Impact of the statistical method, training dataset, and spatial scale of post-processing to adjust ensemble forecasts of the height of new snow

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Context

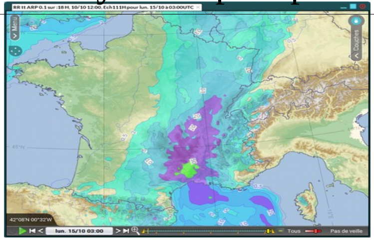
- Forecasting the height of new snow:
  - Safety and economic concerns

- Meteo-France **automatic forecasts** currently available (website and smartphone apps) :

24h height of new snow =

$\sum_{24h}$ (

Hourly NWP precipitation



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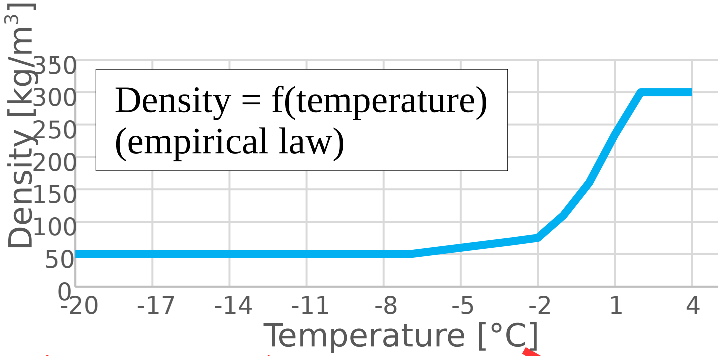

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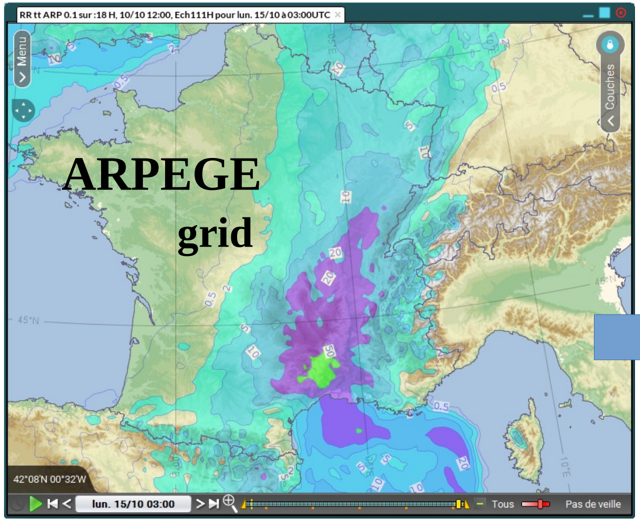
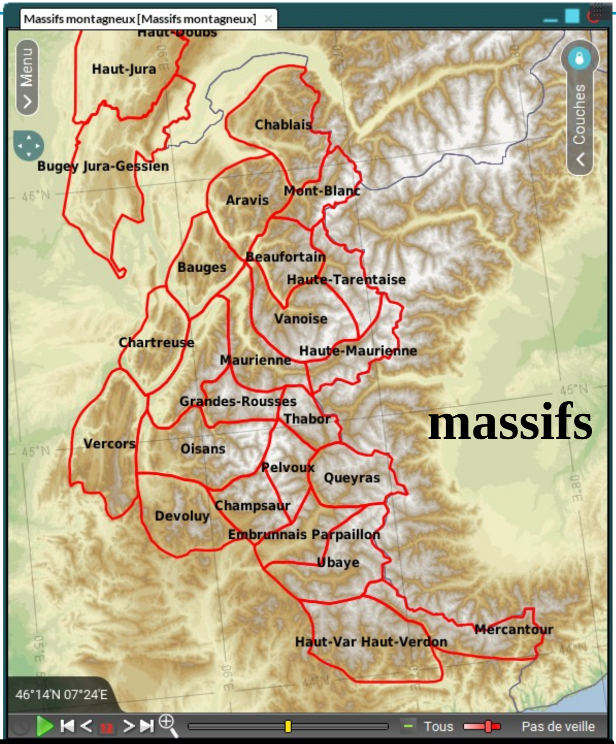
~~**Compaction during snowfall**~~ ~~**Possible melting**~~ ~~**Rain on snow**~~

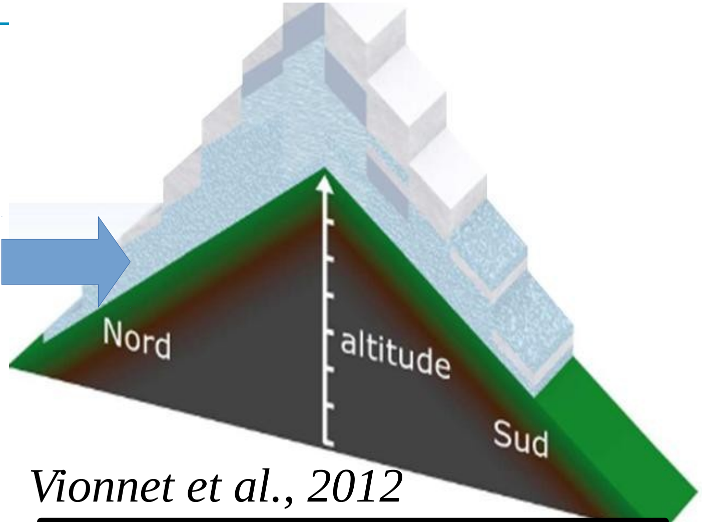
→ **Severe biases**

Alternative : Physical modelling SAFRAN-Crocus





Durand et al., 1998



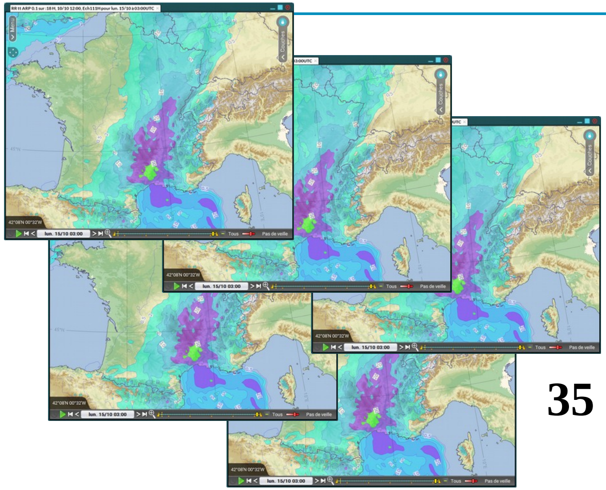
Vionnet et al., 2012

SAFRAN :
- Spatial aggregation of ARPEGE on *massifs* (~1000 km²)
- Adjust meteorological variables at various elevations

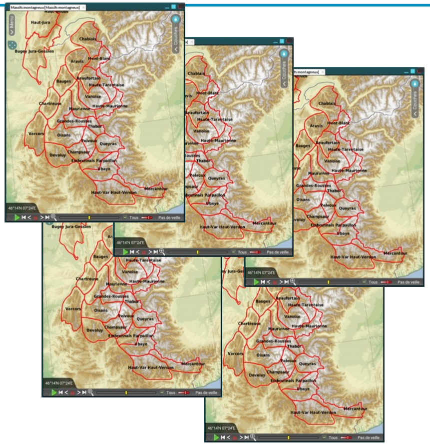
Crocus :
- Falling snow density = f(temperature, wind speed)
- Explicit mechanical compaction
- Melting (energy balance)
- Compaction due to liquid water (rain on snow)

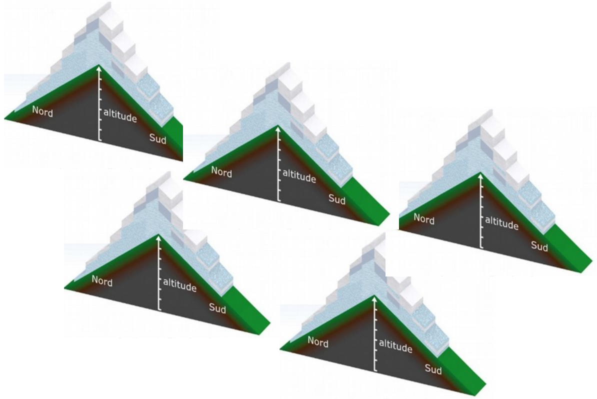
Ensemble forecasts PEARP-S2M

Experimental from 2014
Operational : october 2019



35 members



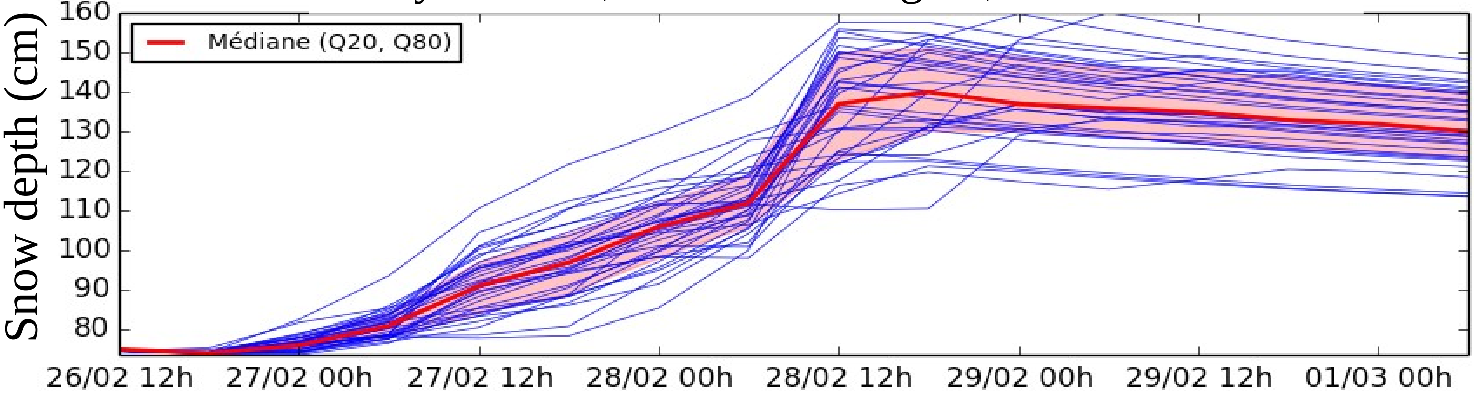


PEARP

SAFRAN

Crocus

4-day forecast, Mercantour region, 2100 m elevation

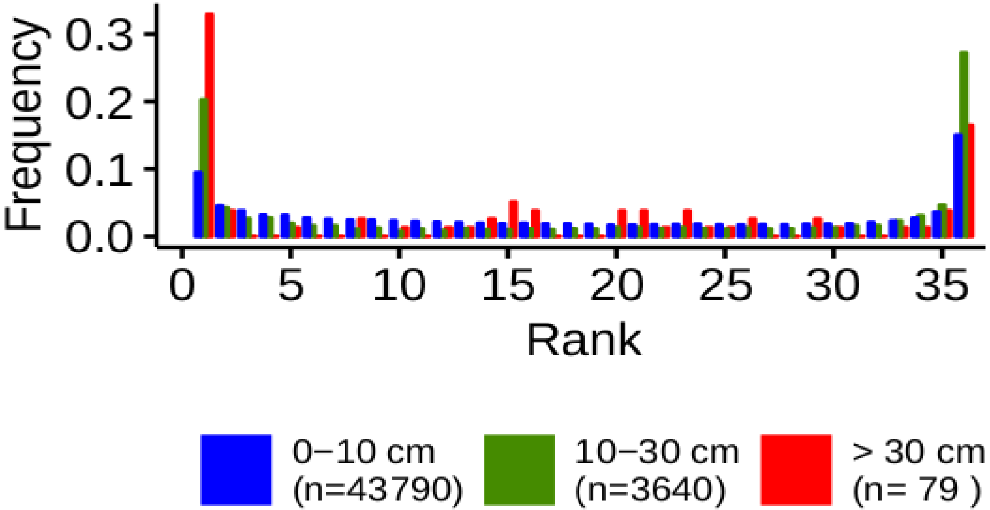


Vernay et al. 2015

Raw ensemble forecasts PEARP-S2M

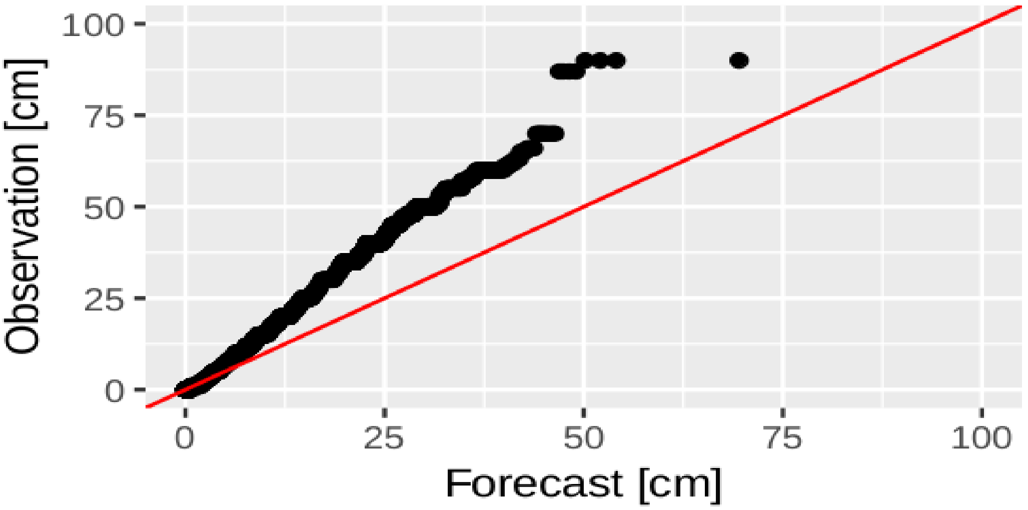
Evaluation over all massifs
Winter 2017-2018

Rank diagram



Underdispersion !

Quantile-Quantile plot



Bias !

State of the art

- Physical ensemble modelling of the snowpack improves the forecast of the height of new snow compared to:
  - **Direct NWP outputs** (*Champavier et al., 2018*)
  - **Deterministic systems** (*Vernay et al., 2015*)

- **Ensemble Model Output Statistics (EMOS)** are useful to forecast the height of new snow from direct ensemble NWP outputs (precipitation and temperature) (*Stauffer et al., 2018 ; Scheuerer and Hamill, 2019*)
- **Quantile Regression Forests (QRF)** can incorporate more predictors and have added value for precipitation forecasts *(Taillardat et al., 2019)*

Questions

- Can **Ensemble Model Output Statistics (EMOS)** improve the forecasts from physical modelling ?
  - What is the best training dataset ?
  - What is the spatial validity of the post-processing ?
- Can **Quantile Regression Forests (QRF)** improve the skill compared to EMOS ?

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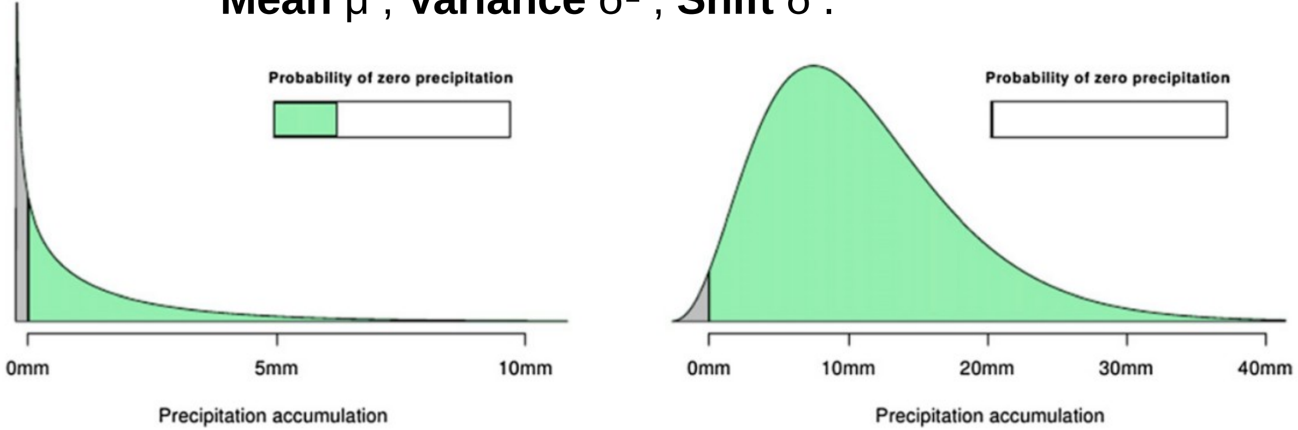
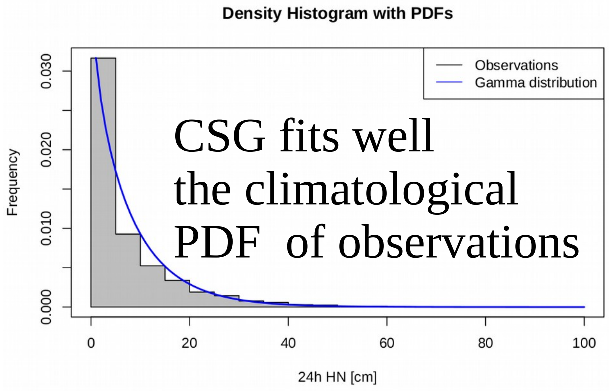
Statistical post-processing: method

- In *Nousu et al., NPG, 2019*, we apply the EMOS method used by *Scheuerer and Hamill (2015 ; 2018)* for precipitation forecasts:
  - We assume that the conditional distribution of the forecast HN to the raw ensemble forecasts follow a Censored Shifted Gamma (CSG) defined by 3 parameters : **Mean** μ ; **Variance** σ^2 ; **Shift** δ .





  - Regression model between CSG parameters and synthetic properties of the raw ensemble (**mean, dispersion, probability of 0 cm**)

Statistical post-processing: calibration

Nousu et al., NPG, 2019

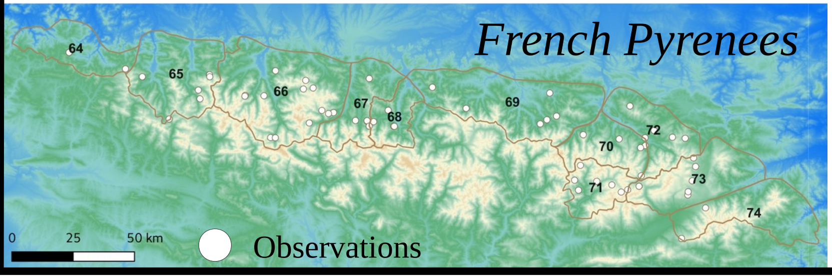
Predictand :
Network of local observations of the 24h height of new snow

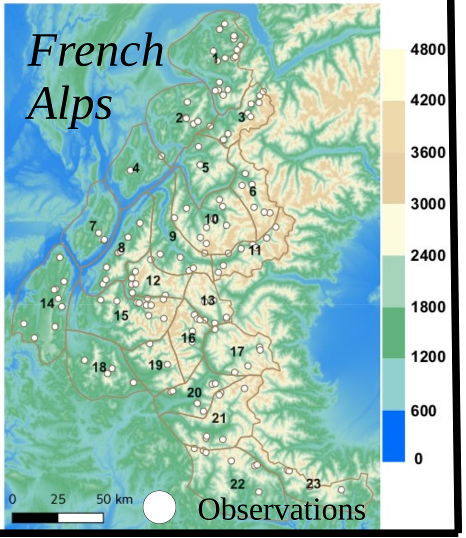
2 Predictor datasets: Ensemble forecasts PEARP-S2M

	Period	Members	Initial conditions	Resolution and physics
Reforecast	1994-2016	10	Unperturbed	Homogeneous
Real-time forecasts	2014-2017	35	Perturbed	Heterogeneous

Spatial scale of the calibration:
- Massif scale
- Station scale

Evaluations :
- From real-time forecasts, winter **2017-2018**



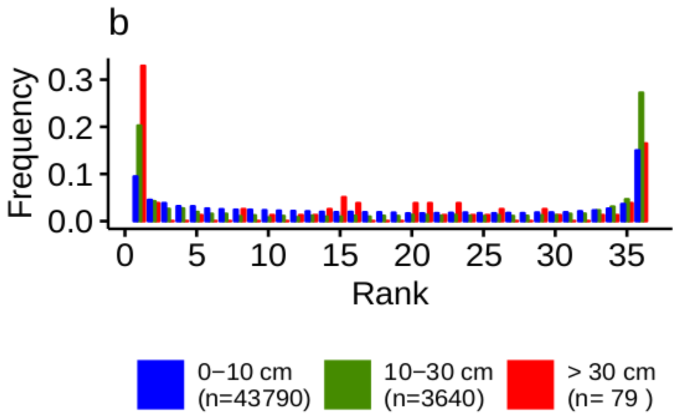


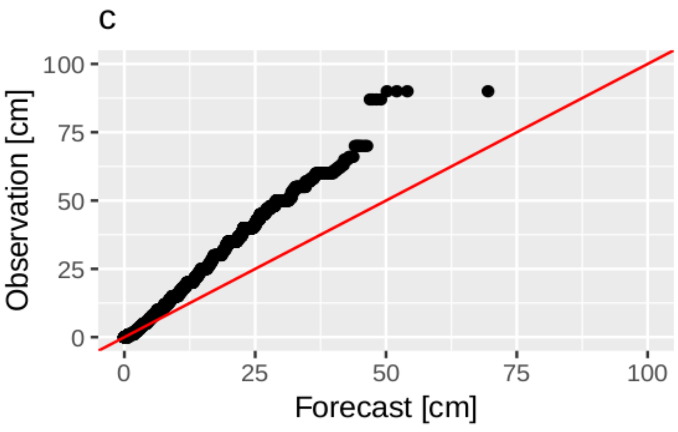
EMOS: results

Nousu et al., NPG, 2019

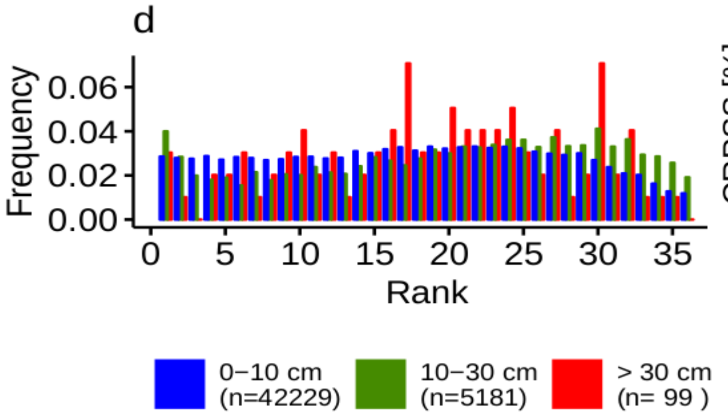
Training: reforecasts 1994-2016
Evaluation: real-time forecasts 2017-2018

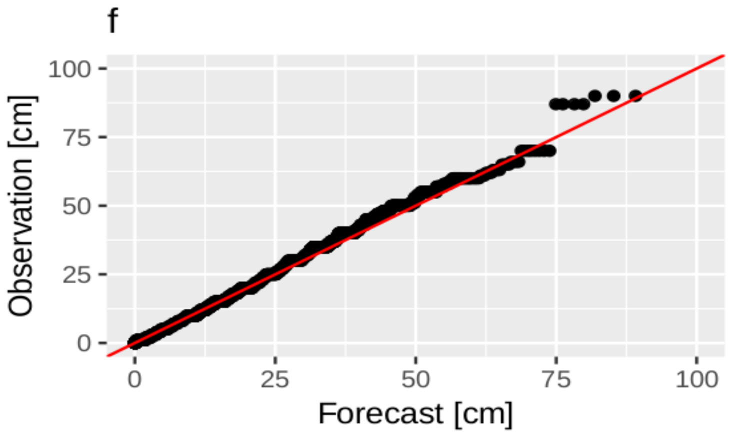
Raw forecasts



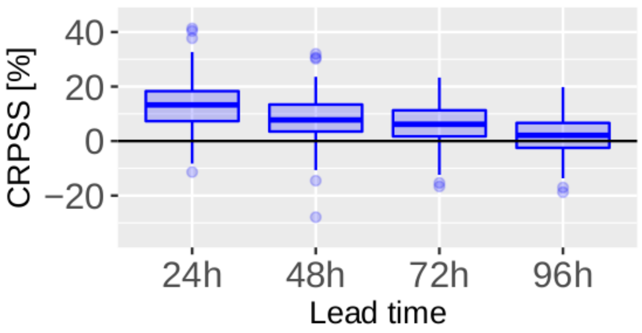


Corrected forecasts





CRPSS (Reference : raw forecasts)



- **Remove bias and underdispersion**

- **Improvement of CRPS** on most stations.

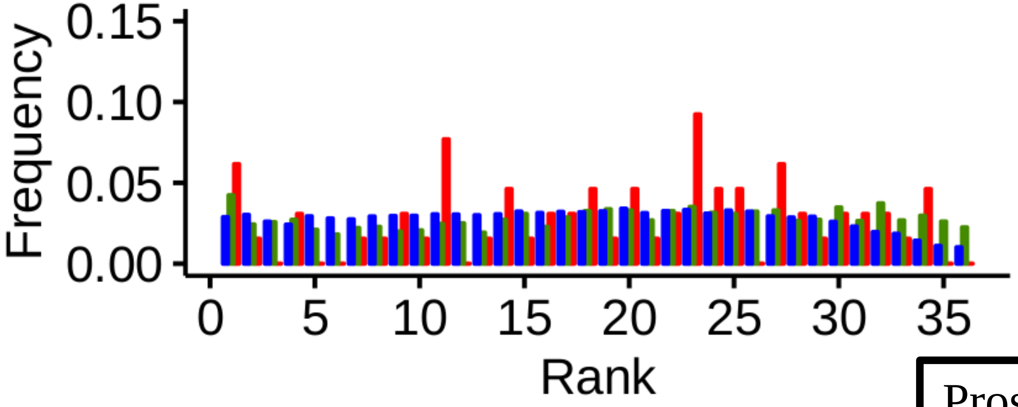
- Larger improvement at short lead times

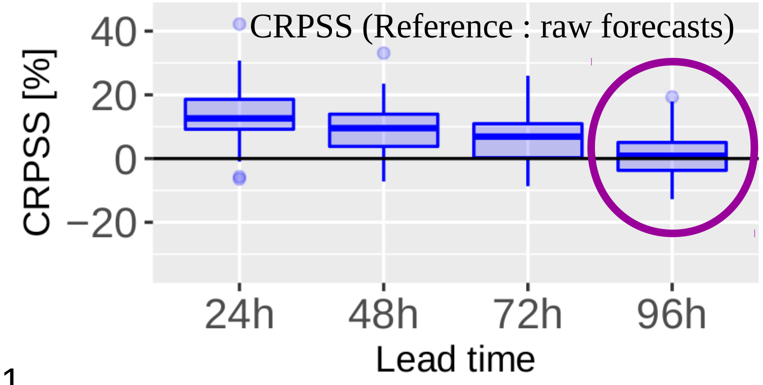
Sensitivity to training dataset

Nousu et al., NPG, 2019

0–10 cm (n=18728) | 10–30 cm (n=2763) | > 30 cm (n= 65)

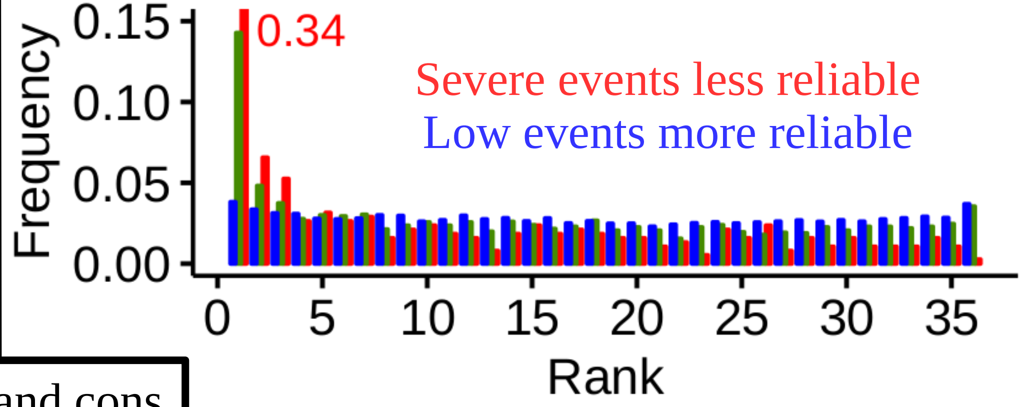
Training: reforecasts 1994-2016
Evaluation: real-time forecasts 2017-2018

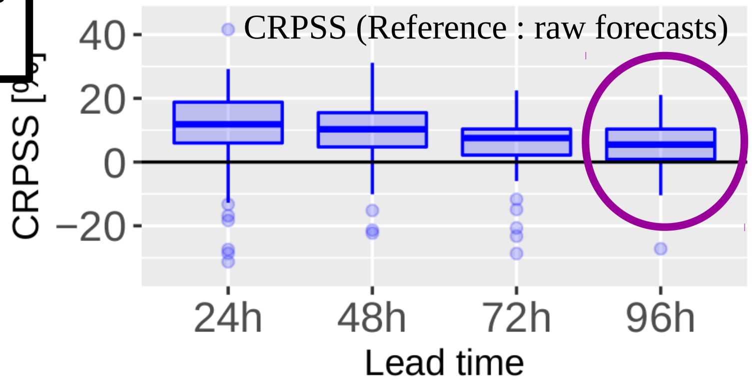




Pros and cons on both sides

Training: real-time forecasts 2014-2017
Evaluation: real-time forecasts 2017-2018





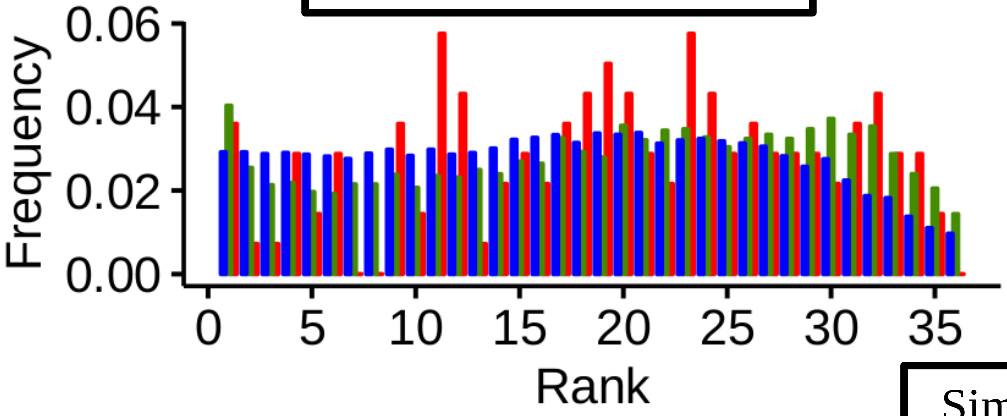
Better skill at the longest lead time

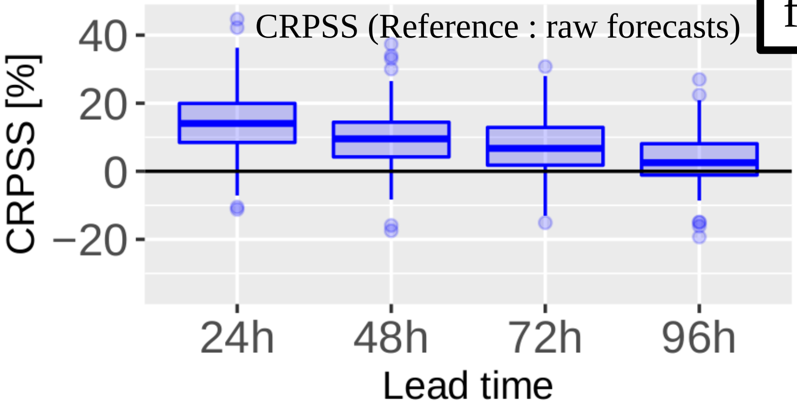
Sensitivity to spatial scale

Nousu et al., NPG, 2019

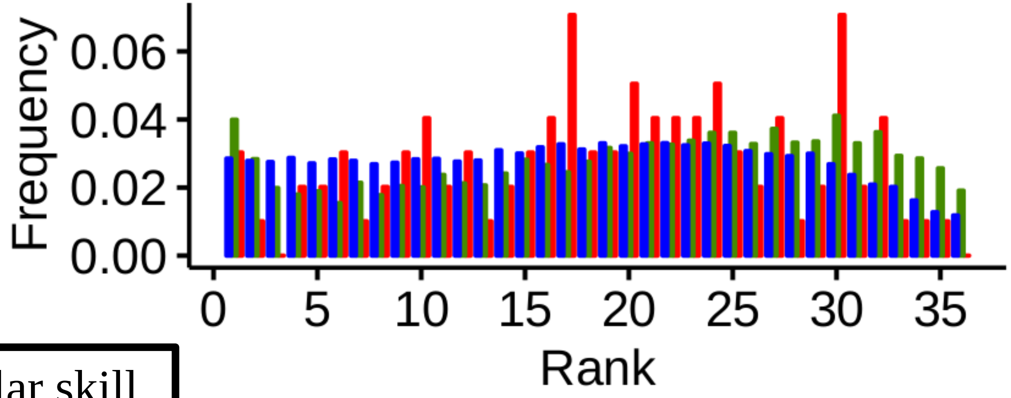
0–10 cm (n=18728)
10–30 cm (n=2763)
> 30 cm (n= 65)

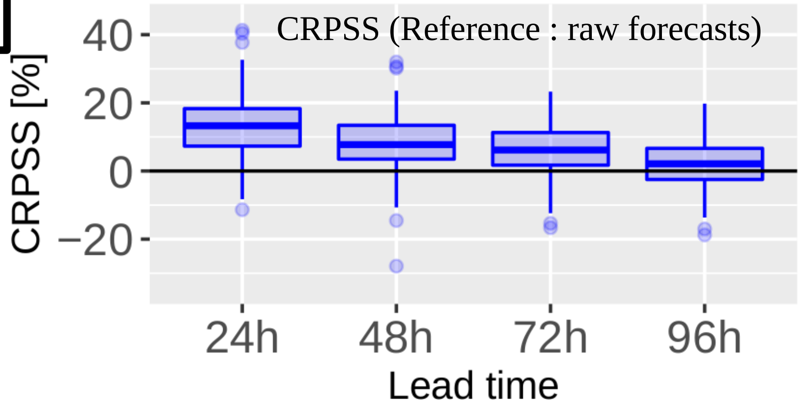
Training: <u>local</u> scale
Evaluation: local scale





Training: <u>massif</u> scale
Evaluation: local scale



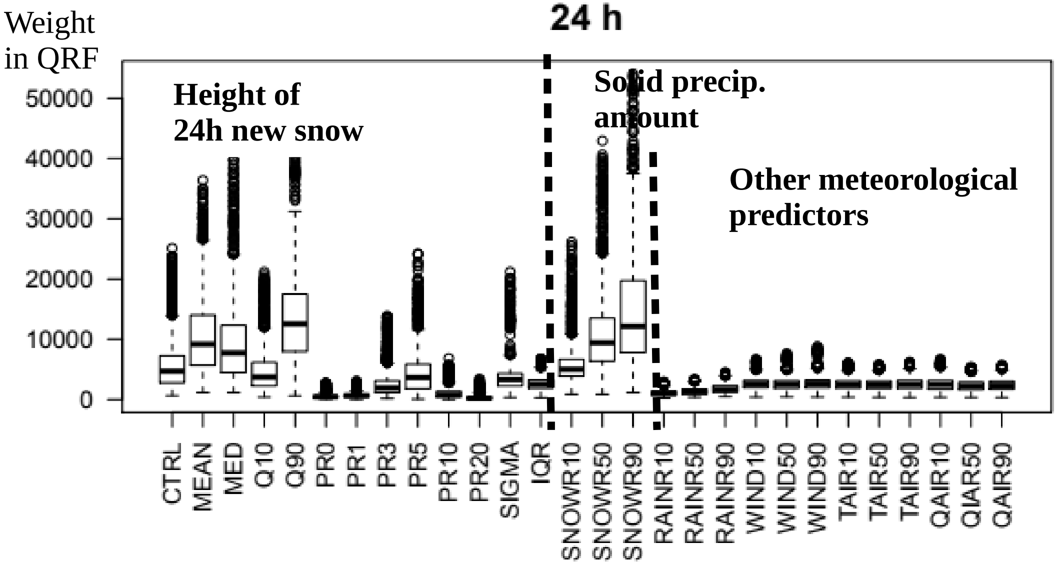


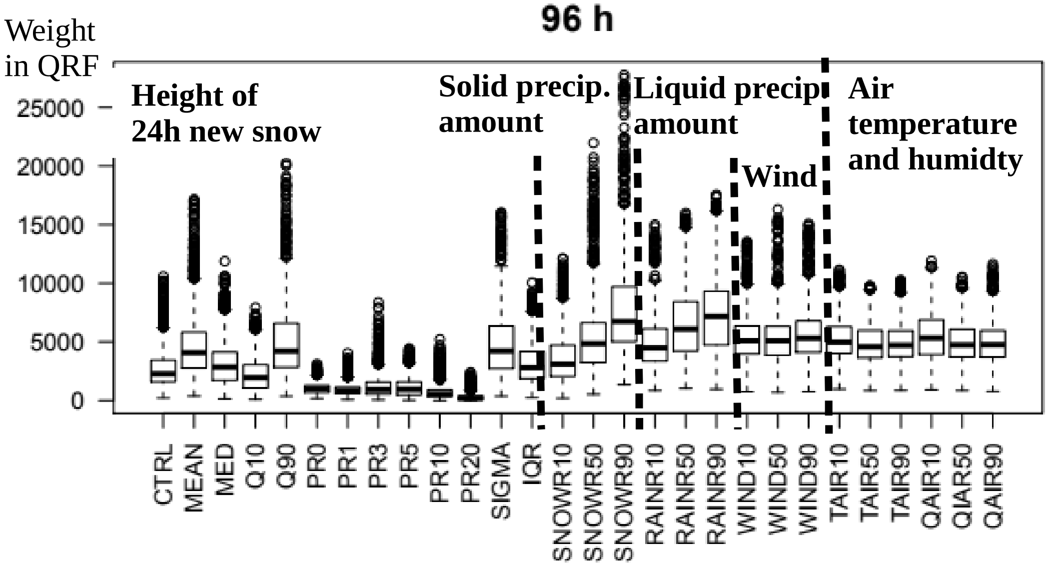
Similar skill for all criteria

Added value of Quantile Regression Forests (QRF)

Evin et al., in prep.

- Limitation of EMOS :
  - When all raw members expect 0 cm of snow but some rainfall, EMOS always forecast 0 cm (it does not account for potential errors in the rain-snow limit elevation)
- **QRF** has been tested with a large set of variables as predictors
  - It is shown that rainfall amount and temperature are useful predictors to be associated with the simulated new snow depth, <u>**especially at the longest lead times**</u>

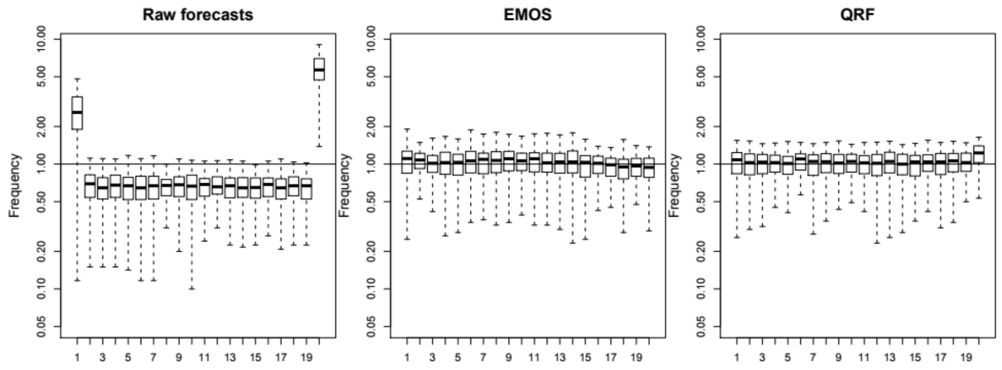




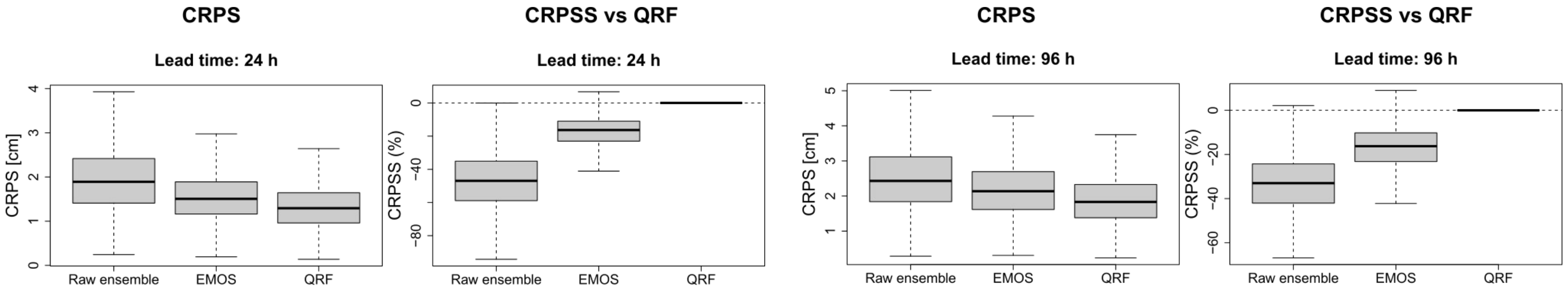
Added value of Quantile Regression Forests (QRF)

Evin et al., in prep.

- The **statistical properties** of the post-processed are **satisfactory** in both cases (flat rank histograms for both EMOS and QRF)



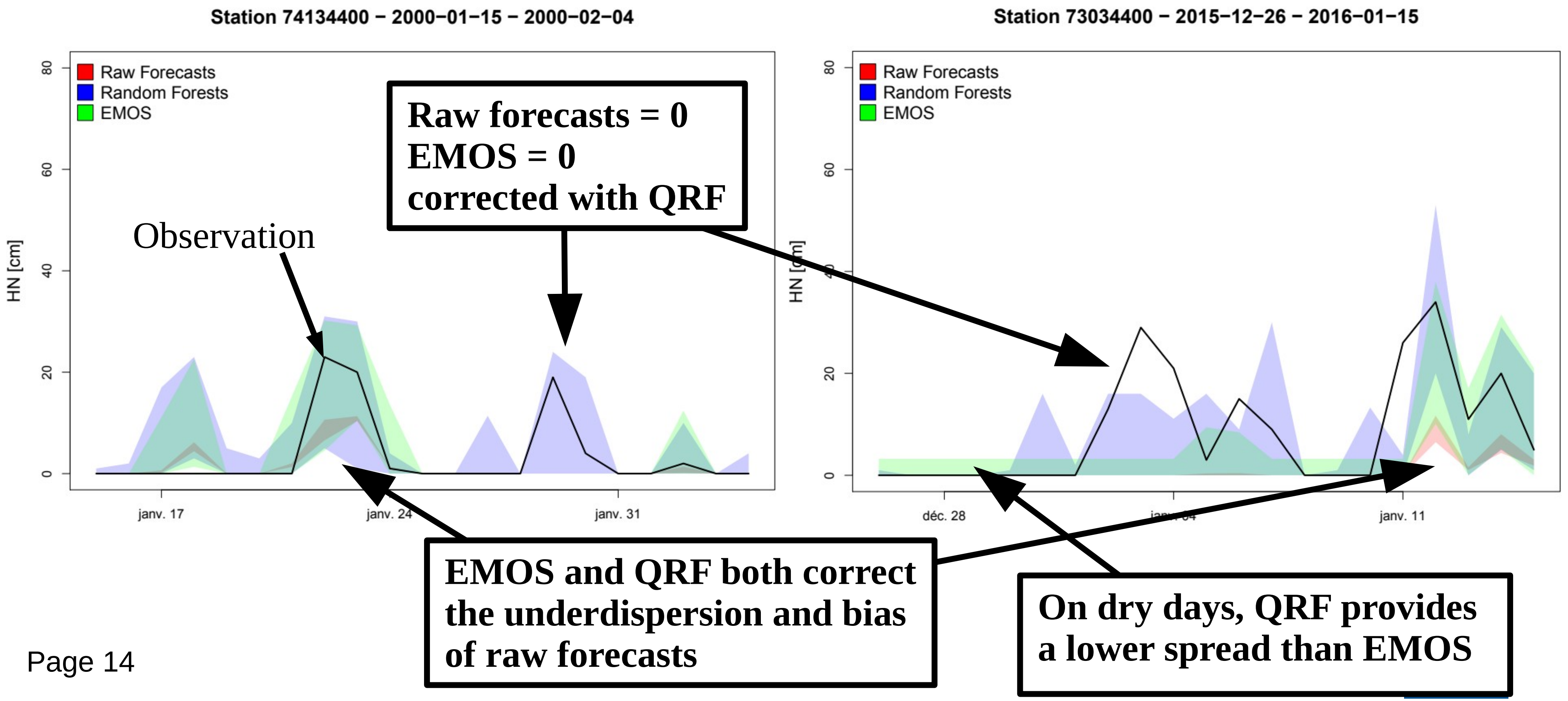
- **A significant improvement of CRPS is obtained with QRF** in theoretical experiments based on the 22-year reforecast dataset (22* [21-year training, 1-year validation])
→ Better predictive power



Added value of Quantile Regression Forests (QRF)

Evin et al., in prep.

- Illustrations on specific cases (24h lead time forecasts):



Conclusions

- Raw ensemble forecasts + snowpack modelling provide predictive but ***biased*** *and* ***underdispersive*** forecasts not well suited for **automated products**.

- **Ensemble Model Output Statistics (EMOS)** improve the forecasts from physical modelling.
  - What is the **best training dataset** ?

    → ***Long reforecasts*** *improve the* ***reliability*** *of the post-processed forecasts for the severe and* ***unusual events***

    → *But they should me* ***more homogeneous*** *with the operational system (initial perturbations)*
  - What is the spatial validity of the post-processing ?

    → ***Spatial consistence of biases*** *allows to apply corrections at the massif scale (1000 km²)*

- **Quantile Regression Forecasts (QRF)**
  - Better predictive skill in theoretical experiments thanks to other predictors
  - Further work required to test the robustness when transfered to real time forecasts

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References

More details for the EMOS results in our main reference:

Nousu, J.-P., Lafaysse, M., Vernay, M., Bellier, J., Evin, G., and Joly, B.: Statistical post-processing of ensemble forecasts of the height of new snow, Nonlin. Processes Geophys., 26, 339–357, https://doi.org/10.5194/npg-26-339-2019, 2019.

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