Will there (still) be snow for the upcoming winter holidays ? On the conditional predictability of snow conditions several weeks to months in advance

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ABSTRACT: Modern societies increasingly require anticipation capabilities in virtually all aspects of human life, including snow conditions in mountain regions, due to their strong socio-economic impact. Winter meteorological conditions vary significantly from one year to another, which is often worrisome for mountain professionals because natural snow conditions heavily depend on meteorological conditions and their variations through the snow season. Current forecasting tools are of little use for prediction timeframes exceeding one week: operational weather forecast cover only time periods on the order of 5 days, and seasonal forecasts are too coarse at the local scale. Here we use meteorological conditions from past snow seasons to generate an ensemble of the many possible meteorological scenarios within a given snow season. Numerical snowpack modelling, initialized with simulated conditions on a given date, allows to generate an ensemble of possible realizations of the unfolding of the snow season, the median of which is assimilated to a prediction. The current study, based on the French reanalysis SAFRAN in mountain regions, and on the detailed snowpack model SURFEX/ISBA-Crocus, provides preliminary insights into how current snow conditions and subsequent meteorological conditions influence the unfolding of a given snow season. This analysis allows to evaluate how useful would it be to further develop fully-fledged seasonal forecasts in mountain regions, which mountain professionals look forward. Last, the possibility to account for snow management practices in ski resorts (through grooming, snowmaking etc.), which plays a significant role for snow conditions besides meteorological conditions, is discussed.

KEYWORDS: snowpack modelling, predictability, seasonal forecast

1 INTRODUCTION

The amount of seasonal snow on the ground results from the mass and energy balance of the snowpack, which is driven by the interactions between meteorological conditions and the intrinsic physical properties of snow. Forecasting future snow conditions thus requires a reliable forecast of the meteorological conditions and of the current snow conditions, and a proper physical understanding of the physical behaviour of the snowpack. The large body of knowledge regarding the time evolution of the seasonal snowpack is best integrated in so-called physically-based detailed snowpack models, which include the various physical processes occurring at the boundaries and within the snowpack with the highest possible level of complexity (Essery et al., 2013). Deterministic meteorological forecasts in Western Europe are currently limited to a time frame of several days at most, and medium range forecasts are currently not directly used to predict the longer-term evolution of the snowpack during a given season. The strong inter-annual variability of snow conditions, combined with the large weight of winter tourism on the economy of mountain regions and the increasing desire of modern societies to predict (if not to control) natural phenomena, lead to frequent requests from various types of stakeholders (journalists, tourism authorities, hydropower companies, managers of snowmaking units, general public) regarding snow conditions over time scales exceeding several weeks in the future. Making accurate weather predictions at such long time scales in Western Europe and in particular mountain regions is scientifically challenging. However, the relative importance of (i) current snow conditions, (ii) date of the prediction and (iii) upcoming meteorological conditions on future snow conditions remains to be quantitatively assessed. The possibility to carry out informative forecasts at time scales exceeding one week may be assessed once the partitioning between these three elements is known. The current study seeks to provide insights into such issues, by means of numerical simulation of snow conditions in the French Alps.

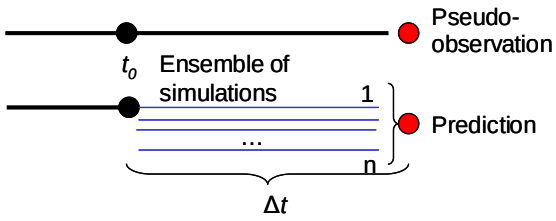
2 MATERIAL AND METHODS

This study is based on a long-term meteorological reanalysis dedicated to mountain regions in the French Alps covering the period 1958 – 2010 (Durand et al., 2009). This reanalysis was generated using the meteorological downscaling and surface analysis tool SAFRAN (Durand et al., 1999). The main original features of SAFRAN is that it operates at the geographical scale of meteorologically homogeneous mountain ranges (referred to as « massifs ») within which meteorological conditions are assumed to depend only on altitude. Based on a robust data

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assimilation scheme combining large-scale output from numerical weather prediction models, ground-based and radiosonde observations and remotely-sensed cloudiness, SAFRAN provides hourly meteorological conditions in mountain ranges for 300m-spaced altitude bands, which includes not only precipitation (rain and snow rate) and air temperature but also relative humidity, wind speed, incoming longwave and shortwave radiation. Such data can be used to feed the detailed snowpack model Crocus (Vionnet et al., 2012), which explicitly solves the energy and mass balance of the 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. Seasonal snowpack simulations using the SAFRAN – Crocus combination are used for daily avalanche hazard forecast. While this exploratory study is purely model-based and does not include explicit comparisons to field measurements, there is strong evidence from operational and research activities that the SAFRAN – Crocus model chain yields realistic results in French mountain regions in terms of integrated snow properties such as total snow height and snow water equivalent. In what follows, only daily snow depth data are dealt with, although the developed framework can readily be extended to snow water equivalent or other ground or snowpack properties.

The method used for this study is outlined below and summarized in Figure 1. For a given calendar date t in a given snow season, SAFRAN – Crocus simulations provide an estimate of snow height based on the actual unfolding of meteorological conditions, which we denote $h(t)$ and refer as a "pseudo-observation". Replacing the meteorological forcing after a given date t_0 by a meteorological time series taken from another snow season, provides an alternative snow simulation $h_i(t)$, which takes into account the actual snow conditions as initial conditions and the meteorological conditions for year i for $t>t_0$. By using all available meteorological conditions from an ensemble of snow seasons as surrogates for possible meteorological scenarios, an ensemble of snow simulations can be built starting from the same initial conditions. In what follow, the median of the $h_i(t)$ values is called a prediction and referred to as $h^p(t)$. Various $h^p(t)$ values can be computed by varying the date t_0 of the initialization of the prediction system built. Comparing $h(t)$ with $h^p(t)$ for various dates of prediction t_0 is used here as a means to evaluate the relative weight of initial snow conditions and subsequent meteorological conditions of near-future snow height estimated



starting from a given date in the snow season.
Figure 1: *Schematic principle of the prediction. See text for more details.*

To quantify the performance of the prediction system, we employ a metric inspired from the Nash-Sutcliffe Efficiency (NSE, Nash and Sutcliffe, 1970), denoted E and defined here as:

$$E(t_0, \Delta t) = 1 - \frac{(h(t_0+\Delta t) - h^p(t_0+\Delta t))^2}{(h(t_0+\Delta t) - h^c(t_0+\Delta t))^2}$$

where, in addition to notations introduced before, Δt is the number of days after the date of the prediction t_0 and $h^c(t)$ is the climatological median value, computed from the full ensemble of pseudo-observations for each calendar date t. By definition, E equals 1 when the prediction system perfectly matches the observation. A value of 0 indicates that the prediction system is as accurate as using the climatological median, and negative values indicate that the prediction system performs worse than simply taking the climatological median. Alternative metrics, based solely on the difference between the predictions and pseudo-observations, could have been used, but given the larger computing cost of the prediction system in contrast to using the climatological data only, the skill of the prediction system is computed here with respect to its benefit over using the climatological value.

For the sake of brevity, the following article reports on simulations carried out at a single location on flat terrain, lying at an altitude of 2400 m in the Mont-Blanc massif, which is representative for ski conditions in the Chamonix Mont-Blanc area (French Alps, 45.9°N, 6.9°E). Simulation were carried out for the time period 1980 – 2010, spanning 30 years of snow seasons as a representative set of various snow conditions. Predictions were initialized for each snow seasons on 1 December, 1 February and 1 April, which correspond to dates representative of various stages of the unfolding of a typical snow season (roughly, inception of the accumulation, core of the season and inception of the melt, respectively). A total of 2640 simulations were carried out and are analyzed below. E values were computed for each of the 90 predictions (3 per year for 30 years) performed and

for Δt values ranging from 1 day to the end of the simulation by steps of 1 day.

We define the skill of the prediction system as the period of time needed until E decreases below 0 for the first time, and denote it Δt^*. Indeed, by construction, the E values obtained just after the date of prediction are very close to 1, because the initialization of the prediction system is carried out using the pseudo-observation at date t_0, and decrease with increasing Δt (not necessarily monotonically). In other words, Δt^* represents the time after the beginning of the prediction when the difference between the prediction and the pseudo-observation becomes higher for the first time than the difference between the pseudo-observation and the climatological value. This definition is arbitrary but allows subsequent quantitative analysis of the large ensemble of data generated.

3 RESULTS AND DISCUSSION

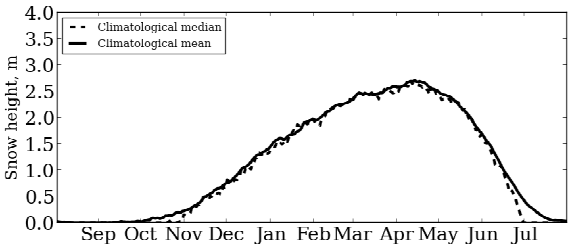


Figure 2: *Climatological median and mean of the pseudo-observations.*

Figure 2 shows the climatological median and means of the pseudo-observations for the time period 1980 – 2010. It indicates that, with the exception of early (October) and late (July) season, the two stastical indicators are very similar. Both display a smooth time series, gradually increasing from early October/November until mid April at the peak of the accumulation season, and decreasing at a higher rate during the ablation period until June-July. In what follows, we use only the climatological median because of its mathematical similarity with the prediction system (median of simulations), but the two could be used interchangeably with very similar results except at the beginning and the end of the season.

Figure 3 shows an example of an ensemble of simulations and their median, initialized at the three chosen calendar dates during the same snow season 1981-1982, together with the pseudo-observations and the climatological median. It clearly shows the wide variability in meteorological conditions translating into a wide range of snow height values when meteorological conditions from different years are used. The range of extreme snow depth values which can be "expected" starting from a given date increases rapidly after the prediction date so that it is anticipated that predicting precisely snow depth values from the median of the ensemble of simulations will have poor predictive power a few days already after the prediction date.

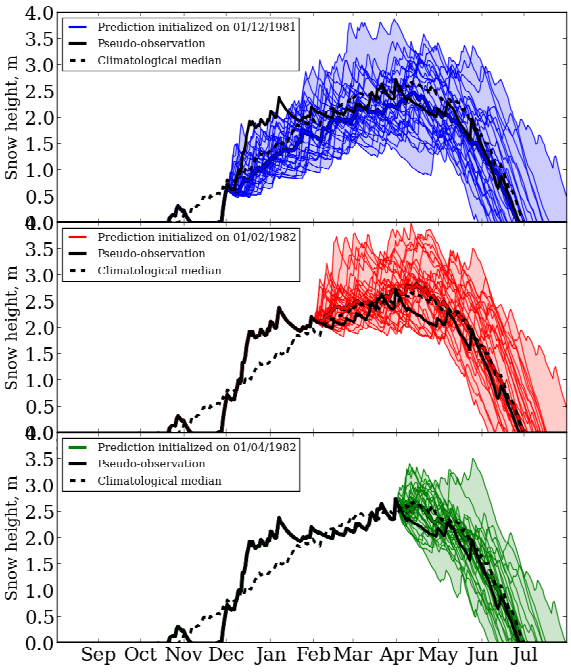


Figure 3: *Ensembles of simulations initialized on 01/12/1981, 01/02/1982 and 01/04/1982 (colored thin lines). The median of the ensemble of simulations is depicted as the black contoured color line. The filled area spans the min/max interval of the ensemble of simulations for a given date. The results are compared to the pseudo-observation for the snow season 1981-1982 (solid line), and the climatological median (dashed line).*

Figure 3 also shows that the distribution within the ensemble of simulations is different depending on the initialization date: while simulations initialized in December and April display a rather symmetrical distribution around the median, the ensemble of simulations initialized in February is strongly asymmetrical, with a higher range of possible values above the median than below. This observation stems from the fact that ablation processes are generally weak in February (mostly due to low incoming radiation) while the accumulation displays a high variability during this time period.

Figures 4 to 7 show a series of prediction results from contrasting snow seasons. They illustrate that the overall match between the prediction and the pseudo-observation is maximized when the unfolding of a given season resembles most the climatological median, which is roughly

the case for the season 1993-1994 (Figure 5). In contrast, predictions made during snow seasons displaying significantly higher or lower snow height than the climatology, such as the snow seasons 1994-1995 and 2008-2009, respectively, will display under- and over-estimated snow heights, respectively. While the approach used here is more refined than a simple vertical shift of the climatological values to match the initial snow conditions, the prediction and the climatological curve exhibit similar patterns (e.g., similar peak date), which simply stems from the fact that the same meteorological forcing data were used to perform both types of simulations. Nevertheless, significant differences between the climatological values and the prediction results can be observed, which are due to the initialization with snow conditions potentially widely different from the climatological median. These figures also illustrate the strong asymmetry in terms of variability between the accumulation and melt periods: while the latter exhibits a low variability in terms of melt rate, leading in many cases to a simple translation in time of the snow height depletion curve, the accumulation period displays a large inter-annual variability. This mainly stems from the inter-annual variability in snow precipitation during the accumulation period, which is thus the main driver of seasonal snow variability in the case studied.

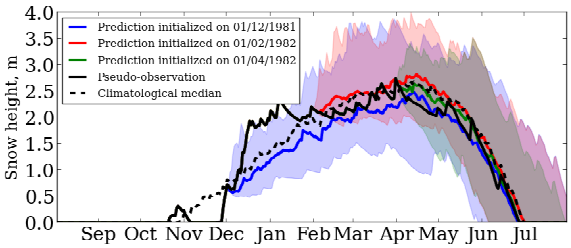


Figure 4: *Overview of predictions carried out during the snow season 1981-1982 (same symbols as Figure 2, but without the individual simulations making up the prediction ensemble).*

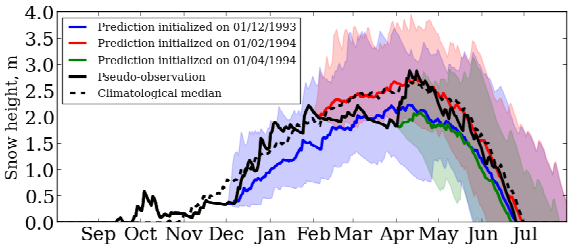


Figure 5: *Overview of predictions carried out during the snow season 1993-1994.*

Figure 4 to 7 also illustrate another aspect of the prediction system: if the goal is to predict snow height a few days after the start of the prediction, the date of the prediction seems to make little difference on the quality of the prediction. Indeed, snow accumulation originates from discrete snow precipitation events that the climatologically-based approach taken here can by construction not capture for future conditions. However, the prediction system is still to provide estimates of best/worst case scenarios (depending on the interest of the data user) which take into account the current snow conditions at the date of the initialization.

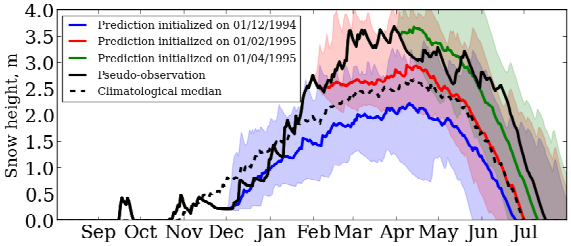


Figure 6: *Overview of predictions carried out during the snow season 1994-1995.*

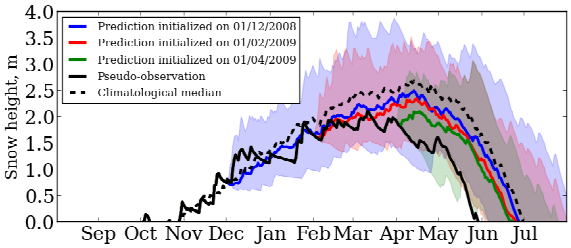


Figure 7: *Overview of predictions carried out during the snow season 2008-2009.*

Below we quantify the skill of the prediction system for medium range forecast of snow height.

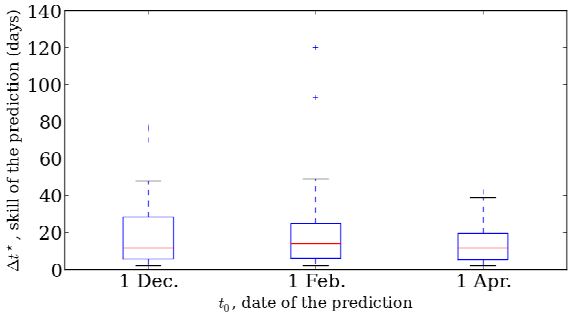


Figure 8: *Summary of Δt* values, i.e. the skill of the prediction system, as a function of t_0 (date of the prediction, i.e. 01/12, 01/02 and 01/04). On each box, the central mark is the median, the edges of the box are the lower hinge (defined as the 25th percentile) and the upper hinge (the 75th percentile), the whiskers extend to the most extreme data points not considered outliers, this ones are plotted individually.*

Figure 8 provides an overview of the skill of the prediction system in terms of Δ*t**, i.e. the time period until which *E* drops below 0, when the results of the prediction are as distant from

the pseudo-observations than the climatological value. The mean values for Δt^* are 26, 24 and 14 days for the 01/12, 01/02 and 01/04 prediction dates, respectively. The standard deviations of these distributions of values are large, approximately equal to the mean in the three cases. This means that in the case studied, the prediction system looses any predictive value with respect to the climatology a few weeks at most after the date of the prediction, in terms of snow height values.

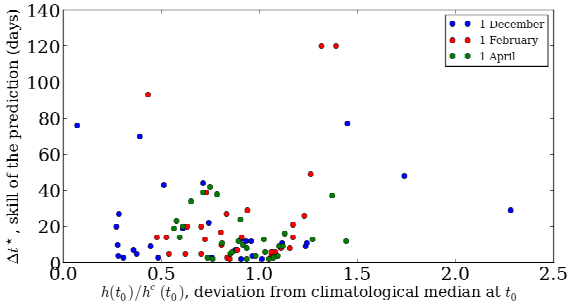


Figure 9: Variation of Δt^* as a function of the deviation of the snow height on the date of the prediction to the climatological median.

Figure 9 shows how the skill of the prediction system varies as a function of the deviation of the snow height on the date of the prediction to the climatological median. In situations where pseudo-observations at the date of forecast are below or equal to the median snow height values, regardless the prediction date Δt^* displays large variations. When pseudo-observations exceed the climatological median value at the date of the forecast ($h(t_0) > h^c(t_0)$), regardless the prediction date Δt^* does not show low values as in the previous case. A coarse estimate of the minimum Δt value (i.e., minimum forecast period with prediction performance at least better than the climatological mean) may be derived from this graph as $\Delta t \geq 20x(1-h(t_0)/h^c(t_0))$, when $h(t_0) > h^c(t_0)$. More work is required to address this issue quantitatively.

4 CONCLUSIONS AND OUTLOOK

The present study was motivated in part by recurring questions from a variety of mountain stakeholders, summarized by the following typical request, usually several weeks in advance: "*Will there (still) be snow for the upcoming winter holidays ?*". Indeed, it is often feared that either the current amount of snow on the ground several weeks before the peak of tourism activity may vanish through melt or other ablation processes, or, in cases when little snow is already present on the ground, that no new snow accumulation will occur, thereby putting at risk some aspects of the mountain tourism economy.

The current study attempted to address the medium-range predictability of snow conditions in mountain regions, starting from a case study in the Mont-Blanc range at an altitude of 2400m for the time period spanning 1980-2010. A prediction system was built, consisting of the median of an ensemble of numerical simulations using the detailed snowpack model Crocus fed by an ensemble of meteorological conditions taken from the SAFRAN reanalysis initiated at several starting dates (here, 01/12, 01/02 and 01/04 of each snow season). It was found that the current version of the prediction system looses interest with respect to climatological values a few days or weeks at most after the prediction date. This indicates that, with respect to climatological snow height values, regardless the initial conditions and the date of the prediction, meteorological conditions are the main driver of snow conditions in mountain regions. This result is not surprising but quantitatively demonstrates that medium range predictions of natural snow conditions will mostly improve through improvements of meteorological forecasts. However, the prediction system provides upper/lower bounds of expected snow conditions starting from given snow conditions which may still prove useful for time spans on the order of days to weeks after the prediction date.

Several additional developments can be envisaged to corroborate or refine the results of this study. Firstly, the statistical framework introduced here deserves to be further improved for example using more complex statistical analysis tools, to be able to fully account for the spread between ensemble members, which was ignored here by simply using the median of the simulations in the quantitative analysis of the results. On the physical side of things, the results may be refined by explicitly accounting for slope angle and aspect, which are known to exert a major influence on the snow surface energy budget, thus the unfolding of the snow season. Extending this case study to other locations and other altitudes ranges is also necessary to assess the generality of the conclusions reached here.

The simple prediction system described above may still have some interesting capabilities for operational applications, as a complementary tool to address questions from mountain professionals during a given snow season, or inform forecasting activities for issues related to snow conditions (e.g. hydrological impact of snowmelt etc.). To this end, the present system may be run regularly (e.g. once weekly) for upcoming snow seasons.

In addition, rather than using the ensemble of meteorological scenarios from the date of the prediction into the future, substituting the deterministic forecast carried out by SAFRAN based on outputs from numerical weather prediction (NWP) will allow to take into account forecast conditions for the first 2 days of the simulations (Durand et al., 1999), before the prediction system presented above can be used. This will most likely extend the time frame over which the prediction system has a predictive power superior to the climatological data. Furthermore, using true operational NWP ensemble forecasts to drive the model will also allow to extend the reach of the prediction system beyond its current capabilities, explicitly accounting for the meteorological situation and its potential development into the future. Also, in the case where the system is used for simulations at snow observing stations, currently developed data assimilation techniques in Crocus will be used to adjust the snow conditions at the initial step of the prediction to field observations. In addition to the current exploratory study and follow-up *a posteriori* exercises, the value of such developments will be assessed through near real-time computations which will demonstrate, or not, the benefit of running such a system operationally.

Last, while the results discussed above were obtained accounting only for natural processes operating on the snowpack, in mountain ski resorts, for a long time not only natural conditions but also snow management practices drive the evolution of snow conditions on ski slopes. Including such processes in the detailed snowpack model Crocus is planned and will allow to refine the present analysis, in the particular case of mountain ski resorts, accounting for various snow management practices (grooming, snowmaking, textile protection etc.).

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