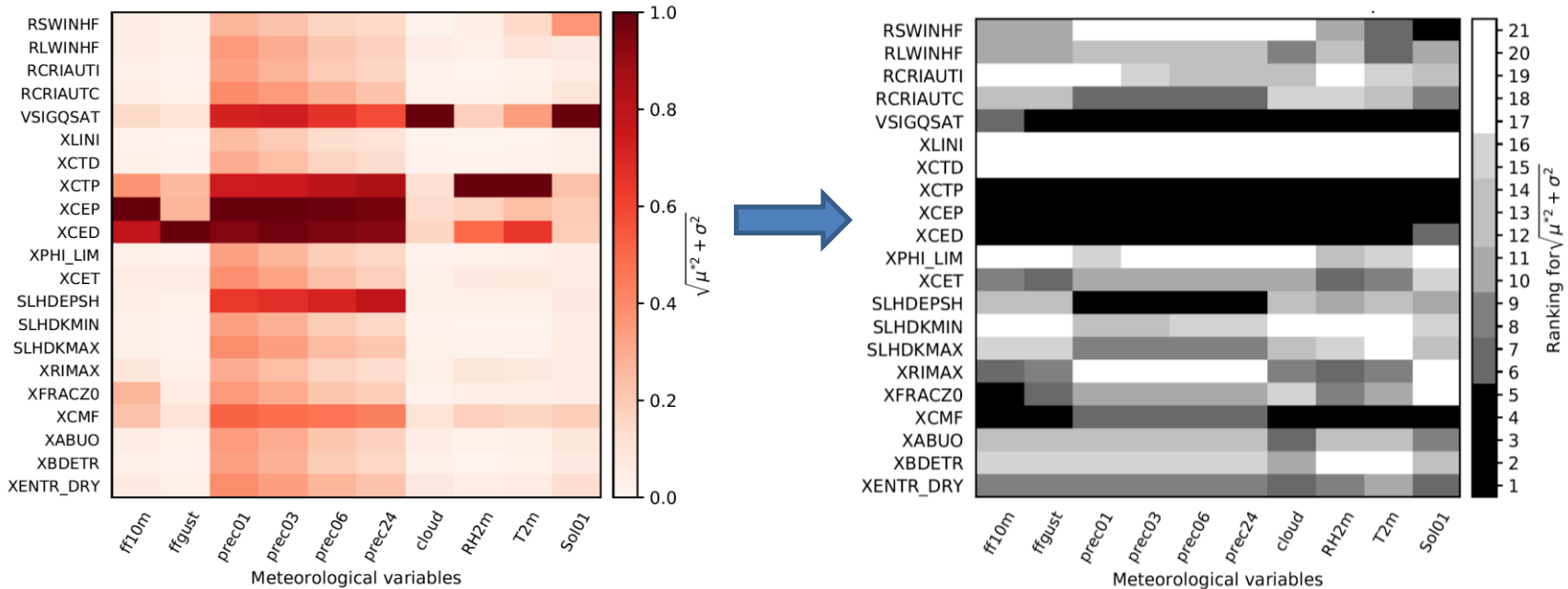
# Mean parameters influence over 3 seasons and all model outputs



# Mean parameters influence over 3 seasons and all model outputs



# Mean parameters influence over 3 seasons and all model outputs



8 influential parameters : RSWINHF, VSIGQSAT, XCTP, XCEP, XCED, SLHDEPSH, XFRACZ0, XCMF

# Model error representation

<b>Perturbation parameter according to ...</b>	<b>...members</b>	<b>...dates</b>	<b>... forecast range</b>	<b>... space</b>
<b>Perturbed Parameter (PP)</b>	✓			
<b>Random Perturbed Parameter (RPP)</b>	✓	✓		
<b>Random Parameter (RP)</b>	✓	✓	✓	
<b>Stochastically Perturbed Parametrization (SPP)</b>	✓	✓	✓	✓

# Model error representation

Perturbation parameter according to ...	...members	...dates	... forecast range	... space
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# 1000 Perturbed Parameter EPS generated from Morris forecasts

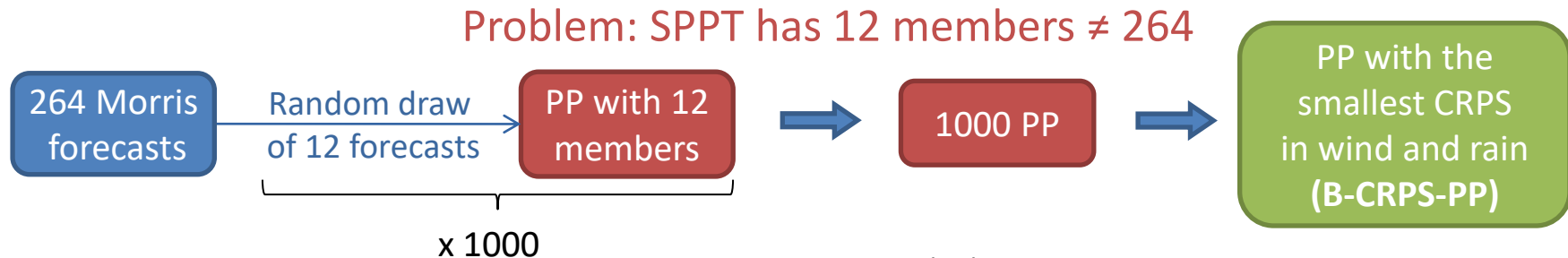
264 forecasts differ only in their parameter values

↳ **264-members EPS**

without initial, surface, lateral condition error representation  
with model error representation

↳ Perturbed Parameters method (PP)

Comparison with the current SPPT approach



# Model error representation

Perturbation parameter according to ...	...members	...dates	... forecast range	... space
<b>Perturbed Parameter (PP)</b>	✓			
<b>Random Perturbed Parameter (RPP)</b>	✓	✓		
<b>Random Parameter (RP)</b>	✓	✓	✓	
<b>Stochastically Perturbed Parametrization (SPP)</b>	✓	✓	✓	✓

# Random Perturbed Parameters (RPP)

for each member and date

RSWINHF  
RLWINHF  
RCRIAUTI  
RCRIAUTC  
VSIGQSAT  
XLINI  
XCTD  
XCTP  
XCED  
XCEP  
XCET  
XPHI\_LIM  
SLHDEPSH  
SLHDKMIN  
SLHDKMAX  
XRIMAX  
XFRACZ0  
XCMF  
XABUO  
XBDETR  
XENTR\_DRY

Random draw of  
parameter values from a  
uniform distribution



# Comparison between 5 different model error representations

Comparison of model error representations only: no initial, surface, lateral perturbations

**Mean PP**: mean PP score, average over the 1000 PP generated from Morris design

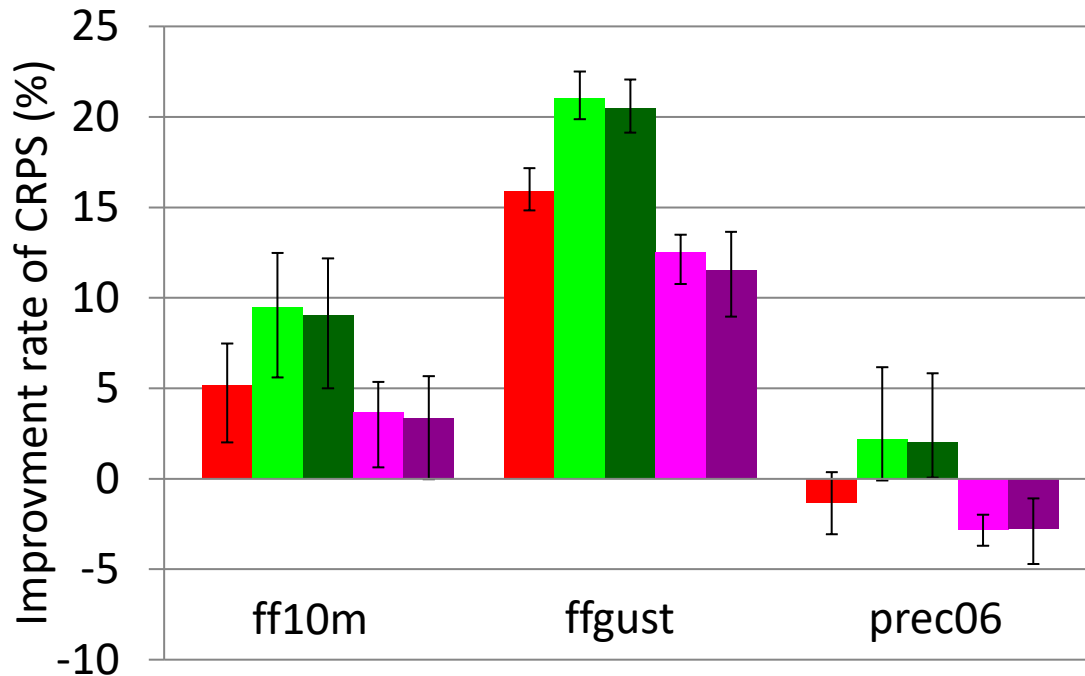
**B-CRPS-PP**: Best PP on 3 seasons, with the smallest CRPS on ff10m and prec03

**B-CRPS-P8P**: Best PP on 3 seasons, with the smallest CRPS on ff10m and prec03 with non-influential parameters put at their default values

**RPP**: Perturbation of all parameters for each member and date

**RP8P**: Perturbation of the 8 most influential parameters for each member and date

## Mean CRPS improvement rate (average over 3 seasons and 45h lead time)



-> High improvement for ff10m and ffgust  
-> Smaller improvement or degradation for prec06

Uncertainty  
on seasons

Remark: Higher improvement on winter than in summer and fall

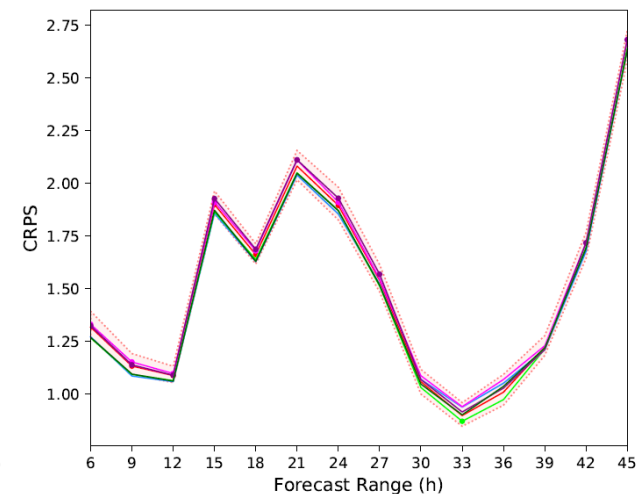
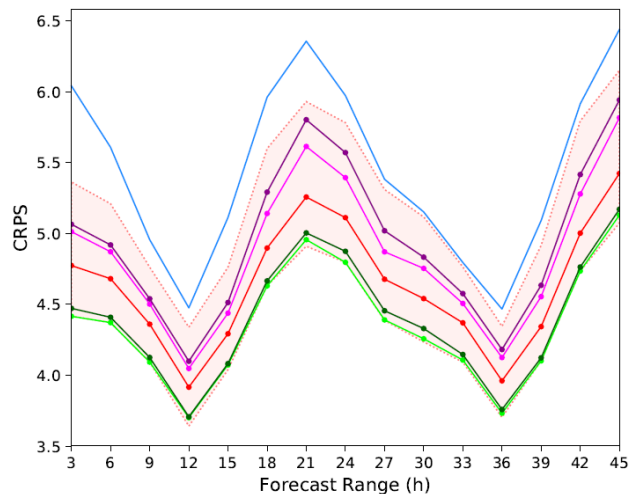
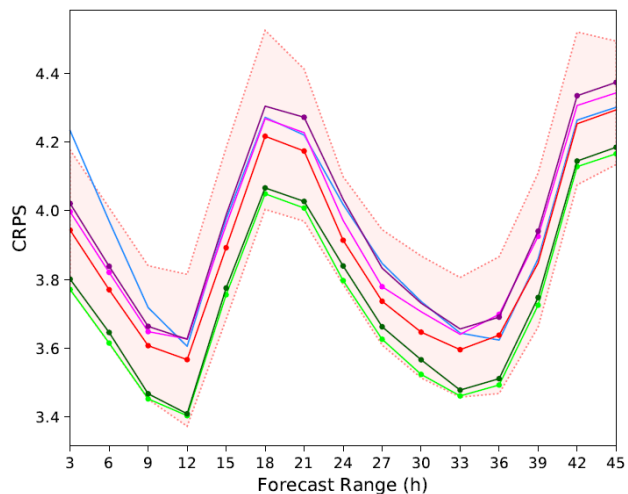
■ Mean PP   ■ B-CRPS-PP   ■ B-CRPS-P8P   ■ RPP   ■ RP8P

# CRPS during summer

ff10m

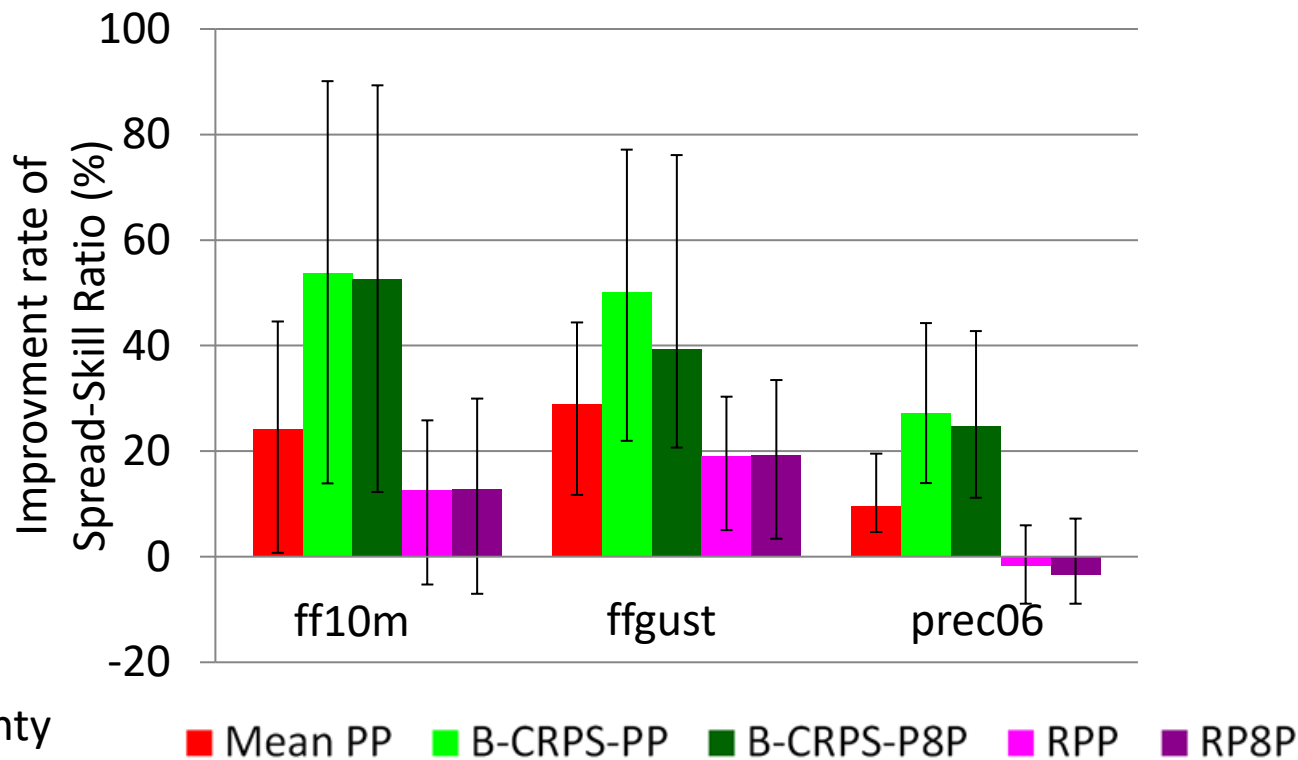
ffgust

prec06



■ PP distribution   
 ■ Mean PP   
 ■ B-CRPS-PP   
 ■ B-CRPS-P8P   
 ■ RPP   
 ■ RP8P   
 ■ SPPT

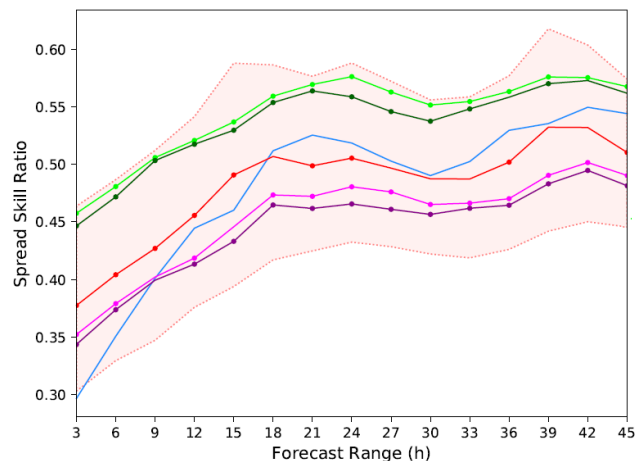
## Mean Spread-Skill ratio improvement rate (average over 3 seasons and 45h lead time)



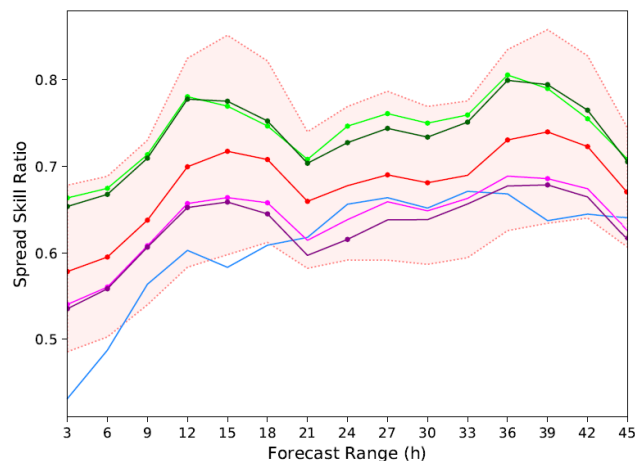
Uncertainty  
on seasons

# Spread-Skill Ratio on summer

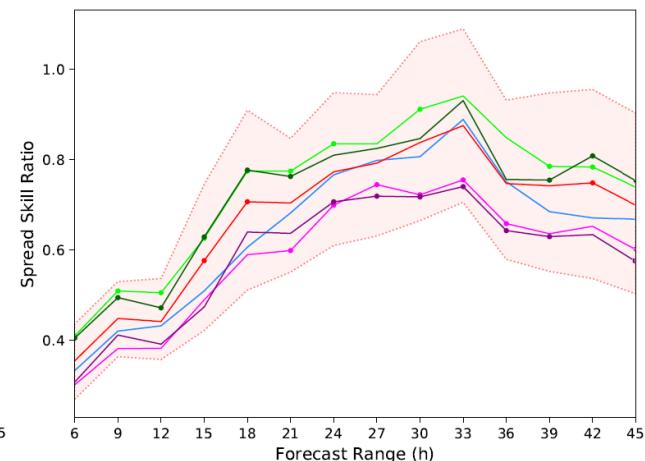
ff10m



ffgust



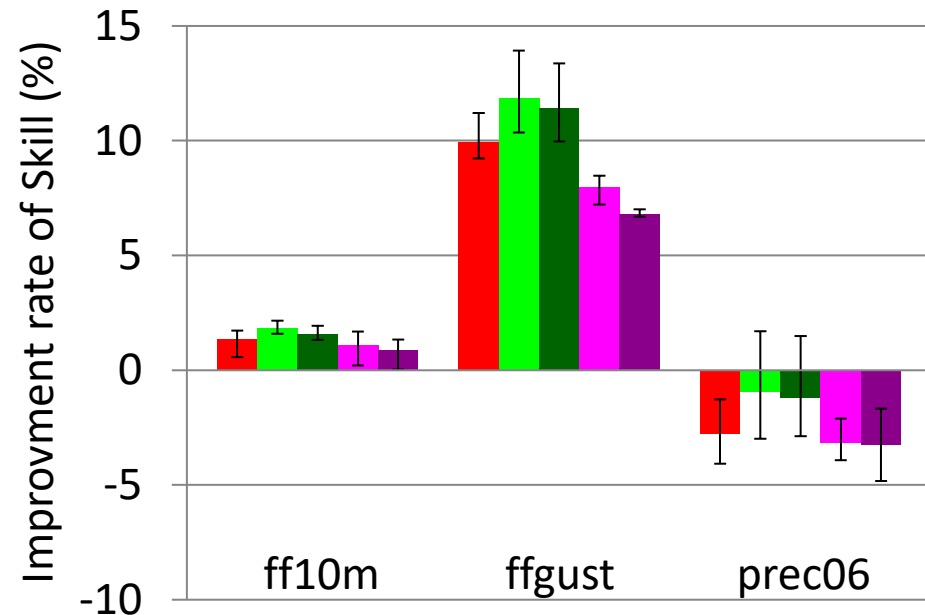
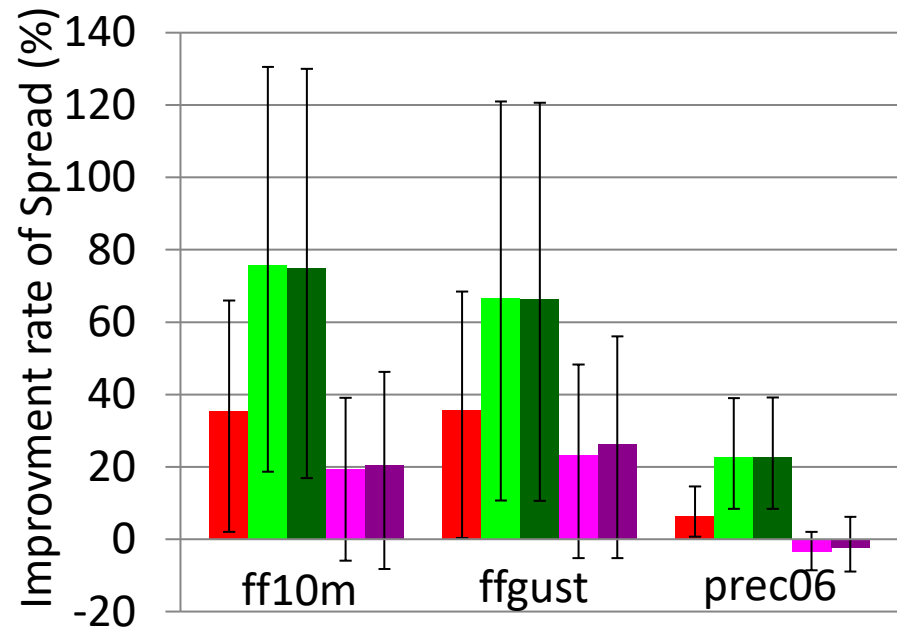
prec06



■ PP distribution 
 ■ Mean PP 
 ■ B-CRPS-PP 
 ■ B-CRPS-P8P 
 ■ RPP 
 ■ RP8P 
 ■ SPPT



## Mean Spread and Skill improvement rate (average over 3 seasons and 45h lead time)



Uncertainty  
on seasons

■ Mean PP ■ B-CRPS-PP ■ B-CRPS-P8P ■ RPP ■ RP8P

# Conclusion

Generally: **PP** and **RPP** improve scores compared to SPPT in particular for ffgust and on winter

**B-CRPS-PP**: optimized for CRPS but still good for other scores

**B-CRPS-P8P**: similar results than **B-CRPS-PP**

**RPP**:

- smaller improvement
- degrades prec06 scores

**RP8P**: similar results than **RPP**

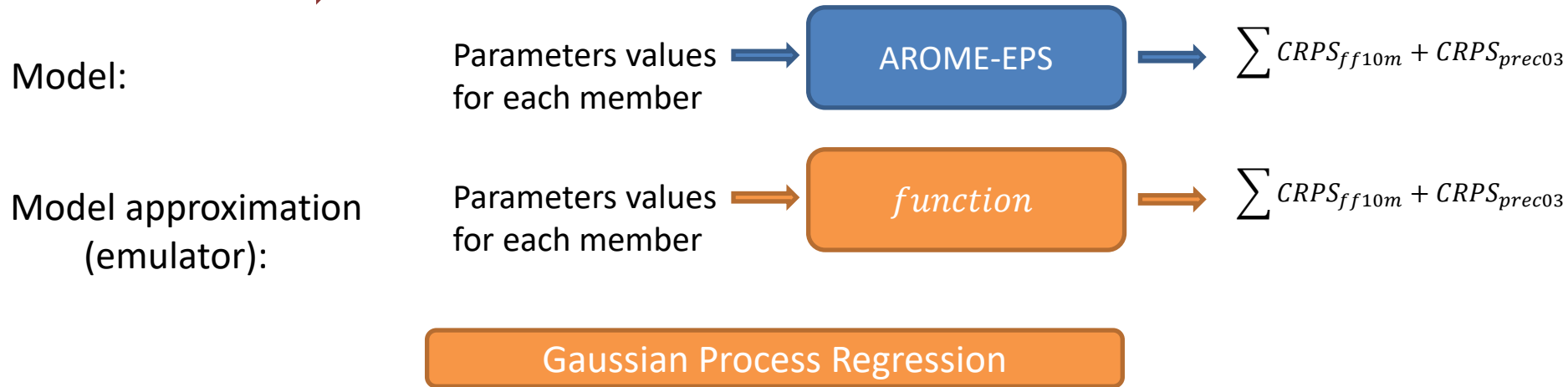
**PP and RPP approaches must be optimized to be performant  
-> Reduction to 8 parameters**

# Improve B-CRPS-PP

Problem: PP generated from Morris forecasts sample only 8 parameter values

- Need to sample the whole parameters space
- High computational cost

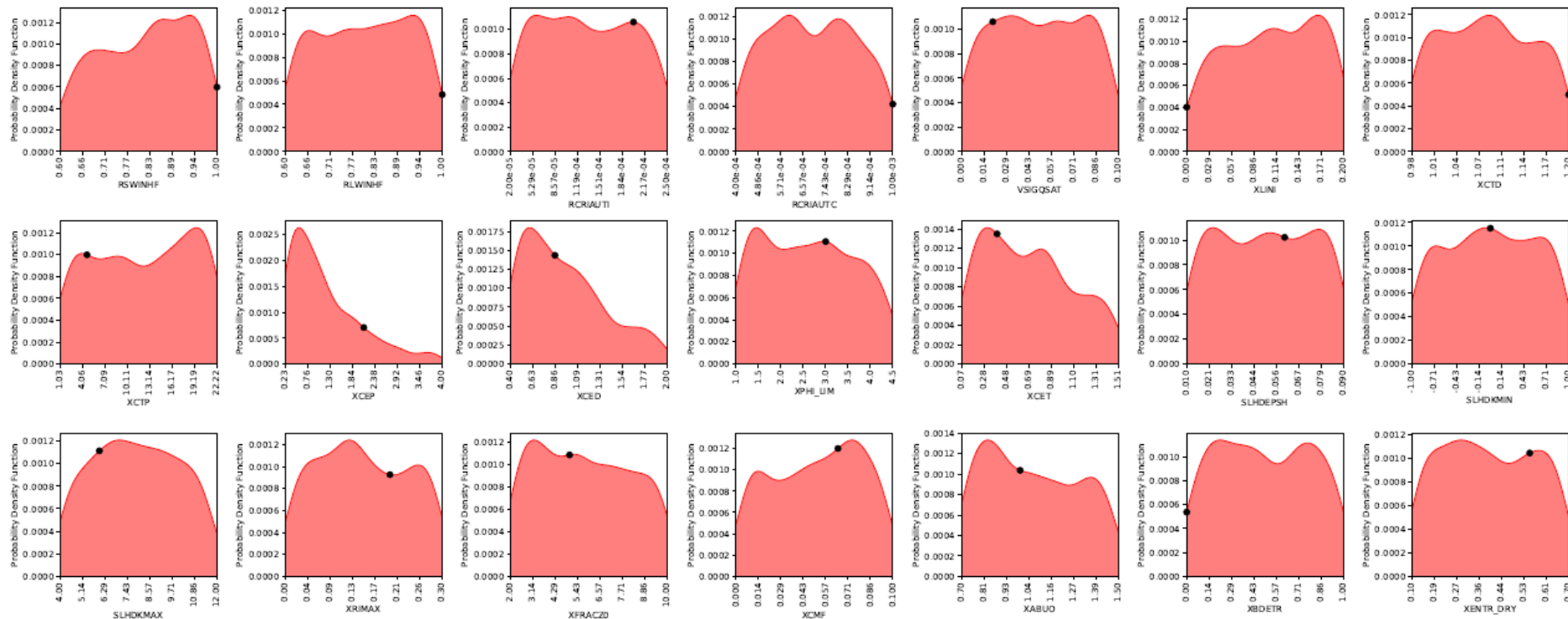
→ Emulator



# A CRPS-emulator in order to find the best PP

- 1) Test different Gaussian Process Regression parameters (covariance kernel, number of input data, ...)
  - ➔ Use a Matern 3/2 covariance function
  - + increase data number by switching members : 1 000 -> 40 000 CRPS
- 2) Emulator trained on 70% of 40 000 CRPS values
- 3) Validation error (on 30% remained data): 0,74% -> validated
- 4) CRPS prediction of 500 000 inputs, generated from a Monte-Carlo sampling
  - The smallest CRPS -> new Best CRPS PP -> B-eCRPS-PP
  - 50 smallest CRPS -> 50 x 12 physical parameters values
  - ➔ Parameter distributions

# PDF of each parameter



# Future Works

## Sensitivity Analysis:

- Scientific article redaction

## PP:

- Compute scores for B-eCRPS-PP

## RPP:

- Optimization with PDF obtained from emulator

## SPP:

- Use PDF from emulator

Evaluate perturbed parameters approaches in the full EPS  
Combination with SPPT



Thanks for your attention