COMBINATION OF CLIMATOLOGICAL INFORMATION AND METEOROLOGICAL FORECAST FOR SEAMLESS PREDICTION OF ALPINE SNOW CONDITIONS

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ABSTRACT:
Ski-resort management strongly depends on meteorological conditions, in particular natural snowfall and conditions favorable for technical snowmaking. Therefore, improved anticipation capabilities up to the seasonal scale hold significant potential to improve the real-time adaptation of ski-resorts to upcoming meteorological conditions. In this context, the H2020 PROSNOW project will build a demonstrator of a meteorological, climate and snow management prediction system from few days to several months ahead, with a seamless approach specifically tailored to the needs of the ski industry. This work presents preliminary results achieved within PROSNOW. A 4 day lead-time numerical weather prediction product has been combined with climatological forcing in order to feed the detailed snowpack model SURFEX/ISBA-Crocus, allowing to generate an ensemble of possible realizations of the unfolding of the snow season. Snow height simulations, carried out at different altitudes in a French ski-resort, are shown and several improvements in the ability to better forecast the observed snow height on the ski slopes are discussed. The relative impact of the current snow conditions and the upcoming meteorological conditions on the future state of the snowpack is assessed using appropriate statistical metrics (Rank Diagrams, Brier Scores, CRPS and CRPSS), highlighting in particular the impact of re-initializing the snow height throughout the winter season and using forecast against mere reanalysis-based forcing to drive the simulations. Overall, our results show the significant potential of the approach combining snow height initialization and forecast forcing to predict the future state of the snowpack, thereby demonstrating the interest of the PROSNOW modeling framework as a decision-making tool for ski-resort managers.

Keywords:
ski-resorts, snow management, snowmaking, snowpack modeling, numerical weather prediction, climate services

1. INTRODUCTION

When looking at weather and snow forecast, ski-resort operators have to rely on various and scattered sources of information, hampering their ability to cope with highly variable meteorological conditions. This makes the snow management optimization particularly challenging, in particular for snowmaking. For example, the required water volumes are currently estimated before the snow season and based on general information, such as the worst encountered snow season in the past, with only one or two decades of historical hindsight. This lack of anticipation can have negative consequences, both in economic terms (premature melt of the snow produced, overproduction, inadequate grooming frequency, etc.) and ecological, not to mention the quality of snow on the slopes and the satisfaction of skiers.

In this context, snow management and slope preparation in ski-resorts could strongly benefit from anticipation tools to assist the decision-making process. Improved anticipation capabilities at all time scales, spanning from "weather forecast" (up to 5 days typically) to "climate prediction" at the seasonal scale (up to several months) holds significant potential to increase the resilience of socio-economic stakeholders and support their real-time adaptation potential to upcoming meteorological conditions. The H2020 PROSNOW project (`www.prosnow.org`) will meet this need by designing, developing and implementing a decision-making service based on meteorological, climate and snow prediction from one week to several months ahead,

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specifically tailored to the needs of the ski industry (Morin et al., 2018).

The key hypothesis behind PROSNOW is that adequately combining in-situ observations of the snow conditions on ski slopes, which form the starting point of any forecast, with atmospheric predictions spanning meteorological to seasonal time scales in a seamless manner (Pappenberger et al., 2011), will provide added value for operational decision-making. This hypothesis is discussed in this work, introducing and quantifying the added value of combining forecast and climatological information for the prediction of snow conditions at the scale of the season. In particular, we have assessed the partitioning of the predictability of snow conditions due to, on the one hand, the initial conditions of the snowpack (i.e. the impact of the "memory of snow") and, on the other hand, the upcoming weather conditions. All these evaluations of the predicted conditions of the snowpack have been performed computing appropriate, proper statistical metrics (Rank Diagrams, Brier Scores, CRPS and CRPSS), well suited for analyzing the skills of probabilistic forecasts. This statistical evaluation is crucial to estimate the uncertainty affecting the forecast and the expected impact of operational decisions taken at various times of the season by the ski-resort managers.

2. MATERIAL AND METHODS

2.1. Crocus snowpack model

In this study, we have used the detailed snowpack model SURFEX/ISBA-Crocus (Vionnet et al., 2012). This model, referred to as Crocus hereafter, explicitly solves the energy and mass balance of the snowpack to simulate the evolution of the physical properties of a multi-layer snowpack in a detailed manner, including internal phenomena such as phase change, water percolation, snow compaction, snow metamorphism and their impact on the radiative and thermal properties of the snowpack. Here we focus only on natural snow processes.

2.2. SAFRAN analysis

In order for Crocus model to be run, consistent meteorological input data are required. The generation of those data necessary to feed the numerical snowpack model Crocus is carried out by the meteorological downscaling and surface analysis tool SAFRAN (Durand et al., 1999). SAFRAN operates at the geographical scale of meteorologically homogeneous mountain ranges (so-called "massifs") within which meteorological conditions are assumed to depend only on altitude. For the analysis of meteorological surface fields, the guess used by SAFRAN consists of vertical atmospheric profiles from numerical weather prediction (NWP) models. A robust assimilation scheme corrects the initial guess using ground-based and radiosonde observations as well as remotely-sensed cloudiness. Thus, SAFRAN provides hourly meteorological conditions for each massif for 300 m-spaced elevation bands, also accounting for aspect and slope.

2.3. PEARP-SAFRAN ensemble forecast

In this study we have used a probabilistic version of ARPEGE, called PEARP for Prévision d'Ensemble ARPEGE (Descamps et al., 2014), to generate an ensemble of 35 different predicted meteorological conditions. PEARP has been post-processed to provide forecast data matching the type (variables) and geometry (massifs, elevations) of SAFRAN. This PEARP-SAFRAN forecast (also referred to as PEARP hereafter) has a 4 day lead-time and it is initialized each day at 6 UTC.

2.4. Snowpack modeling configurations

The forcing data described above (SAFRAN analysis and PEARP-SAFRAN ensemble forecast) have been combined in different ways to provide the Crocus snowpack model with the required meteorological driving data. The resulting configurations are presented in Fig. 1.

Analysis (A). The SAFRAN analysis has been taken as a proxy for the meteorological observations, since, as explained earlier, it already integrates measurements from various sources and the spatial scale of simulated variables does not have observation equivalents. Analysis-based snowpack simulations have been run starting from the 1st of August and are considered as "pseudo-observations" of the snow season of interest.

Reanalysis (R). The SAFRAN reanalysis of 35 past winter seasons (from 1982/1983 to 2016/2017) has been used to generate an ensemble of meteorological conditions. This ensemble has then been used to drive Crocus to obtain 35 possible evolutions of the snow conditions. The median value of this ensemble is considered as a climatological reference, since it represents the expected snow conditions for each location of interest based on

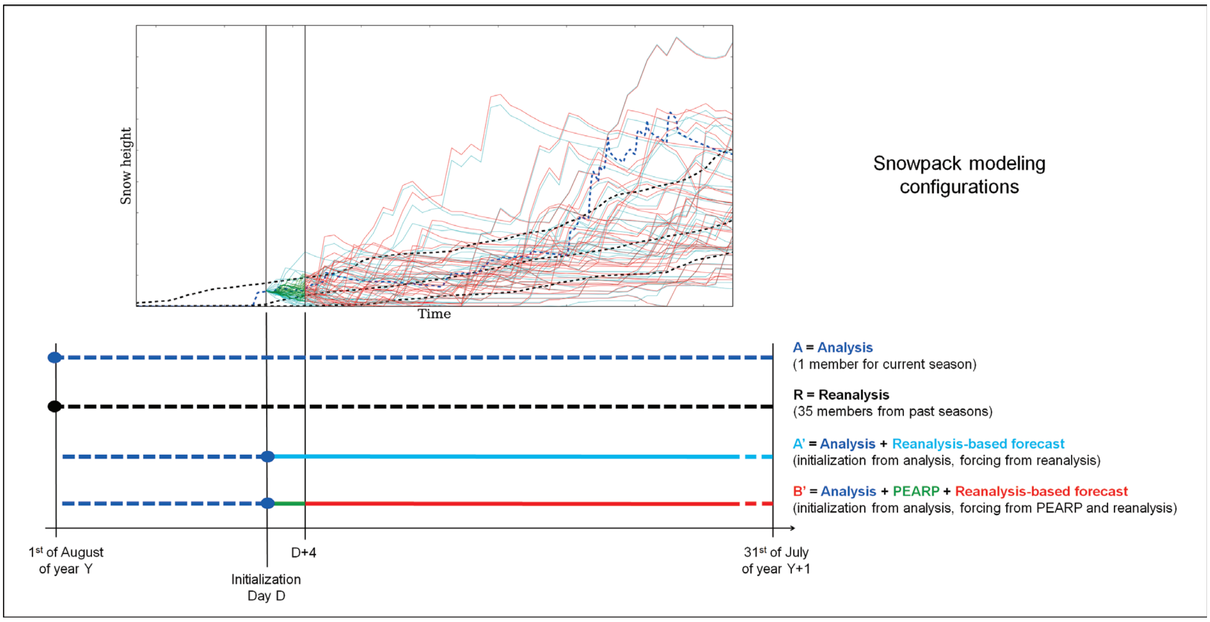

Figure 1: Snowpack modeling configurations obtained with different combinations of meteorological forcing data. For the reanalysis, in the graphic only the quantiles q20, q50 and q80 are shown.

climatology.

Analysis + Reanalysis-based forecast (A'). This configuration is a combination of the first 2. For each calendar date, the outputs of the SAFRAN-Crocus analysis have been used to provide the initial state of the snowpack, starting from which an ensemble of snow simulations has been built by using the SAFRAN reanalysis of past seasons as a surrogate for possible meteorological future conditions for the next weeks to months. This configuration, called A' with reference to Fig. 2 of Morin et al. (2018), shows the impact of initializing the state of the snowpack, compared to configuration R which does not include any initialization during the snow season.

Analysis + PEARP + Reanalysis-based forecast (B'). This configuration is similar to A', with the difference that the first 4 days of forecast are taken from PEARP-SAFRAN, instead of reanalysis. It is called B' with reference to Fig. 2 of Morin et al. (2018) and allows to highlight the combined contributions of initializing the state of the snowpack and using NWP to drive the simulations instead of mere reanalysis.

We expect that moving from R to A' to B' (i.e. starting from the reanalysis and complexifying the system by progressively accounting for the initialization and using NWP) will improve our ability to match the actual behavior of the snowpack represented by model run A.

2.5. Statistical metrics

Forecast *scores* are used to quantify the accuracy and/or degree of association of a forecast to an observation (or an estimate of the actual value of what is being predicted), whereas *skill scores* are used to evaluate the skills of a forecast with respect to the skills of a reference method, supposedly simpler to implement. In this work, the performances of the ensemble simulations have been evaluated using the 3 metrics described below.

Rank Diagrams

Rank Diagrams (sometimes also called verification rank histograms or Talagrand diagrams) are a way to show how reliable an ensemble forecast is compared to a set of observed data (Hamill, 2000). In other words, they measure how well the ensemble spread of the forecast represents the true variability (uncertainty) of the observations, by counting where the verifying observation falls with respect to the ensemble forecast data.

In an ensemble with perfect spread, each member represents an equally likely scenario, so the observation is equally likely to fall between any two members. A flat diagram then means that the ensemble is accurate (or reliable): the observed values are indistinguishable from any forecast member of the ensemble and the ensemble spread correctly represents forecast uncertainty. Conversely, deviations from a uniform distribution mean that the model is biased. U-shaped diagrams are obtained when the ensemble spread is too small, many observations falling outside the extremes of the ensemble (in particular, a peak on the right side of the diagram indicates that the ensemble members are systematically lower than the observations). Finally, a dome-shaped diagram means that the ensemble spread is too large, too many observations falling near the center of the ensemble.

Brier Score

The most common probabilistic score is the Brier Score (Brier, 1950), which describes the ensemble forecast system performance in terms of a given threshold exceedance. In its most common formulation, the Brier Score (BS) is defined as the mean squared error of the probabilistic forecast:

$$BS = \frac{1}{N} \sum_{i=1}^{N} \left(P_i^f - P_i^o \right)^2 \quad (1)$$

where N is the number of prediction instances, P_i^f is the forecast probability of exceeding a given threshold at instance i and P_i^o is the observed outcome of the event at instance i (1 if the observation is above the threshold, 0 otherwise). The Brier Score ranges from 0 (representing a perfect score) to 1, since this is the largest possible difference between a predicted probability (which must be between 0 and 1) and the actual outcome (which can take values of only 0 or 1).

Continuous Ranked Probability Score

The Continuous Ranked Probability Score ($CRPS$) compares a forecast with an observation, where both are represented as Cumulative Distribution Functions ($CDFs$). The equation for calculation of the $CRPS$ is the following:

$$CRPS = \frac{1}{N} \sum_{i=1}^{N} \int_{x=-\infty}^{x=+\infty} \left(CDF_i^f(x) - CDF_i^o(x) \right)^2 dx \quad (2)$$

where CDF_i^f is the forecast probability CDF at instance i and CDF_i^o is the observed probability CDF at instance i. If the observation is represented by a single value, then the corresponding CDF is a single step-function with the step from 0 to 1 at the observed value of the variable (Heaviside function). The calculation of the $CRPS$, which can be seen as a Brier score integrated over all possible thresholds (Brown, 1974), results in a value expressed in the units of the forecast variable (meters, in the case of snow height). The perfect score is achieved when $CRPS$ is equal to 0, meaning that the forecast ensemble is both accurate (low bias) and sharp (small spread).

The skill of a prediction system can also be computed with respect to its benefit over a simpler ensemble prediction method. To this aim, the $CRPS$ of a forecast can be compared to the $CRPS$ of a reference, baseline method via the Continuous Ranked Probability Skill Score ($CRPSS$):

$$CRPSS = 1 - \frac{CRPS}{CRPS_{ref}} \quad (3)$$

By definition, $CRPSS$ equals 0 when the prediction performs similarly to the baseline method used as a reference, approaches 1 when the prediction over-performs the reference and tends to -∞ when the prediction under-performs the reference.

2.6. Implementation and evaluation data

This work reports on simulations carried out during the 2017/2018 winter season, characterized by very large snow accumulations in the French Alps, especially above 2000m. Results obtained at different altitudes and on flat terrain in the French ski-resort of Les Saisies (in the Beaufortain mountain range, Haute-Savoie, with elevations ranging approximately from 1200m to 2100m) are shown. Les Saisies is one of the 8 pilot ski-resorts of the PROSNOW project.

The snowpack model Crocus (Sect. 2.1) has been run using different combinations of forcing data provided by the SAFRAN analysis (Sect. 2.2) and the PEARP-SAFRAN forecast (Sect. 2.3), generating several ensembles of possible realizations of the unfolding of the snow season (Sect. 2.4). Then, results have been evaluated in terms of snow height using the metrics described in Sect. 2.5. During this evaluation process, each of the 3 snow height ensembles (R, A' and B') has been compared to A to assess its performances.

For the Rank Diagrams, for a given elevation and a given initialization date D, the percentages of curves falling above or below the pseudo-observations have been computed for each lead-time ($D+1$, $D+2$, etc.) and then added. Finally, the results obtained for all 151 daily initializations along the season (from 01/11/2017 to 31/03/2018) have been aggregated and normalized in order to end up with a single diagram per elevation per season.

For the Brier Scores, a similar approach has been followed, with 2 main differences. First, for each lead-time the members of the ensembles and the pseudo-observations have been compared to 3 predefined snow height exceedance thresholds (set to 0.5, 1 and 2m) through Eq. 1. The values of N in the equation correspond to the number of days ($D+1$, $D+2$, etc.) after each initialization and then decrease when the initialization date D is moved along the season and less lead-time dates remain

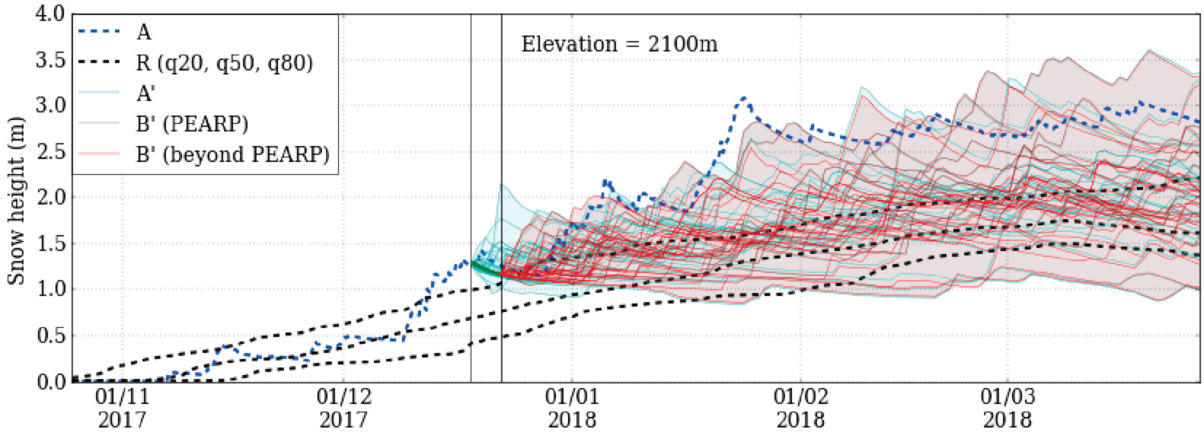

Figure 2: Simulated snow heights during the 2017/2018 winter season at 2100m at Les Saisies ski-resort. Colors correspond to different snowpack modeling configurations (see Fig. 1 for more details).

available. Second, in this case the results from different initialization dates have not been aggregated, so that the evolution of the Brier Scores over the season can be represented.

For the CRPS, Eq. 2 has been applied for all initialization dates along the season and computed for all lead-times. Then the results have been aggregated for each lead-time value. In this case, the values of N in the equation represent the total number of results obtained for each lead-time and decrease with increasing lead-time (when the lead-time is $D + k$, N is equal to the number of days in the season, 151, minus k). The CRPSS has been calculated through Eq. 3 using the CRPS of the reanalysis as a reference. This way, it is possible to highlight the impact of initialization only (A') and a combination of initialization and NWP (B') against the performances of mere reanalysis (R).

3. RESULTS AND DISCUSSION

Figure 2 shows the time evolution of snow height during the 2017/2018 winter season, at 2100m on flat terrain within Les Saisies ski-resort. The snowpack simulations have been fed with a combination of different forcing datasets: the blue dashed line represents the analysis of the current season, the black dashed lines represent the quantiles 20, 50 and 80 of the reanalysis, the cyan curves represent the simulations initialized on the 18th of December 2017 with the analyzed state of the snowpack and driven by the reanalysis-based forecast, the green curves represent the simulations driven by the PEARP forecast from the 18th to the 22nd of December 2017 and the red curves represent the simulations initialized with the state of the snowpack at the end of PEARP and driven by the reanalysis-based forecast.

The ensemble simulations of Fig. 2 eloquently show how the wide variability in meteorological conditions translates into a wide range of snow height values, when meteorological conditions from different years are used. The range of snow height values which can be "expected" starting from a given initialization date increases rapidly with lead-time, so that predicting precisely snow height values using only forcing data from the reanalysis has poor predictive power at the seasonal scale. Using PEARP to force the snowpack simulations during the first 4 days after the initialization improves the forecast even after the 4 day timespan. However, this effect fades over time and less than 2 weeks after the initialization the benefit of having used the NWP product instead of mere reanalysis is almost negligible.

Since we have used forcing data coming from the reanalysis of past winter seasons to drive the snowpack simulations (except for the first 4 days after the initialization, when PEARP was also used), we expect that the overall match between the prediction and the analysis is maximized when the unfolding of a given season resembles most the climatological median. In contrast, predictions made during snow seasons displaying significantly higher or lower snow height than the reanalysis will display under- and over-estimated snow heights, respectively (the example shown in Fig. 2 belongs to the first case). For the same reason, the prediction curves and the reanalysis exhibit similar patterns, which is simply due to the fact that the same meteorological forcing data have been used to perform all simulations. Nevertheless, significant differences between the climatological values and the prediction results (with and without using PEARP) are present, due to the initialization with snow conditions potentially widely different from the climatological median. This mainly stems from the inter-annual variability in snow precipitation during the accumulation period, which is the main driver of seasonal snow variability in the case studied.

In order to generalize these first conclusions and to better quantify the relative importance of current snow conditions, date of the prediction and upcoming meteorological conditions on future state of the snowpack, we have run different snowpack ensemble simulations (Sect. 2.4) for a larger number of initialization dates and then computed the statistical scores (Sect. 2.5) with the approach described in Sect 2.6. Some results are shown in Fig. 3, Fig. 4 and Fig. 5, which present, respectively, the Rank Diagrams, the Brier Scores and the CRPS and CRPSS for the whole 2017/2018 winter season at Les Saisies ski-resort.

The Rank Diagrams (Fig. 3) generally show a peak on the right side, indicating that the ensemble members are systematically lower than the observations. Indeed, the snow cover during this particular season was more abundant than the average, which leads to an overall under-estimation of the observed snow height by the simulations driven by the reanalysis. This effect increases with altitude, since snow accumulation during the 2017/2018 winter season was particularly large at higher elevations. For example, the performances of the reanalysis with respect to the analysis at 2100m (top right panel) indicate that almost 80% of the times at least 34 members of the reanalysis are below the pseudo-observations. More interestingly, the effect of initializing the snow conditions (middle row) leads to a flatter diagram, meaning that the forecast ensemble tends to be more accurate compared to the one obtained without initialization (top row). In this representation, the added-value of PEARP (bottom row) is not easy to capture and leads to results similar to those obtained with an entirely climatological forcing.

The Brier Scores (Fig. 4) improve with elevation, since larger snow accumulations make it easier to reach a given snow height threshold faster in the season. Similarly, for a given elevation scores improve when the snow height threshold is reduced. Looking at the performances of the ensembles, the graphics clearly show the improved skill of the prediction system in which the simulations are initialized with the analyzed snow height (cyan curves) compared to the skill of reanalysis alone (black curves). Indeed, the Brier Scores of the reanalysis are always worse (higher) then those obtained with an initialization of the snow conditions and this difference remains as long as the snowpack builds up and diverges from the climatological behavior. The benefit of using PEARP during 4 days (red curves) is small, because, as explained in Sect. 2.6, the scores are calculated for each initialization date by aggregating results for all lead-times, and the effect of using PEARP becomes negligible after a few weeks.

The CRPS and CRPSS (Fig. 5) show an obvious degradation of the scores with lead-time. Regardless of the lead-time, however, it is clear that accounting for the current snow conditions significantly improves the skill and the usefulness of the model chain. The predictability of snowpack conditions using the snow height initialization keeps a predictive value with respect to the reanalysis for a few weeks after the date of the prediction, in terms of snow height values. These scores also allow to highlight the improving effect of adding PEARP, whose benefit lasts beyond the 4 day lead-time and is more significant when larger amount of snow are present on the ground. These results assess the possibility to carry out informative forecasts at time scales exceeding one week and provide the foundation for the development of the PROSNOW operational chain.

4. CONCLUSIONS AND OUTLOOK

The current study addresses the predictability of snow conditions in mountain regions, providing quantitative insights into how current snow conditions and subsequent meteorological conditions influence the unfolding of a given snow season. To this goal, a prediction system was built, consisting of an ensemble of numerical simulations performed with the detailed snowpack model Crocus, fed by a combination of meteorological conditions and initialized daily with pseudo-observations.

It was found that the current version of the prediction system keeps an interest with respect to reanalysis until a few weeks after the prediction date. Two comments can be made in this regard. First, this result highlights the importance of the initialization, since the snowpack can keep memory of its past state during several days, as the statistical scores presented in this work clearly show. Second, this result also indicates that, regardless of the initial conditions and the date of the prediction, meteorological conditions are the main driver of snow conditions in mountain regions beyond a lead-time of a few weeks. This is not surprising but quantitatively demonstrates that medium-range predictions of natural snow conditions will mostly improve through improvements in meteorological forecast. Indeed, we found that using a numerical weather prediction product with a 4 day lead-time (PEARP) improves the scores with respect to a simple climatological forcing, and this despite the main known limitations affecting the PEARP product, i.e. an under-dispersion of the ensemble and a relative underestimation of the forecast probabilities of snowfall (Vernay et al., 2015).

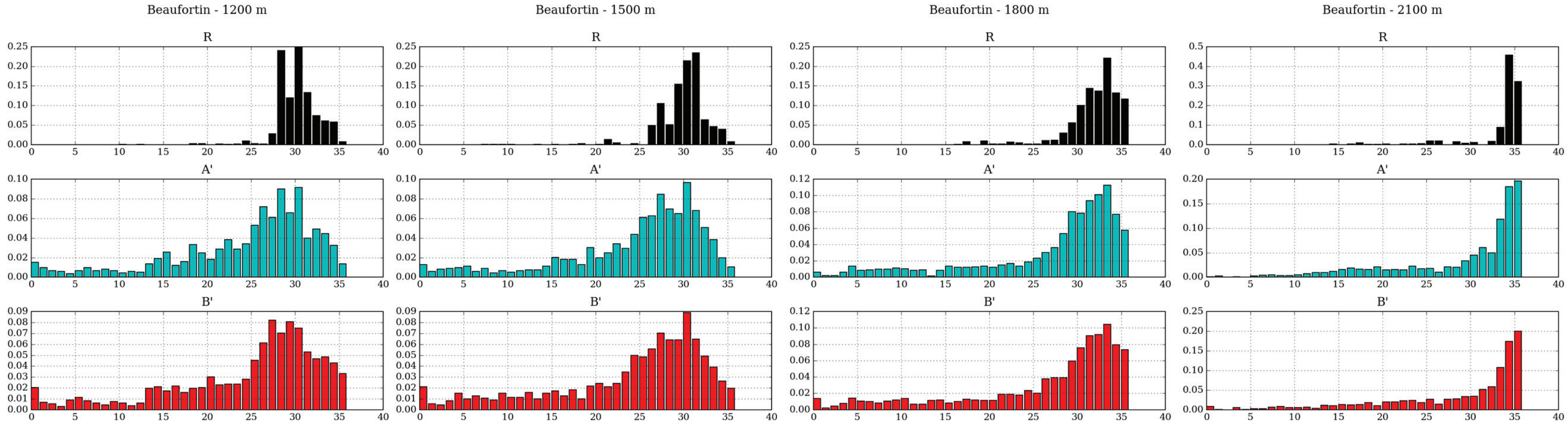

Figure 3: Rank Diagrams for the season 2017/2018 at 4 elevations at Les Saisies ski-resort. Please note that the vertical scales are different to better highlight the shapes of the diagrams. The configurations R, A' and B' are explained in Fig. 1.

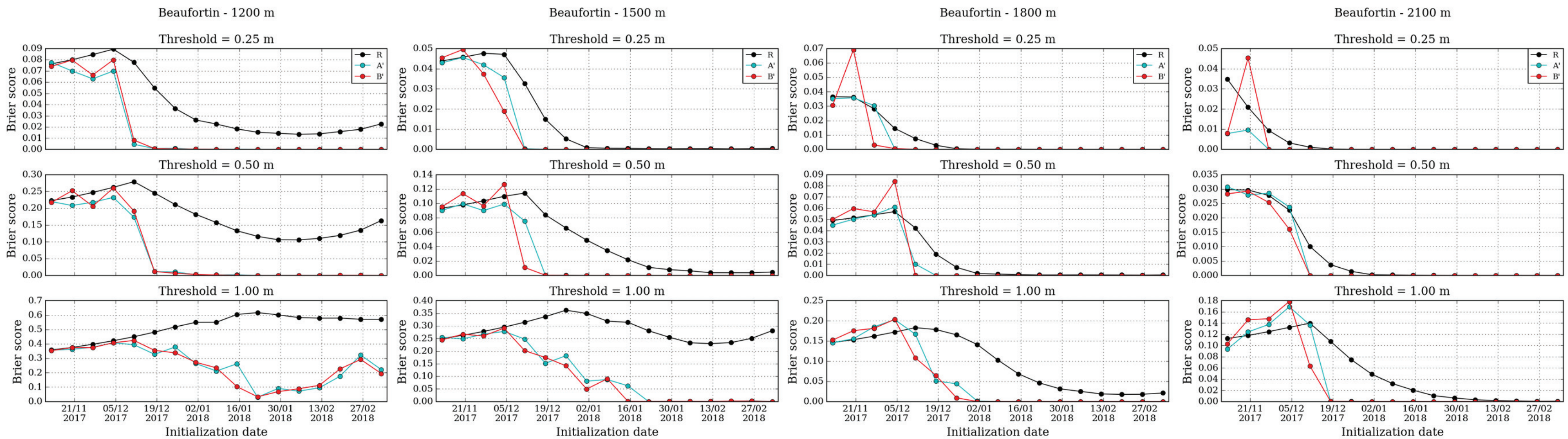

Figure 4: Brier Scores for the season 2017/2018 at 4 elevations at Les Saisies ski-resort. Scores are computed for different initialization dates accounting for the remainder of the snow season. Three snow height thresholds are considered: 0.25, 0.5 and 1.0m. Please note that the vertical scales are different to better highlight the shapes of the curves. The configurations R, A' and B' are explained in Fig. 1.

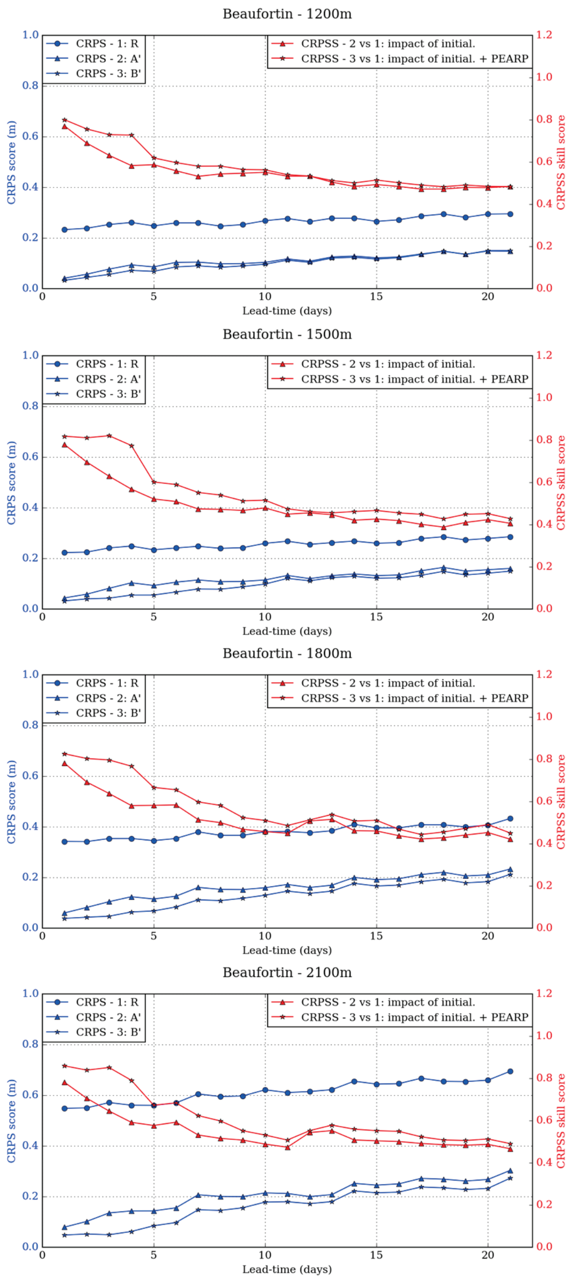

Figure 5: CRPS and CRPSS for the season 2017/2018 at 4 elevations at Les Saisies ski-resort. The configurations R, A' and B' are explained in Fig. 1.

Our modeling framework was inspired by the approach developed by Morin et al. (2013), which has been refined and extended here through 3 main improvements. First, the statistical analysis introduced by Morin et al. (2013) has been improved using more complex statistical metrics, in order to fully account for the spread between ensemble members. Second, the work of Morin et al. (2013) was limited to only one point at 2400m in the Mont-Blanc massif, whereas here we have performed simulations at different elevations, thereby assessing the generality of the conclusions reached by Morin et al. (2013). Third, in addition to the climatological forcing, we have introduced the use of an ensemble weather forecast product, allowing to take into account predicted conditions for the first 4 days after the initialization. We have demonstrated that this improvement, by explicitly accounting for the meteorological situation and its potential development into the future, extends the time frame over which the forecast system has a predictive power superior to the climatological data.

Several additional developments are currently in progress to corroborate and refine the results of this study. First, other NWP products will be seamlessy integrated into a fully-fledged modeling chain to extend the meteorological forecast period, combining different progressively increasing lead-times up to the seasonal scale. In particular, the Ensemble Prediction System (EPS) probabilistic forecast developed at the European Center for Medium-range Weather Forecast (ECMWF) will be used until lead-times of 15 days. To assess the added-value of seasonal forecast over climatologically-based prediction for lead-times beyond 15 days, the Copernicus Climate Change - Seasonal Prediction (C3S-SP) system will be added to the modeling chain. Second, the snow management practices (grooming, snowmaking) will be explicitly accounted for in the snowpack simulations (Hanzer et al., 2014; Spandre et al., 2016; Hanzer et al., 2018), to represent the actual state of the snow on the ski slopes. And third, daily measurements of water consumption for snowmaking and snow height on the ski slopes will be integrated into the chain to adjust the snow conditions at the initial step of the prediction to field observations.

All these combined developments will make it possible to build up the PROSNOW real-time operational chain, which will help ski-resort operators to improve the snow management through a better anticipation of the weather and snow conditions on the slopes.

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