Development and evaluation of an "optimal" perturbed parameter approach in the convective-scale AROME-EPS

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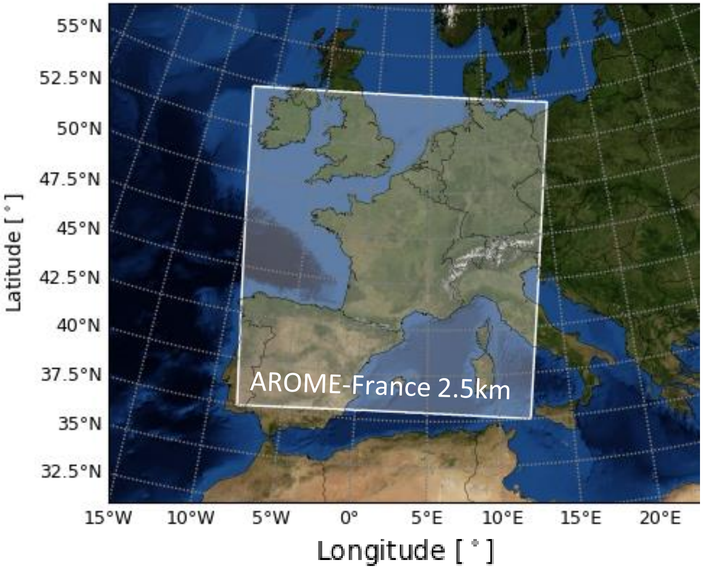
AROME-EPS

AROME-EPS (Bouttier et al., 2012):

- Operational at Météo-France since 2016
- Based on the convection-permitting **AROME** model (Seity et al., 2011)
- Horizontal resolution of **2.5km**
- **90 levels**
- **12** members
- 4 runs/day (03, 09, 15, 21 UTC) up to 45/51h



Representation of errors from :

- Initial condition: **EDA** (Raynaud et al. 2016)
- Lateral condition: selection of **ARPEGE-EPS** (Descamps et al. 2015) members with a **clustering** method (Bouttier and Raynaud, 2018)
- Surface condition: random **perturbations** of surface **parameters** (Bouttier et al. 2016)
- Model error: **SPPT** (Bouttier et al., 2012)

Objective: develop and evaluate model error representations based on perturbed parameters approaches

Determine uncertain parameters to perturb

Microphysics

Autoconversion threshold of rain (**RCRIAUTC**) and snow (**RCRIAUTI**)

Diffusion

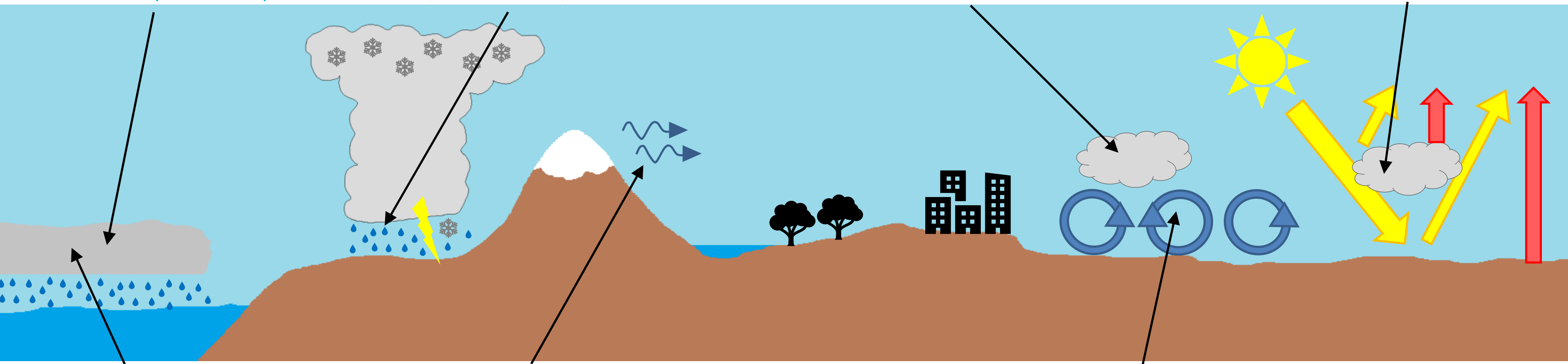
Hydrometeors diffusion (strength, minimum, maximum) **SLHDEPSH, SLHDKMIN, SLHDKMAX**

Convection

Coefficients for the updraft at bottom level (**XCMF**), buoyancy (**XABUO**), detrainment (**XBDETR**), dry entrainment (**XENTR_DRY**)

Radiation

Cloud inhomogeneity factor for shortwave (**RSWINHF**) and longwave (**RLWINHF**)



Variability of sub-grid condensation **(VSIGQSAT)**

Surface

Coefficient of orographic drag (**XFRACZ0**)
Critical Richardson number (**XRIMAX**)

Turbulence

Minimum of mixing length (**XLINI**),
Const. for turbulent kinetic energy (dissip. **XCED**, trans. **XCET**),
Correlations of temperature, humidity, wind, (**XCTD, XCTP, XCEP**),
Threshold for Prandtl and Schmidt numbers (**XPHI_LIM**)

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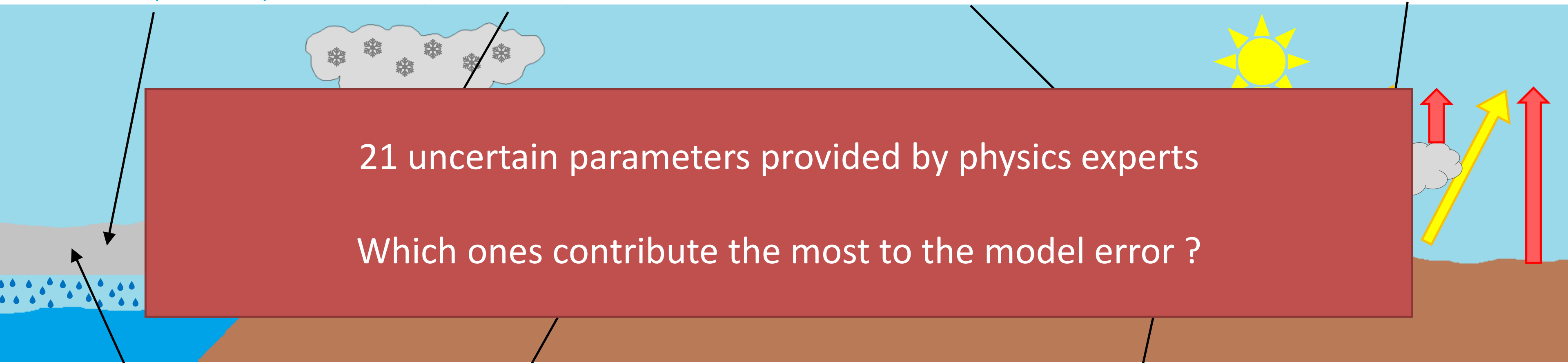

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Sensitivity Analyses

To calculate sensitivity indices in order to qualify and quantify
the impact of input parameters perturbation, following a design of experiment, on the model outputs

Two used methods :

- **Morris (1991):** sensitivity according to seasons, days, forecast time ranges, grid points on the AROME-France domain
- Sobol' (1990): interactions between parameters

Parameters influence may change according to seasons:

➡ sensitivity analyses repeated for 3 seasons (31 days)

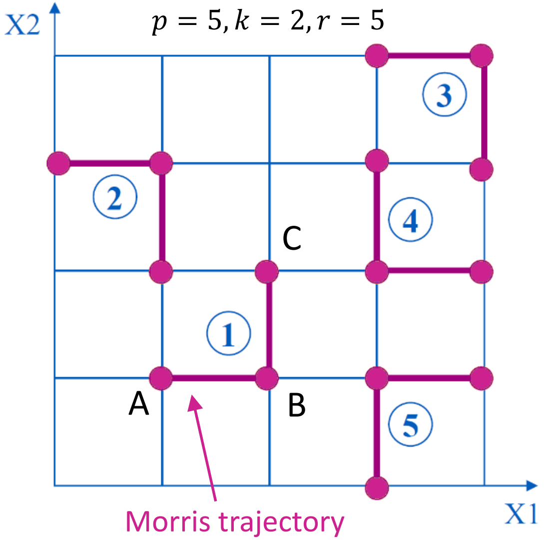
- Summer 2018
- Fall 2018
- Winter 2018-2019

Consider 4 scalar model outputs:

- Mean Bias, RMSE, MAE
  ➡ calculated from RADOME + SYNOP : 1500 obs.
- Averaged meteorological fields
  - ff10m
  - ffgust
  - prec01, prec03, prec06, prec24
  - Tcc,
  - T2m,
  - RH2m,
  - Sol01

RADOME Network

Morris Sensitivity Analysis (1991)



For AROME: $k = 21,\ r = 12$
Number of simulations needed:
$r(k+1)$ = **264 simulations**

$$(\times 3\ seasons\ \times 31\ days)$$
$$= 24\,552\ forecasts$$

Design of experiment:

➡ modify of one parameter after another

Example:

- Parameters : X1, X2 ($k = 2$)
- Elementary effect (EE_i) for each parameter i:

$$EE_{X1} = \frac{f(B)-f(A)}{X1(B)-X1(A)} \qquad EE_{X2} = \frac{f(C)-f(B)}{X2(C)-X2(B)}$$

- Number of Morris trajectories: $r = 5$

➢ Mean of $|EE_i|$:
$$\mu_i^* = E(|EE_i|)$$

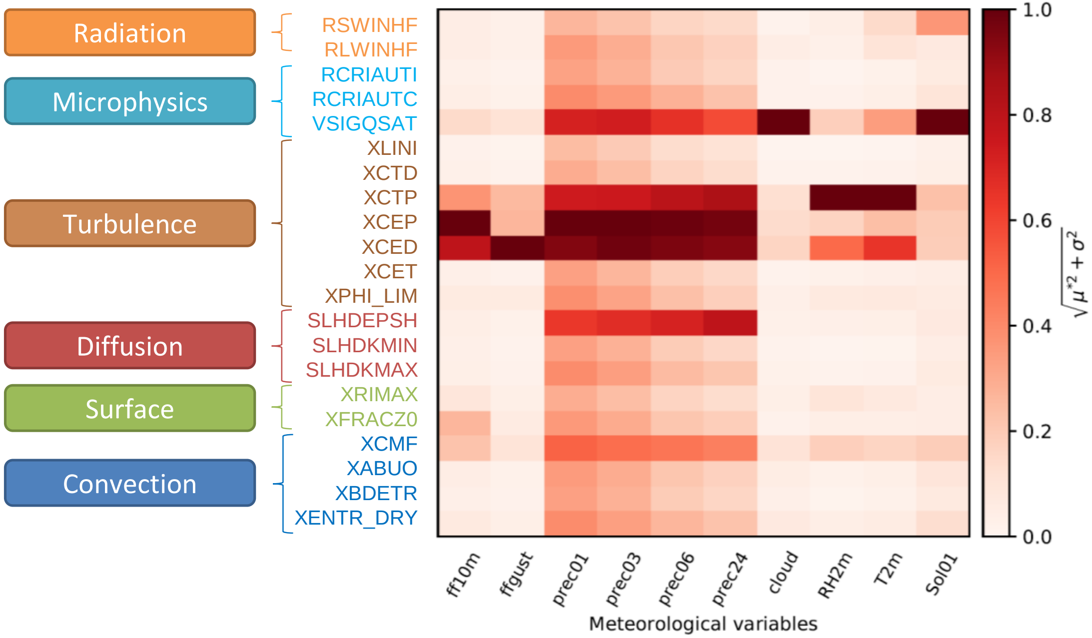
➢ Standard deviation of EE_i:
$$\sigma_i = \sigma(EE_i)$$

Morris Sensitivity Indice:
(Ciric, 2012)

$$MSI_i = \sqrt{\mu_i^{*2} + \sigma_i^2}$$

Identify the most influential parameters

Parameters influence, averaged over 3 seasons
and on all (4) scalar model outputs



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

Implementation of different Perturbed Parameters approaches:

Perturb parameters according to…

… members:

Perturbed Parameter (**PP**)

Morris design of experiment:

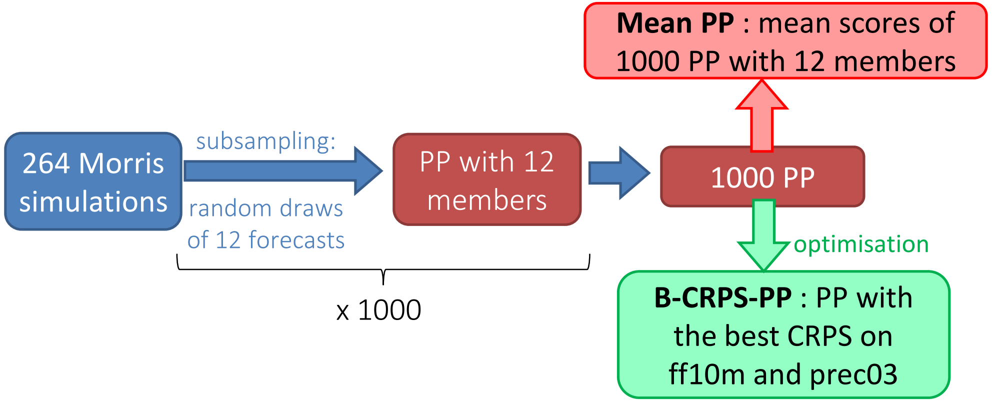
264 forecasts which differ by their parameters values

→ like an EPS with **264 members** with model error representation based on PP method only

Problem:

AROME-EPS has 12 members -> need same number of members

Production of 1000 PP and optimisation:



… members and initial dates:

Random Perturbed Parameter (**RPP**)

Need a random draw of parameters value following a probability density function

Test of different distributions:

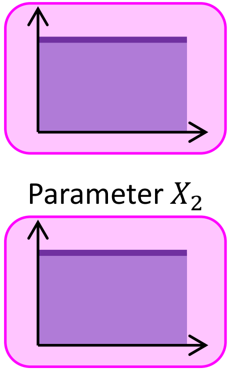
Uniform : **uRPP**

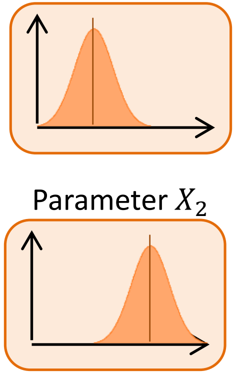
Gaussian $\mathcal{N}(m, s)$: **gRPP**

m: optimal parameter value defined by the B-CRPS-PP

Parameter X_1

Parameter X_1

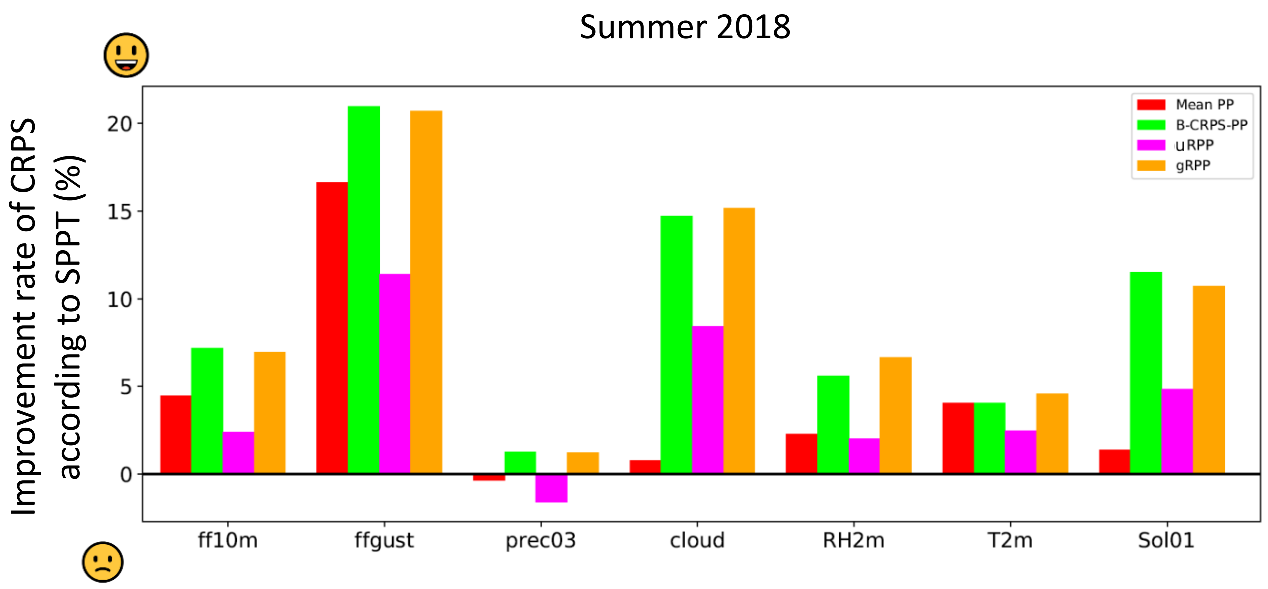




Parameter X_2

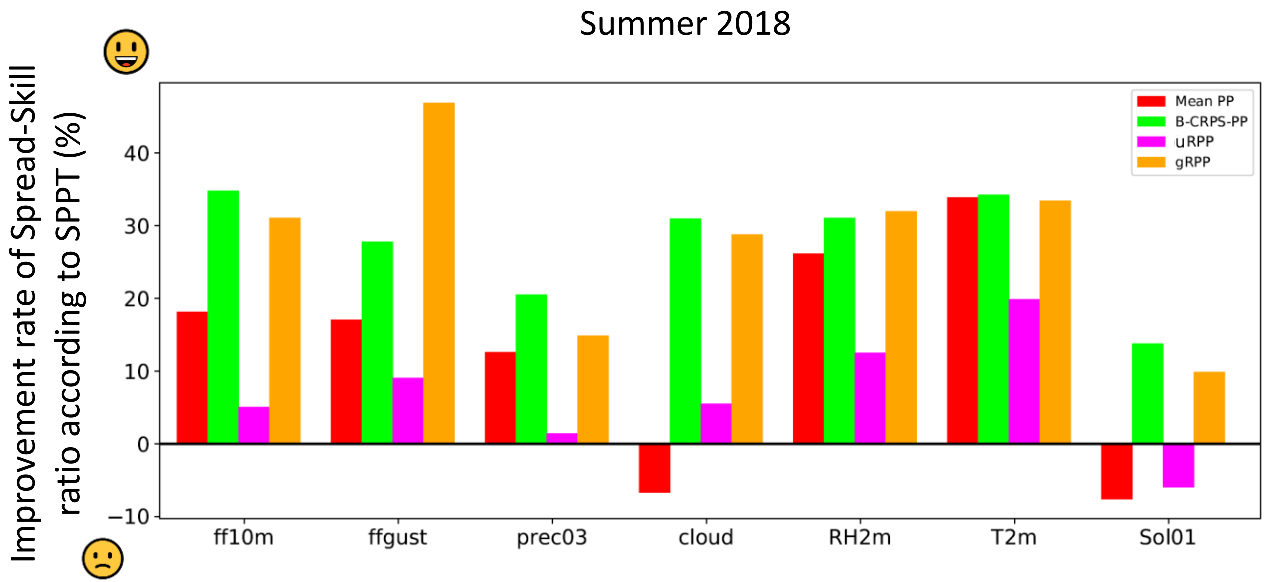
Parameter X_2

Improvement rate of CRPS according to SPPT (%)



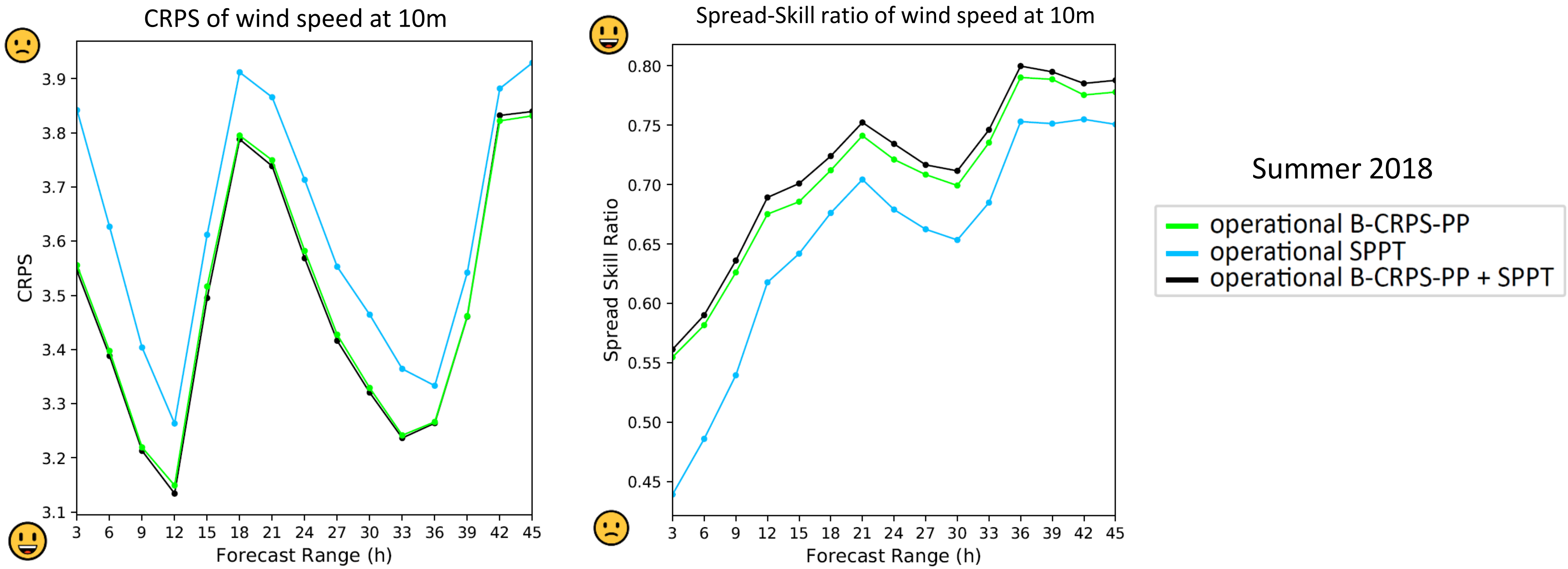
- All PP approaches improve all CRPS (particularly ffgust)
- B-CRPS-PP improves ff10m and prec03's CRPS, but not only
- Perturbing parameters according to initial date (RPP) does not give better results than fixed PP (Mean PP)
- B-CRPS-PP and gRPP give similar improvement rates
- Scores unchanged between 8 or 21 perturbed parameters

Improvement rate of Spread-Skill ratio according to SPPT (%)



- Spread-skill ratio also improved for mainly all PP approaches
- B-CRPS-PP ang gRPP have the highest improvement
- B-CRPS-PP is generally better than gRPP (except for ffgust)

Operational configuration: add perturbation of IC, LC, SC



- Representing model error with B-CRPS-PP gives better scores than SPPT
- Combination of the two approaches gives similar results than B-CRPS-PP (SPPT does not perturb near the surface)

Conclusion

Goal: New model error representation in AROME-EPS based on perturbed parameters approaches

Sensitivity Analyses:

- Identification of **21 parameters** from physics and dynamics **to perturb**
- Sensitivity of AROME to 21 parameters according to seasons, days, forecast range, grid points
- Morris result: **8 influential parameters**
- Results have been published in QJRMS: Wimmer et al. (2022); doi: 10.1002/qj.4239

Model error representation:

- Production of **1000 PP and optimisation** according to CRPS (B-CRPS-PP): **improve** all probabilistic scores
- RPP : perturb parameters using **different distributions**

  -> **Gaussian distribution** with mean at B-CRPS-PP values seems to be the best
- gRPP not as good as B-CRPS-PP: **Fixed** parameter perturbation is **sufficient**
- Perturbation of 8 parameters ≈ perturbation of 21 parameters:

  -> Possibility to **reduce the list** of perturbed parameter **to 8**

Perspectives:

- Continue to test other distribution in RPP but also other sampling method (LHS)
- add a **spatial** (SPP) or **time range** (RP) variability

Thank you for your attention

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