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

Jari-Pekka Nousu^{1,2}, [Matthieu Lafaysse](#)¹, Guillaume Evin³
Matthieu Vernay¹, Joseph Bellier^{4,5}, Bruno Joly⁶,
Maxime Taillardat^{6,7}, Mickaël Zamo^{6,7}

1 Univ. Grenoble Alpes – Université de Toulouse – Météo-France – CNRS – CNRM, Centre d'Etudes de la Neige, Grenoble, France
2 University of Oulu, Finland ; 3 Univ. Grenoble Alpes – INRAE, UR ETNA, Grenoble, France ; 4 NOAA Earth System Research Lab., Boulder, USA ; 5 Univ. Grenoble Alpes, CNRS, IRD, Grenoble INP, IGE, Grenoble, France ; 6 CNRM – Université de Toulouse – Météo-France – CNRS, GMAP, Toulouse, France, 7 Météo-France, DirOP/COMPAS, Toulouse, France

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 =

~~Compaction during snowfall~~

~~Possible melting~~

~~Rain on snow~~

→ **Severe biases**

Alternative : Physical modelling SAFRAN-Crocus

Durand et al., 1998

SAFRAN :

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

Vionnet et al., 2012

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

Rank diagram

Underdispersion !

Quantile-Quantile plot

Bias !

- 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 ?

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**)

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**

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

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

Pros and cons on both sides

Better skill at the longest lead time

Sensitivity to spatial scale

Nousu et al., NPG, 2019

Training: local scale
Evaluation: local scale

Training: massif scale
Evaluation: local scale

Similar skill
for all criteria

- 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, **especially at the longest lead times**

- 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

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

Station 74134400 – 2000-01-15 – 2000-02-04

Station 73034400 – 2015-12-26 – 2016-01-15

EMOS and QRF both correct the underdispersion and bias of raw forecasts

On dry days, QRF provides a lower spread than EMOS

- 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 be **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 transferred to real time forecasts

More details for the EMOS results in our main reference:

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