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

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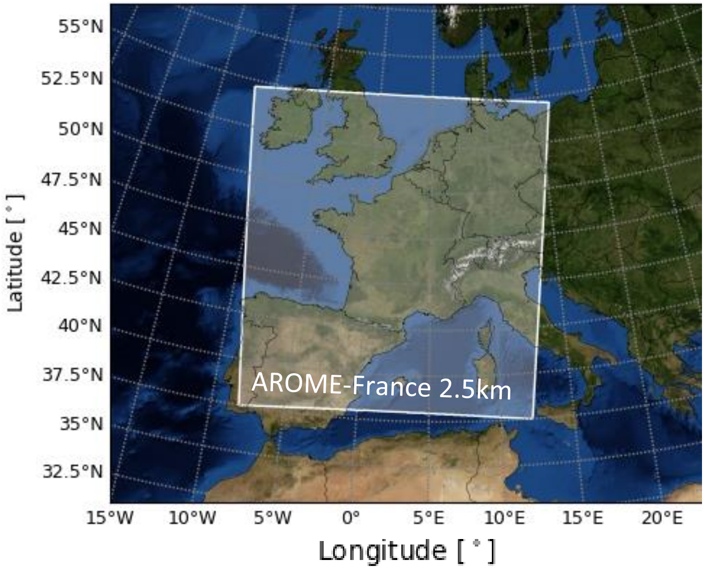
AROME-EPS



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 (16 since July 2019)
- 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 a **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)

Goal of the PhD: Study model error representation based on perturbed parameters approaches

Perturbed Parameter implementation steps

1 Determine uncertain parameters to perturb

2 Sensitivity Analysis
Morris (1991), Sobol'(1990)

3 Implementation of different model error representation

- Radiation
- Microphysic
- Turbulence
- Diffusion
- Surface
- Convection

→ Reduce the parameters list to the most influential ones → Parameter perturbations → Probabilistic evaluation with scores

Identification of uncertain parameters to perturb

Microphysics

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

Diffusion

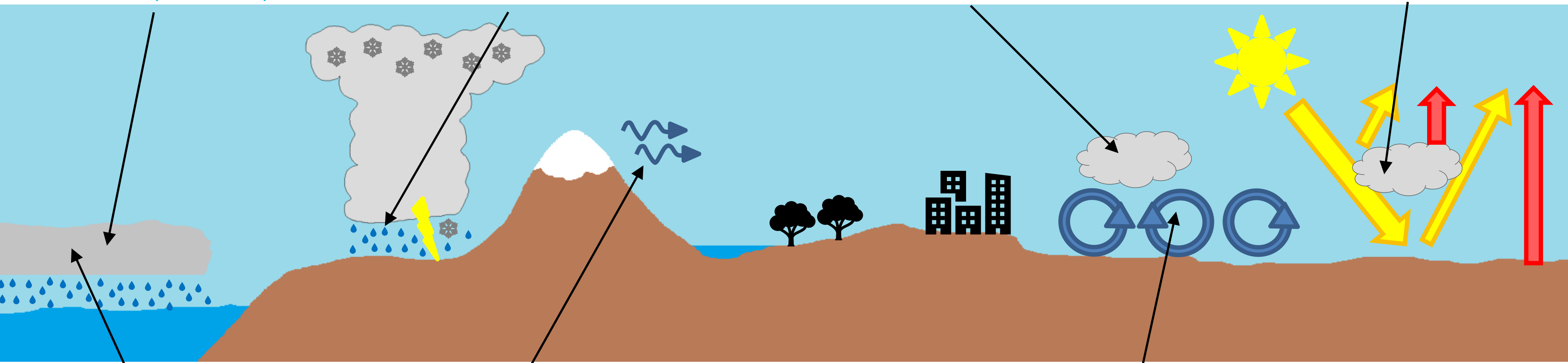
Hydrometeors diffusion (strength, minimum, maximum) **SLHDEPSH, SLHDKMIN, SLHDKMAX**

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**)

Identification of uncertain parameters to perturb

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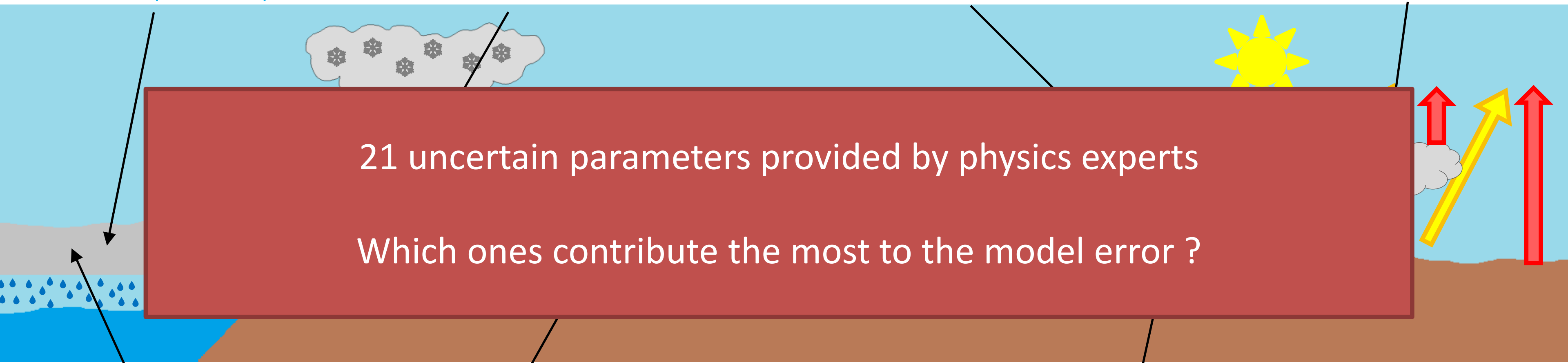

21 uncertain parameters provided by physics experts

Which ones contribute the most to the model error ?

Variability of sub-grid condensation **VSIGQSAT**

Surface

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

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Wimmer et al. (2021)

Sensitivity Analyses

Compute sensitivity indices 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, time range, grid point on the AROME-France domain
- Sobol' (1990): interactions between parameters
  - ➢ Use of machine learning technique (Le Gratiet et al., 2016)

Parameters influence may change according to seasons:

➡ sensitivity analyses repeated for 3 seasons (31 days)

- Summer 2018
- Fall 2018
- Winter 2018-2019

Study impact on 4 scalar model outputs:

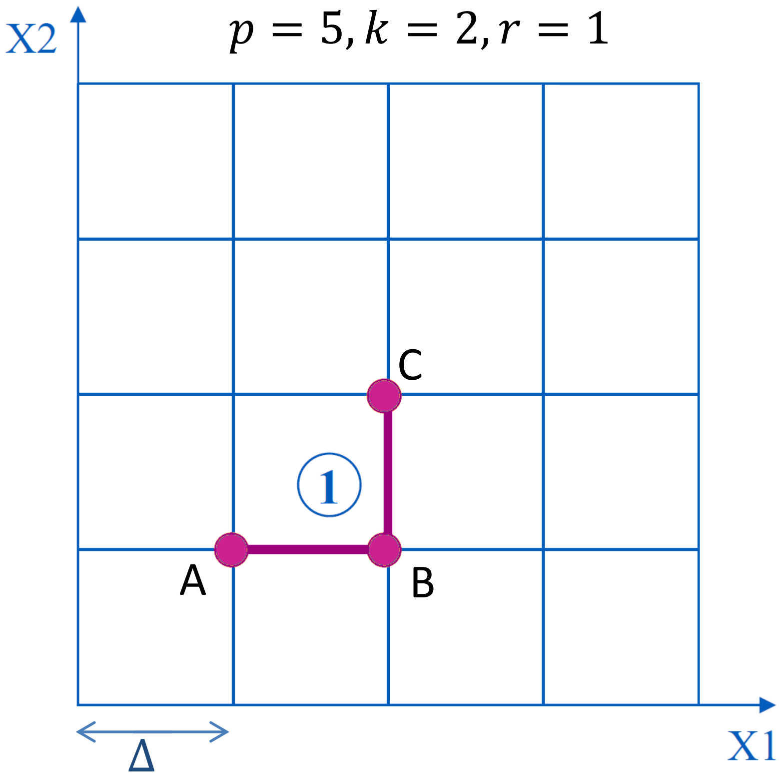
- Mean Bias, RMSE, MAE (RADOME + SYNOP : 1500 obs.)
- Mean meteorological fields

➢ Wind speed at 10m (ff10m),
➢ Wind gusts at 10m (ffgust),
➢ Precipitation accumulated during:
  - 1h (prec01),
  - 3h (prec03),
  - 6h (prec06),
  - 24h (prec24),
➢ Total cloud cover (tcc),
➢ Temperature at 2m (T2m),
➢ Relative Humidity at 2m (RH2m),
➢ 1h downward solar radiation at the surface (Sol01)

RADOME Network

Wimmer et al. (2021)

Morris Sensitivity Analysis (1991)



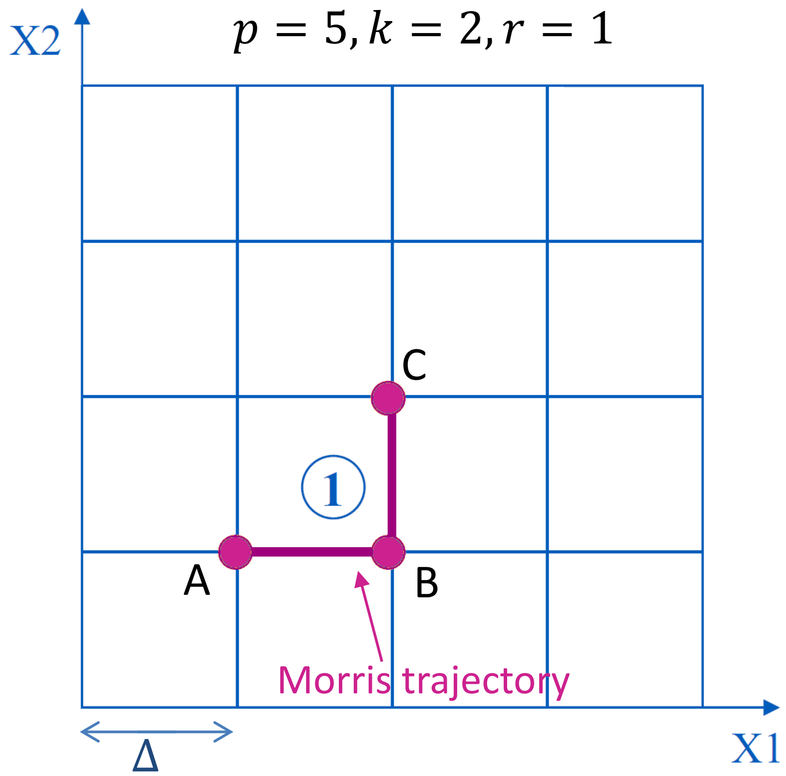
Parameters : X1, X2 ($k = 2$)

Modification of one parameter after another

→ One-At-a-Time design

Wimmer et al. (2021)

Morris Sensitivity Analysis (1991)



Parameters : X1, X2 ($k = 2$)

Modification of one parameter after another

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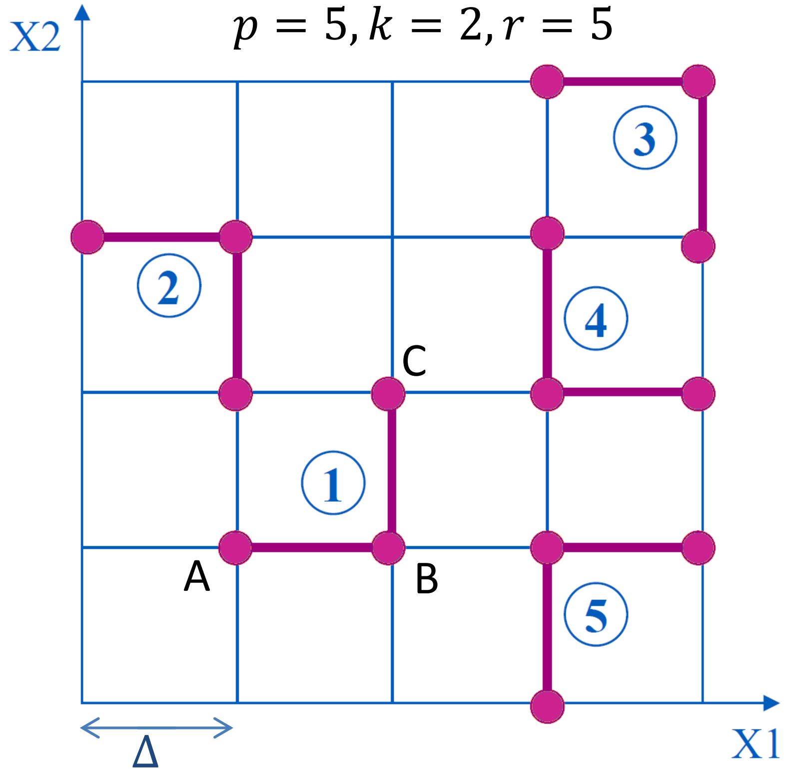
Elementary effect (EE_i) for each parameter i:

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

Wimmer et al. (2021)

Morris Sensitivity Analysis (1991)



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Repeat : r times → $r(k+1)$ simulations

Wimmer et al. (2021)

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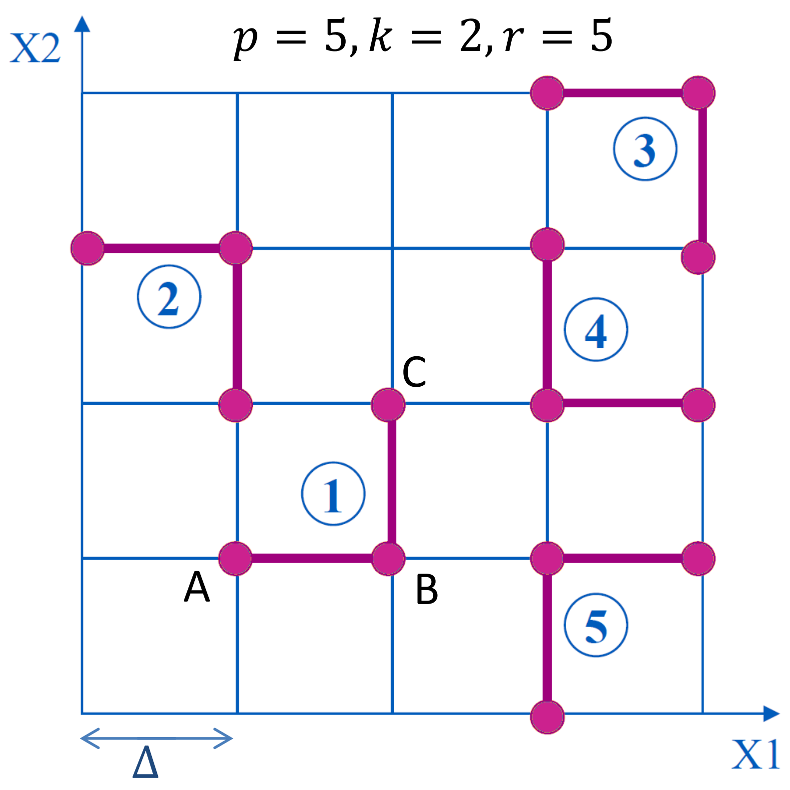

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Mean of $|EE_i|$:

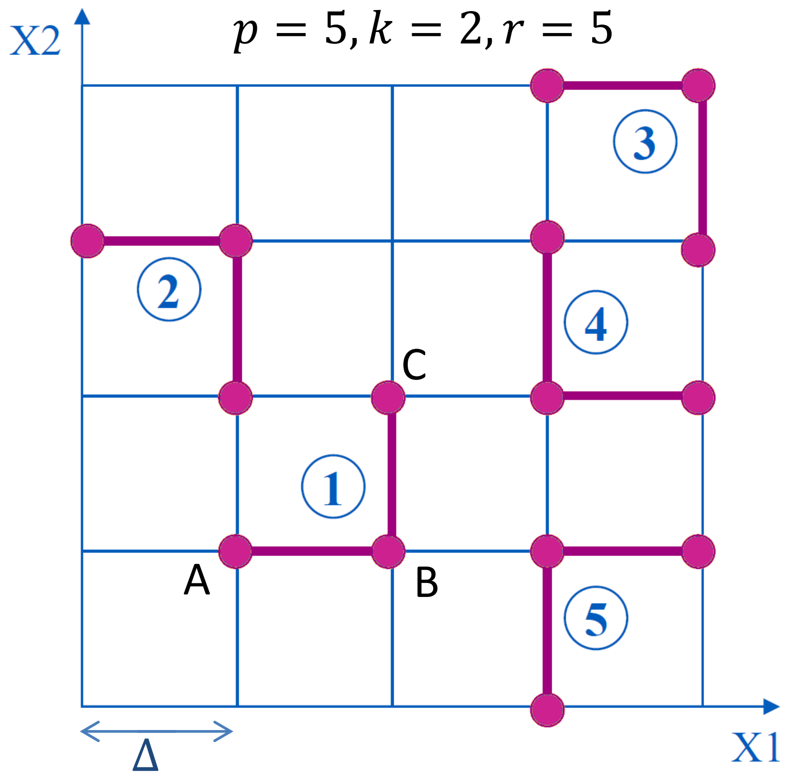
$$\mu_i^* = E(|EE_i|)$$

Standard deviation of EE_i :

$$\sigma_i = \sigma(EE_i)$$

Wimmer et al. (2021)

Morris Sensitivity Analysis (1991)



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Morris Sensitivity Indice:

(Ciric, 2012)

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

Wimmer et al. (2021)

Design of experiment and reduction of calculation cost

Design of experiment: $r = 12, k = 21, p = 8$

$$r(k+1) = 12 \times (21+1)$$
$$= \mathbf{264\ simulations}$$
$$(\times 3\ seasons\ \times 31\ days)$$
$$= 24\,552\ forecasts$$

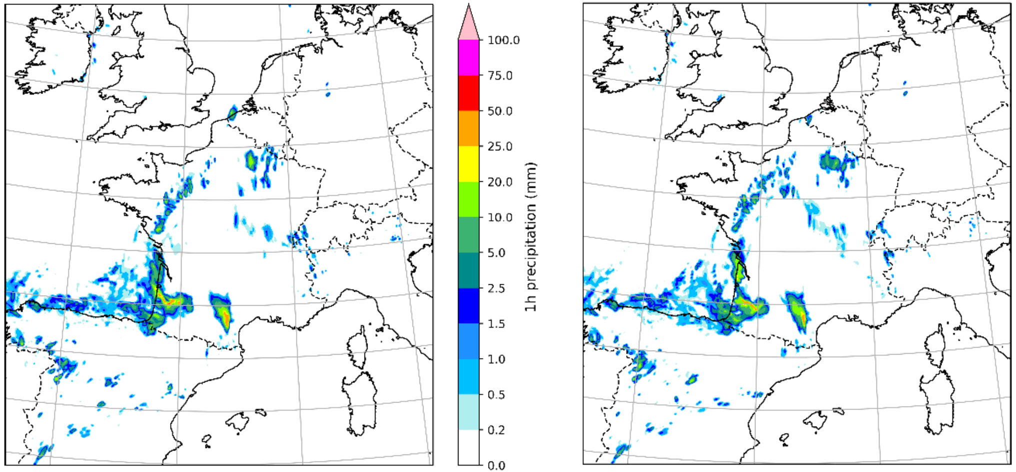
Cost equivalent to:

- 1,4 year of AROME-EPS forecasts (12 mb, 4 runs per day)
- 16,8 years of AROME forecasts (4 runs per day)

Reduce of calculation cost:

- Non-hydrostatic -> Hydrostatic
- Delete Predictor/Corrector Scheme

16 June 2021 21-22h



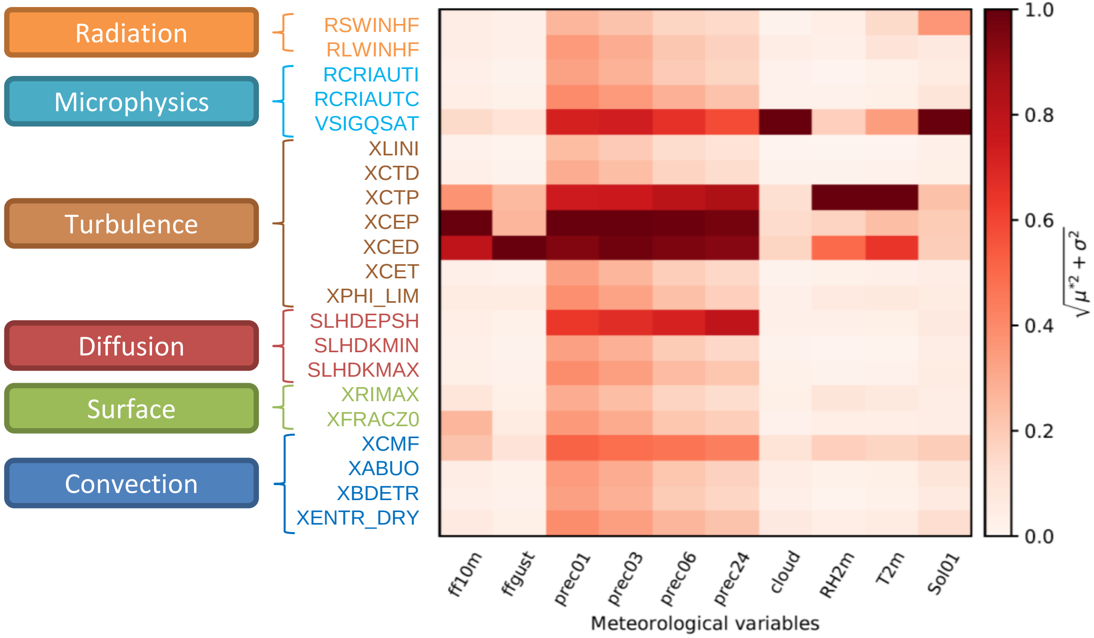
Hydrostatic
Without Predictor/Corrector Scheme

Non-Hydrostatic
With Predictor/Corrector Scheme

Wimmer et al. (2021)

Identify the most influential parameters

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

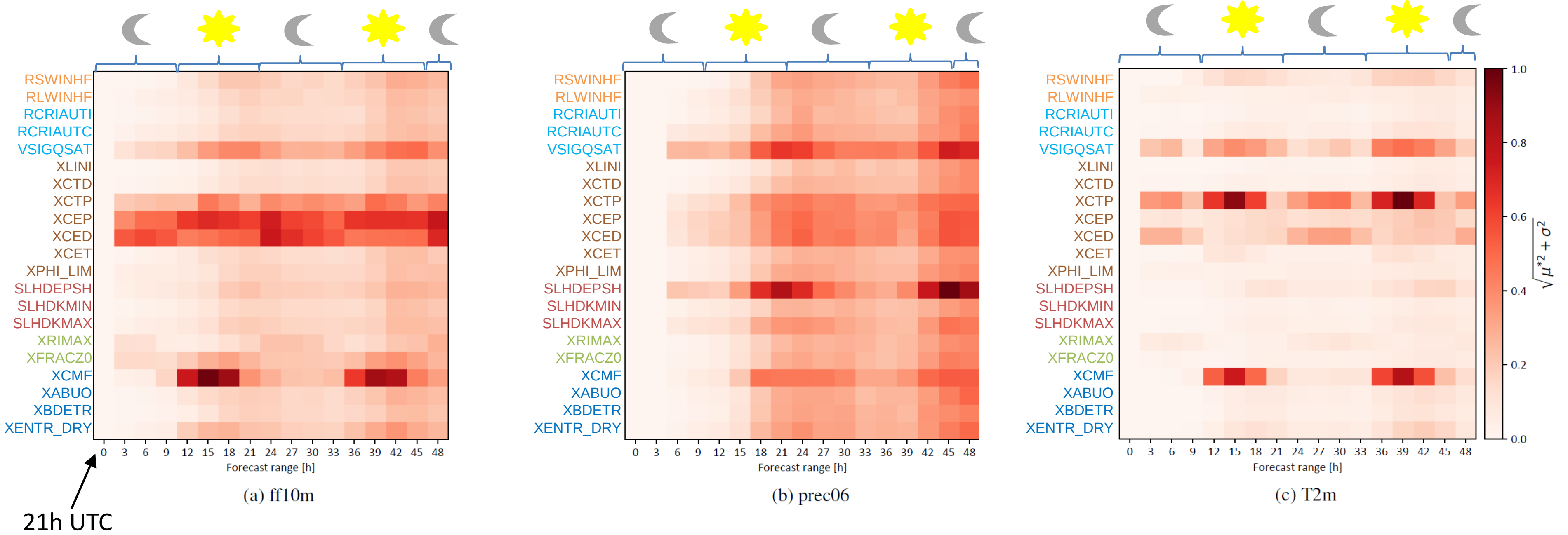


8 influential parameters: RSWINHF, VSIGQSAT, XCTP, XCEP, XCED, SLHDEPSH, XFRACZ0, XCMF

only 4 influential parameters in winter

Wimmer et al. (2021)

Parameters influence according to forecast range in summer 2018

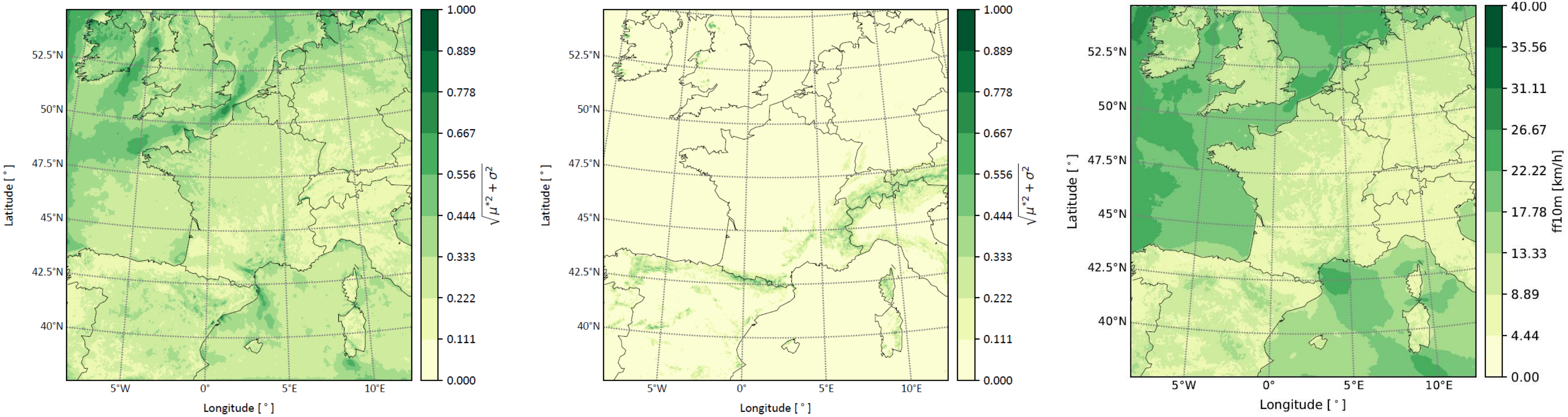


(a) ff10m (b) prec06 (c) T2m

Summer: Diurnal cycle -> parameters influence linked to convective activity
Winter: Reduction of the diurnal cycle

Wimmer et al. (2021)

Spatial parameters influence in summer 2018



(a) Influence of XCEP on wind at 10m
(b) Influence of XFRACZ0 on wind at 10m
(c) Averaged wind field at 10 meters

Influence depends:
on meteorological field (XCEP influential on windy areas),
on orography (XFRACZ0), …

Sensitivity Analyses

- Morris (1991) method:
  - **8 influential parameters** identified :
    RSWINHF, VSIGQSAT, XCTP, XCEP, XCED, SLHDEPSH, XFRACZ0, XCMF
  - Sensitivity depends on days
    Need to conduct sensitivity analyses over **long periods**
  - **Diurnal Cycle** during summer
  - **Sensitivity maps**: influence linked to surface and meteorological fields

- Sobol' (1990):
  - Mostly **confirms Morris** results
  - Identification of **parameters interactions** (even with non influential parameters)

Different model error representations based on parameters perturbation

Parameters perturbation according to…	… members	… initial dates
Perturbed Parameter (PP)	✓	
Random Perturbed Parameter (RPP)	✓	✓

Producing 1000 PP from Morris simulations and PP optimisation

Morris sensitivity analysis:

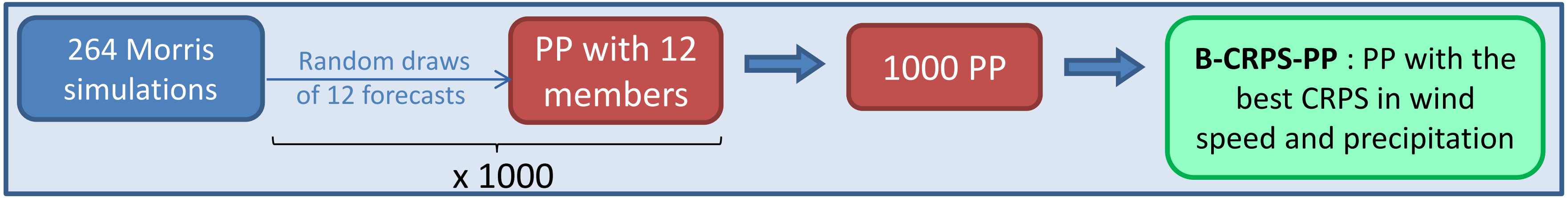
Create 264 forecasts which differ only in their parameters values

- like an EPS with 264 members
- without initial, surface, lateral condition error representation
- with model error representation based on PP method

Comparison with the current SPPT approach:

Problem : SPPT has 12 members -> need the same number of members

Production of 1000 PP of 12 members from the 264 simulations de Morris



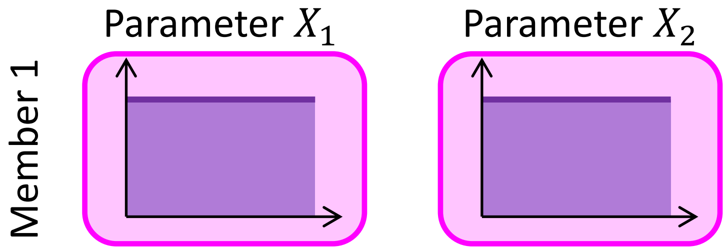
RPP optimisation

RPP : parameters perturbation **at each date**

→ random draw of parameters value following a probability density function

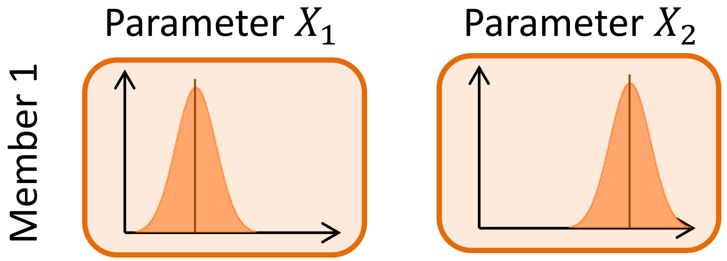
Test of different distributions:

- **Uniform** distributions ⇒ **uRPP**



- **Gaussian** distributions ⇒ **gRPP**

→ Gaussian distribution: $\mathcal{N}(m, s)$
where m is the optimal parameter
value of each member of the B-CRPS-PP



Perturbed Parameters method

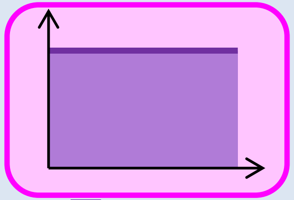
264 Morris simulations

↓ subsampling

Mean PP : mean of 1000 PP with 12 members

↓ optimisation

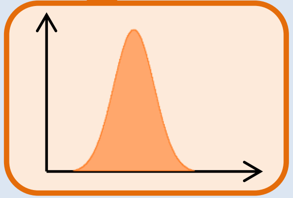
B-CRPS-PP : PP with the best CRPS in wind speed and precipitation



↓ **uRPP**

Random draw of parameters values according to a probability density function

↑ **gRPP**



→

- RSWINHF
- RLWINHF
- RCRIAUTI
- RCRIAUTC
- VSIGQSAT
- XLINI
- XCTD
- XCTP
- XCEP
- XCED
- XCET
- XPHI_LIM
- SLHDEPSH
- SLHDKMIN
- SLHDKMAX
- XRIMAX
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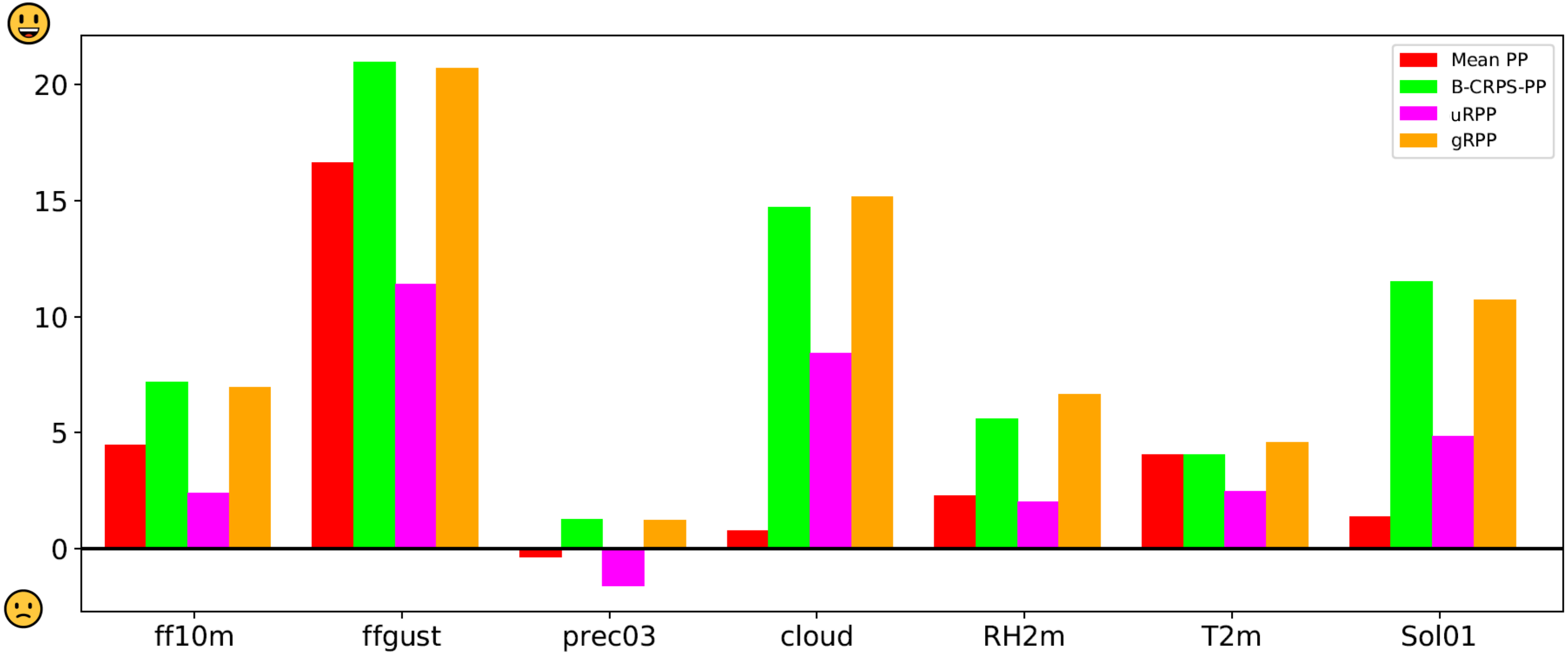
- XCMF
- XABUO
- XBDETR
- XENTR_DRY

Improvement rate of CRPS according to SPPT (%)

Summer 2018



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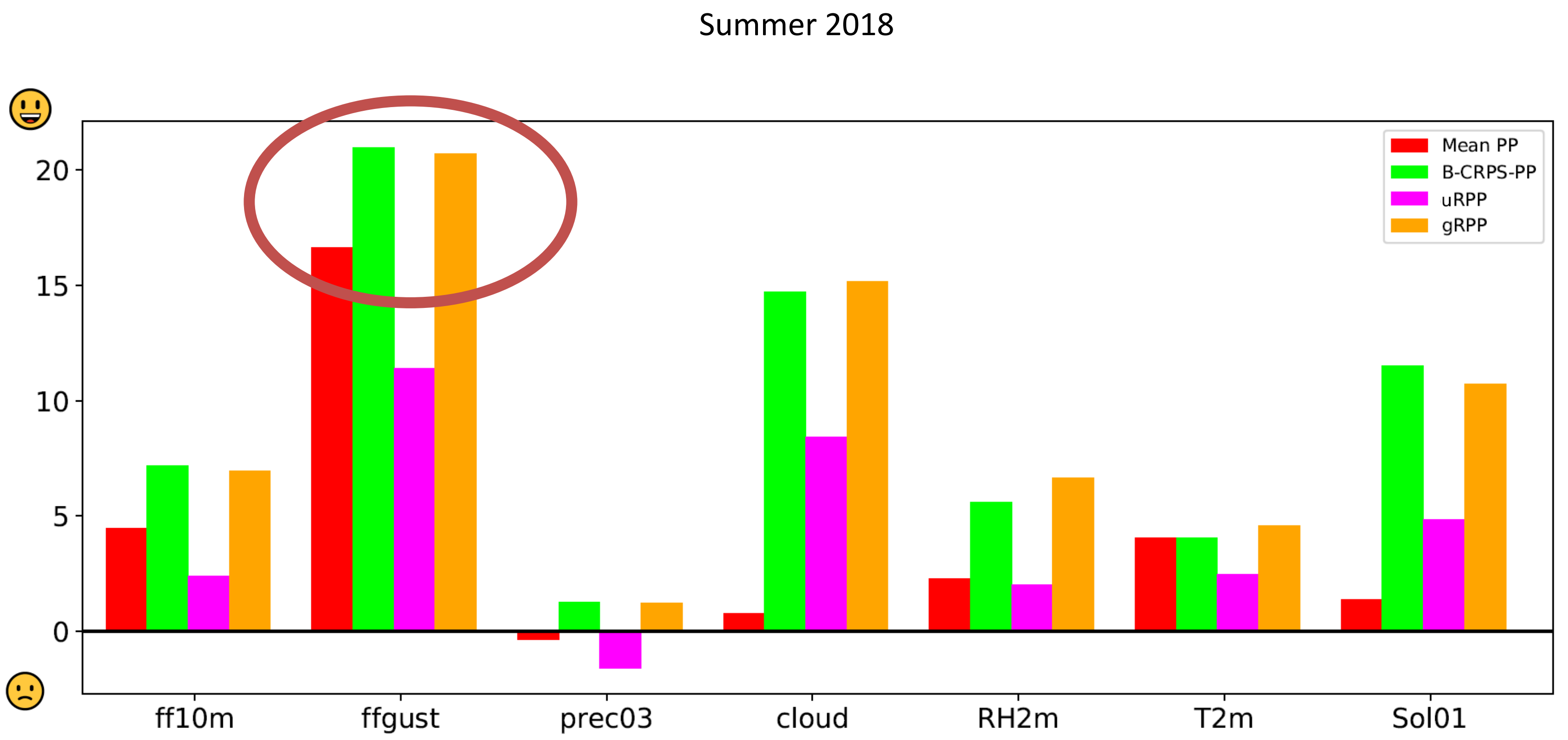

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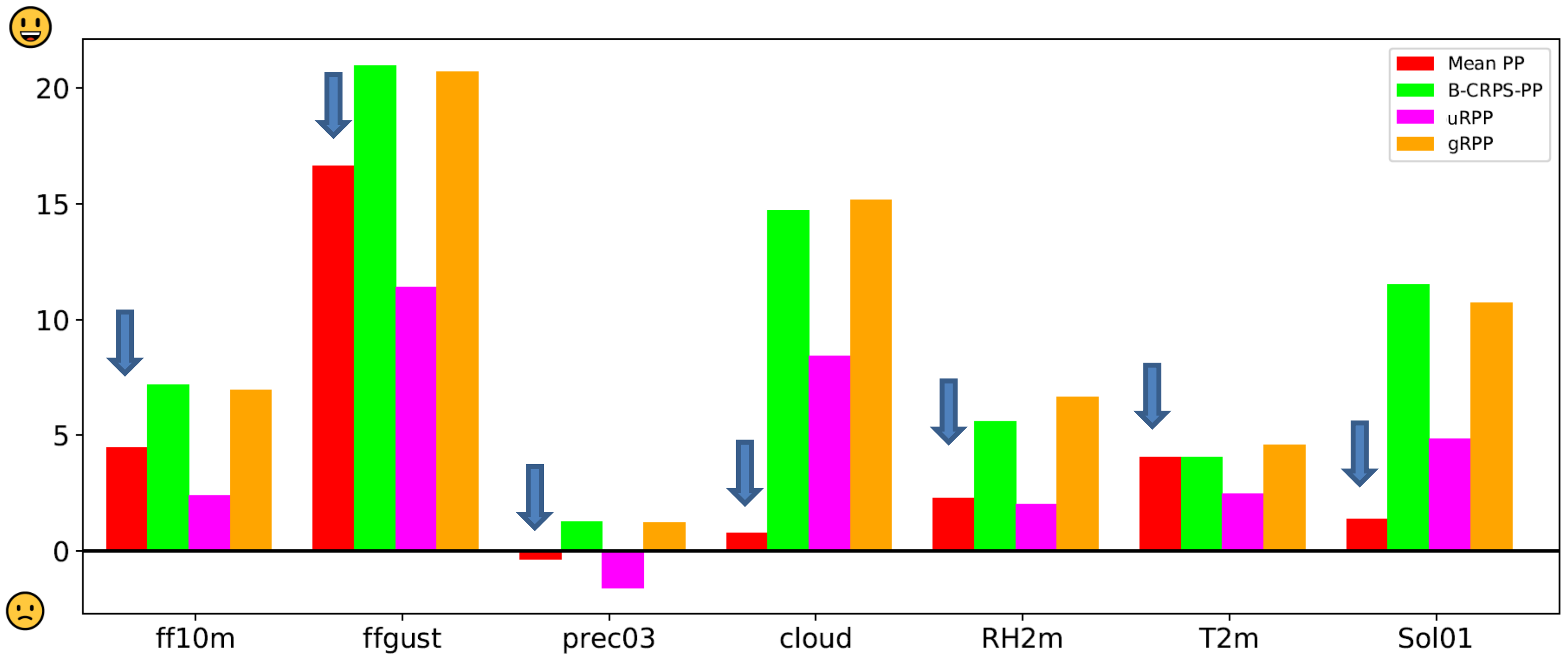

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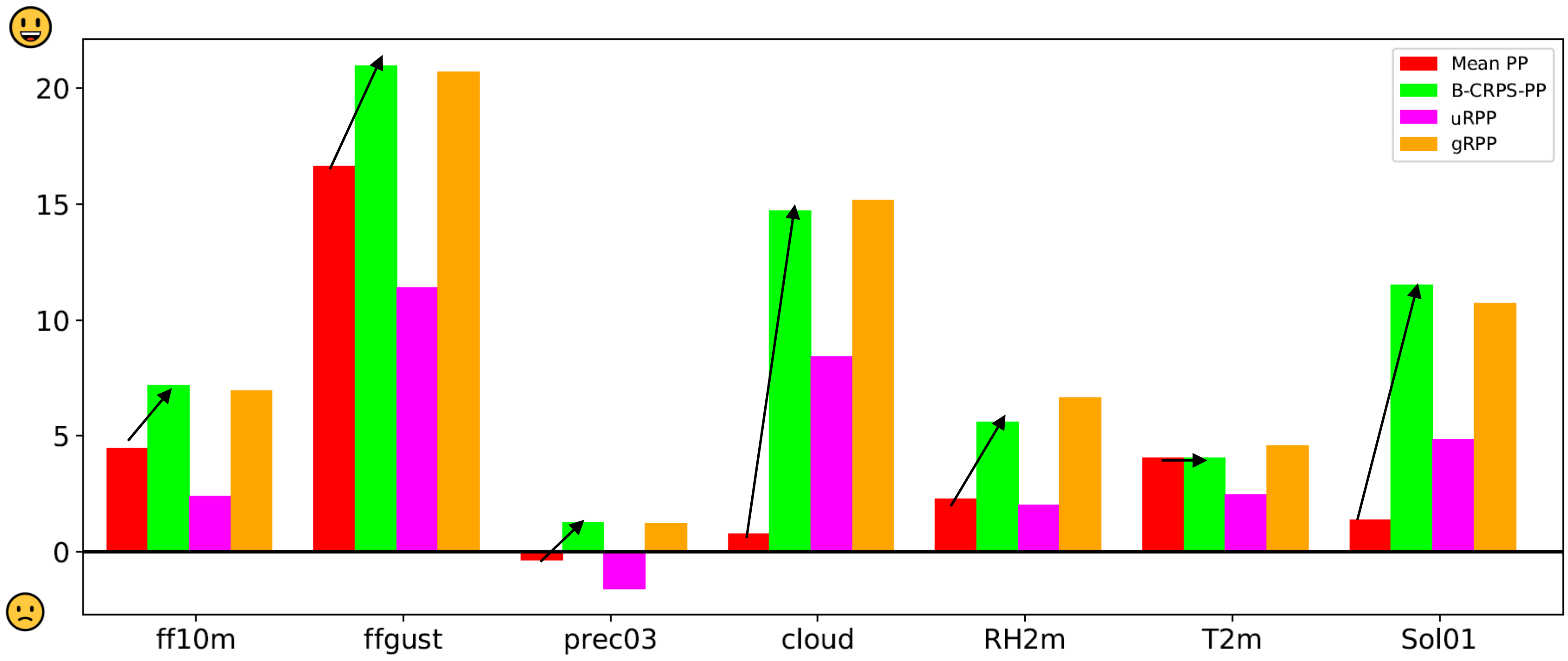

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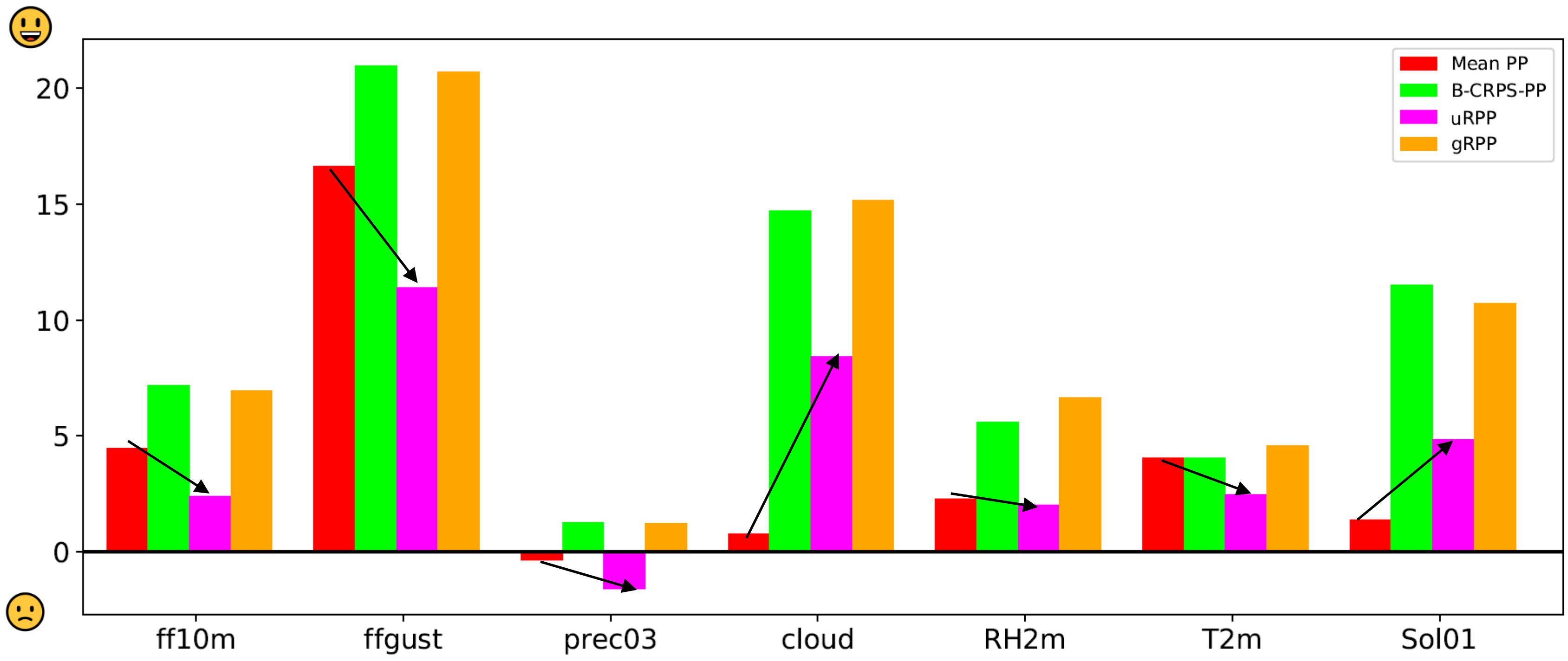

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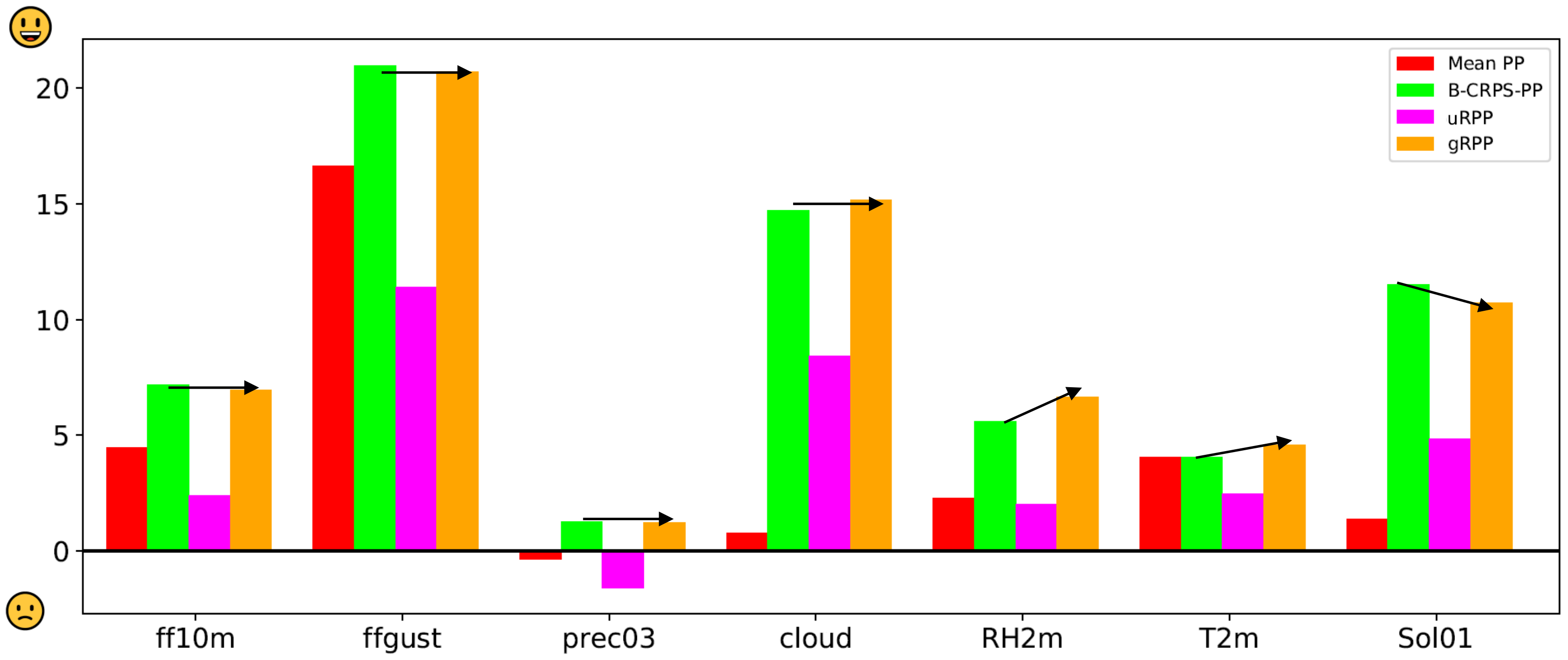

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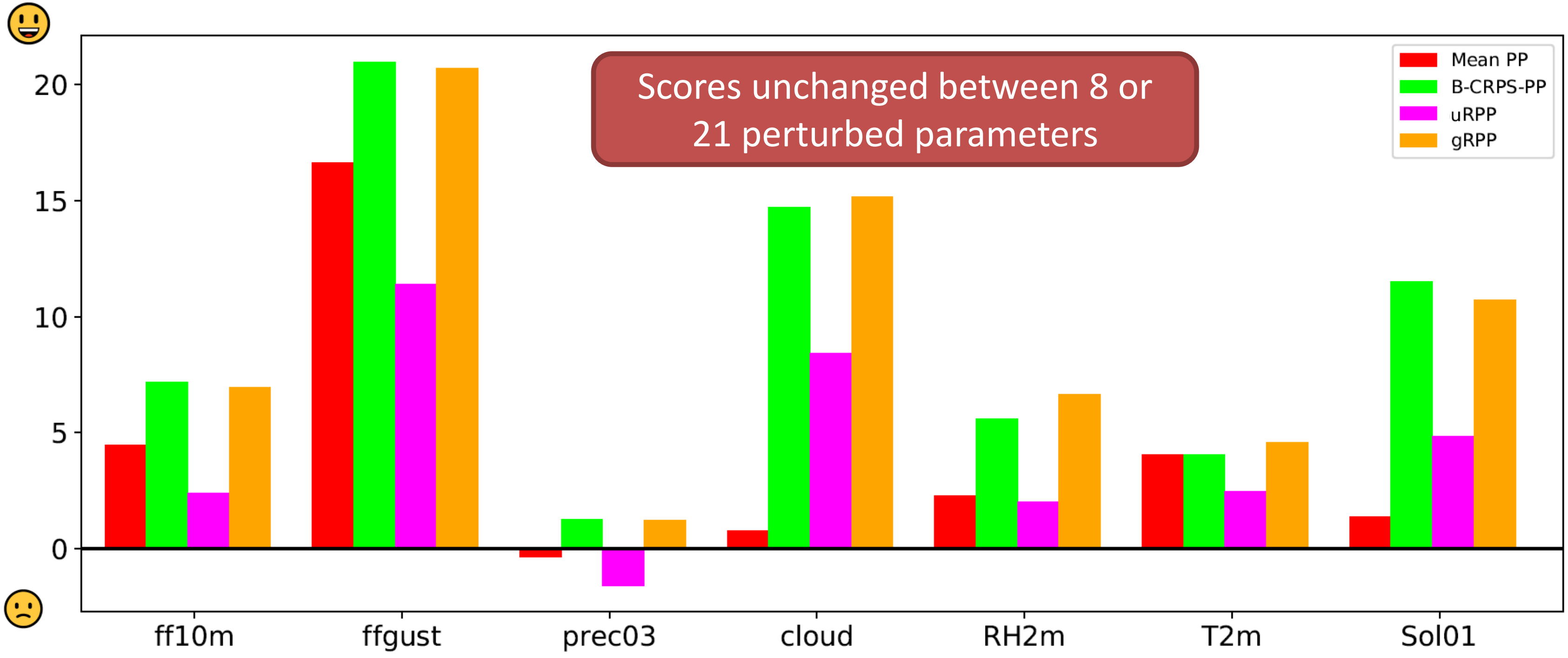
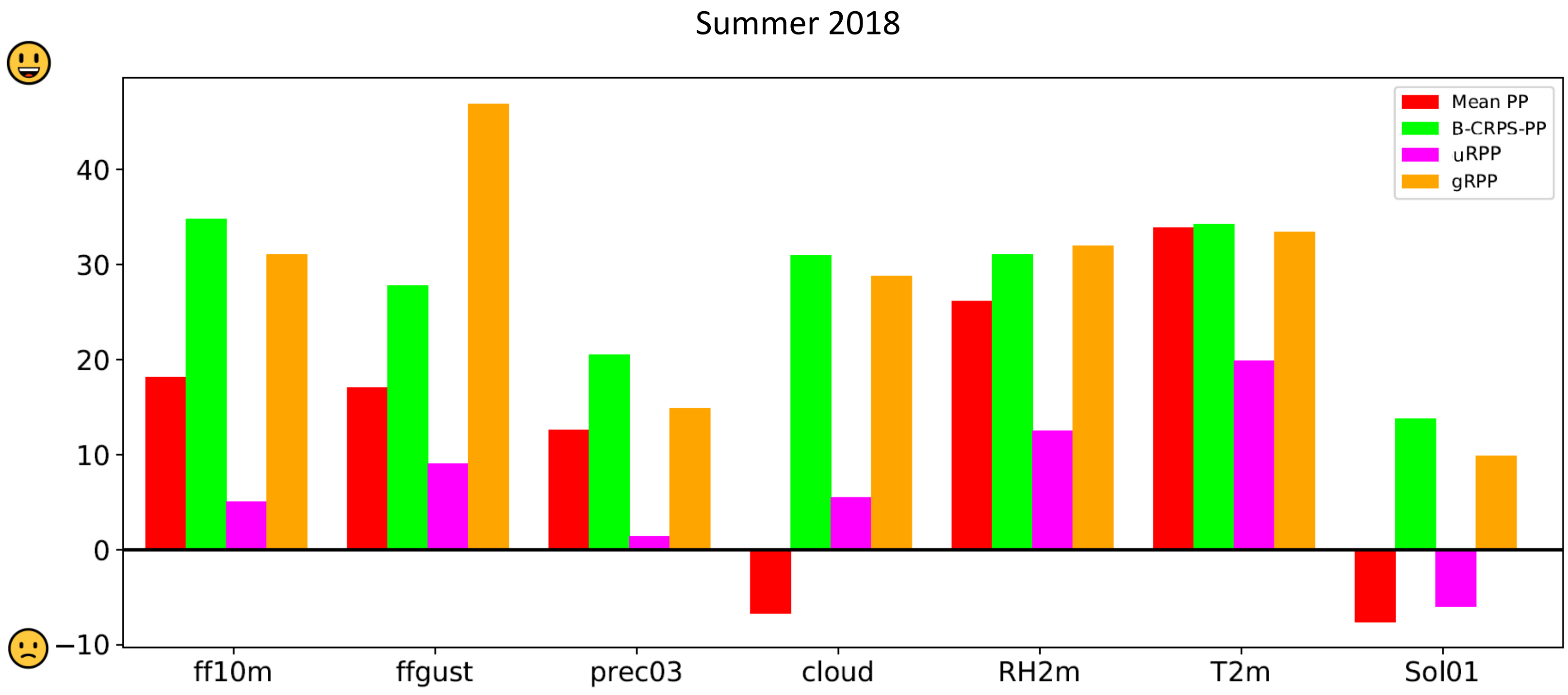


Improvement rate of Spread-Skill ratio according to SPPT (%)



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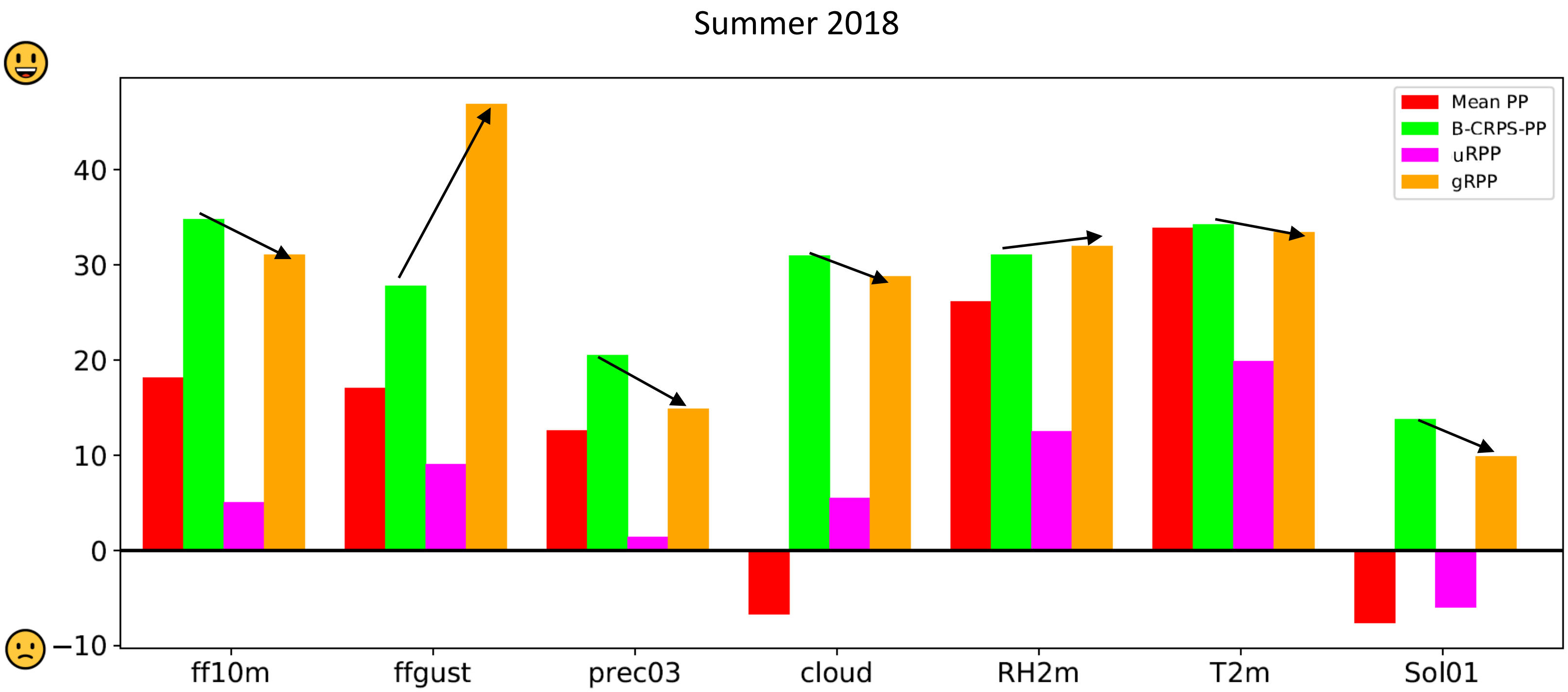
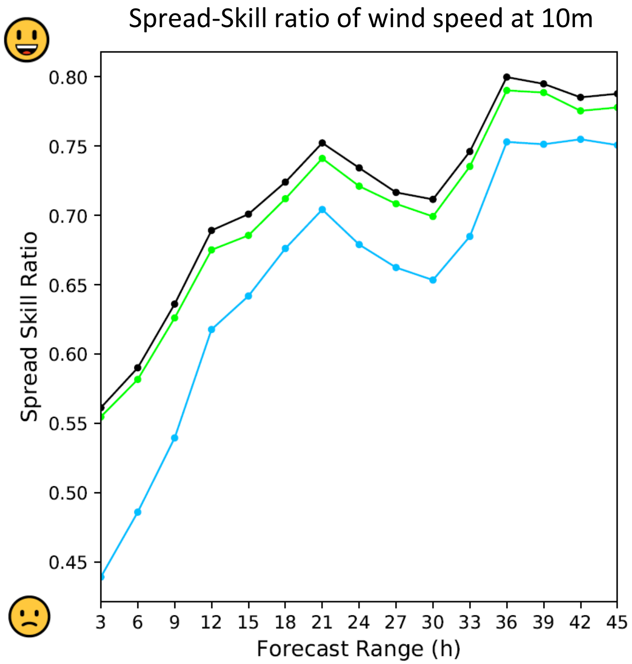
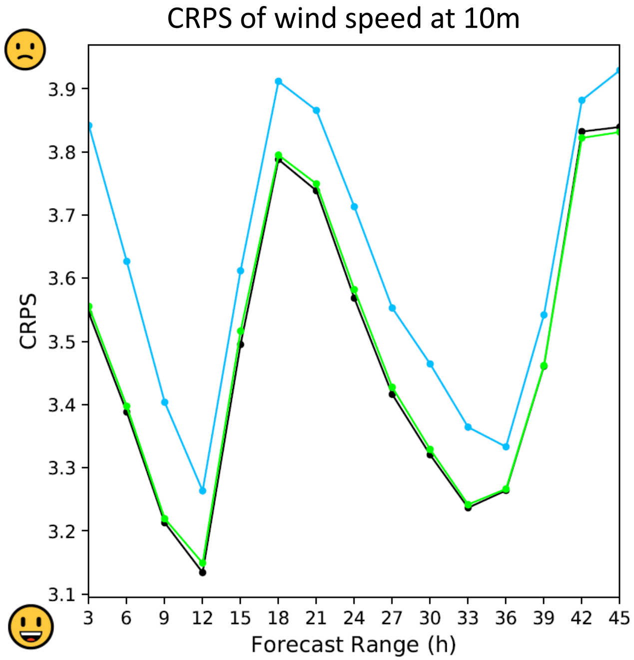


Operational configuration: add perturbation of IC, LC, SC

Summer 2018





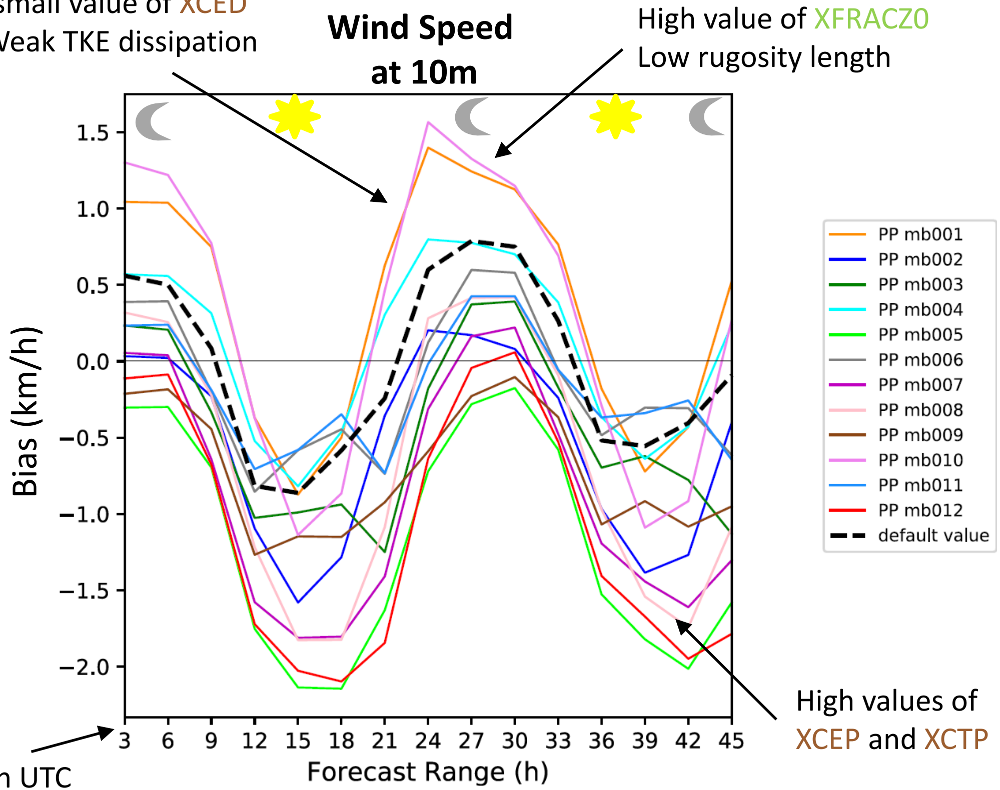
Bias of B-CRPS-PP members

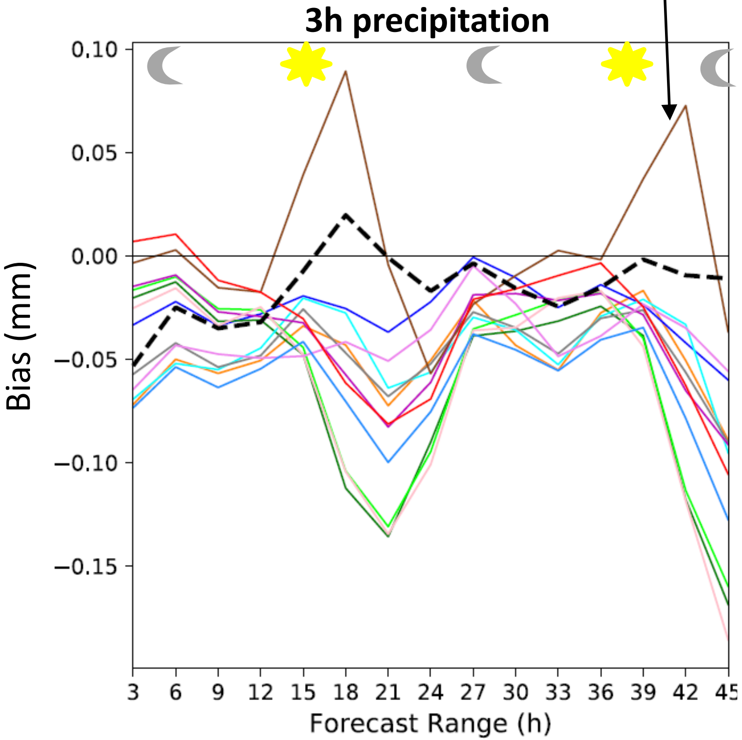
Summer 2018

small value of XCED
Weak TKE dissipation

High value of XFRACZ0
Low rugosity length

Low values of XCMF



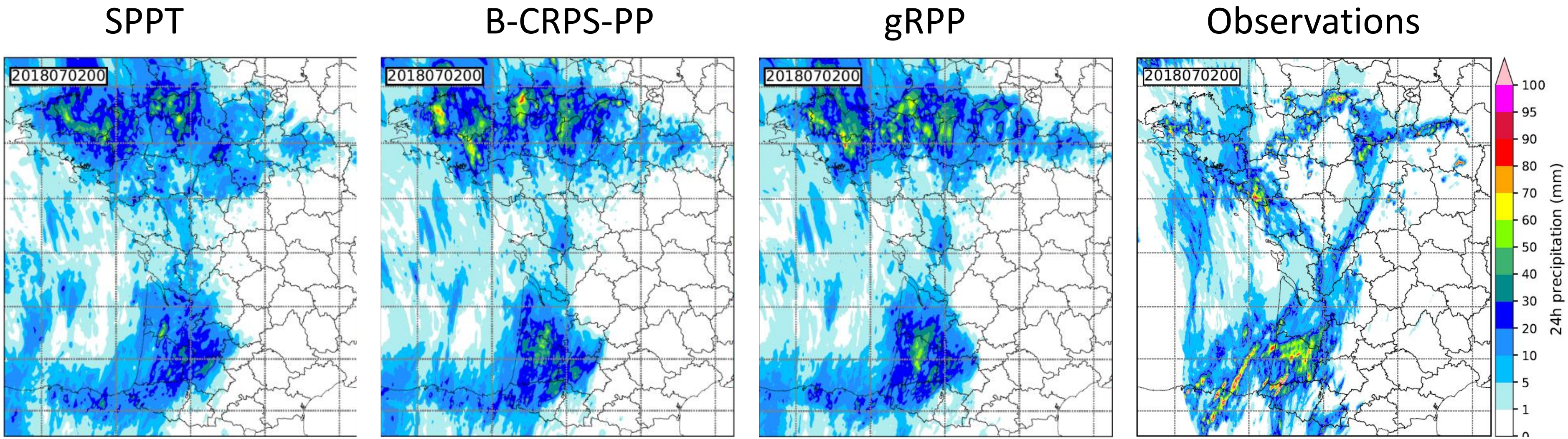


0h UTC

High values of XCEP and XCTP

90th percentile of 24h cumulated precipitation

Initial condition: the 30th June 2018 at 21h UTC
Time range: + 27h



Better intensity and sharper focus in B-CRPS-PP and gRPP in South-West of France

Model error representation

- Perturbed Parameters approaches **improve** scores compared to SPPT
  - PP performs better than RPP
- **Optimisation according to CRPS** : improve also **other scores**
- Perturbation of **only 8 parameters** give **similar results** than perturbing **21 parameters**
- Operational configuration:
  - B-CRPS-PP **still better** than SPPT
  - Adding SPPT has few impacts on surface
- Members bias can be explained by **specific parameters values**
- Study case: optimised PP produce stronger convection with **sharper focus**

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**
- Morris result: **8 influential parameters**
- Sensitivity of AROME to 21 parameters according to seasons, days, forecast range, grid points

Model error representation:

- Production of **1000 PP and optimisation** according to CRPS (B-CRPS-PP)
  -> improve probabilistic scores
- RPP : parameters perturbations with **different distributions**
  -> **Gaussian distribution** with mean at B-CRPS-PP values
- gRPP not as good as B-CRPS-PP
  -> **Fixed** parameter perturbation **sufficient**
- Perturbation of 8 parameters ≈ perturbation of 21 parameters
  -> Possibility to **reduce the list** of perturbed parameter **to 8**

Perspectives

- RPP : Parameters perturbation according to members and initial dates

  ⇒ add a **spatial** (SPP) or **time range** (RP) variability

- Parameters influence depends on hours and location

  ⇒ deduce **characterictic length and time** for stochastic perturbations

- Study of members bias

  ⇒ **Bias correction** by using probability density function for **non biased members**

- **EDA** : currently uses SPPT model error representation

  ⇒ add or replace by **perturbed parameters** approaches

- Other model error representation

  ⇒ **Stochastic parameterization** (presentation of A. Fleury)

Forthcoming change of AROME-EPS

- from 12 to 16 members in July 2019

  ⇒ Optimisation for **16 members**

- from 2,5km to 1,3km like the deterministic run in summer 2022

  ⇒ Validation of results at **high resolution**

- AROME without SLHD in summer 2022

  ⇒ Validation of results **without perturbing parameters** from **SLHD**

- ARPEGE-EPS with **new physics** and **higher resolution** (7,5km to 5km over France) in summer 2022

  ⇒ Multiphysics replaced by **perturbed parameters** with 2 deep convection schemes (L. Descamps, C. Labadie, P. Cebron)

Thank you for your attention

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