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ORIGINAL ARTICLE

Can we infer avalanche–climate relations using tree-ring data? Case studies in the French Alps

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Abstract Dendrogeomorphology is a powerful tool to determine past avalanche activity, but whether or not the obtained annually resolved chronologies are sufficiently detailed to infer avalanche–climate relationships (in terms of temporal resolution) remains an open question. In this work, avalanche activity is reconstructed in five paths of the French Alps and crossed with a set of snow and weather variables covering the period 1959–2009 on a monthly and annual (winter) basis. The variables which best explain avalanche activity are highlighted with an original variable selection procedure implemented within a logistic regression framework. The same approach is used for historical chronologies available for the same paths, as well as for the composite tree-ring/historical chronologies. Results suggest that dendrogeomorphic time series allow capturing the relations between snow or climate and avalanche occurrences to a certain extent. Weak links exist with annually resolved snow and weather variables and the different avalanche chronologies. On the contrary, clear statistical relations exist between these and monthly resolved snow and weather variables. In detail, tree rings seem to preferentially record avalanches triggered during cold winter storms with heavy precipitation. Conversely, historical avalanche data seem to contain a majority of events that were released later in the season and during episodes of strong positive temperature anomalies.

Keywords Dendrogeomorphology · Snow avalanche · Avalanche–climate relations · Logistic regression · Hazard assessment · French Alps

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Introduction

Snow avalanche activity depends on the interactions between terrain variables, precipitation, wind, temperature, and snowpack stratigraphy. If long avalanche series are available, quantitative analyses can be used to relate these factors to snow and weather data at the time of release (McClung and Tweedy 1993; Jomelli et al. 2007). In general, however, long and continuous historical observations are relatively scarce, so that avalanche–climate studies have remained restricted to a few areas in the world.

Dendrogeomorphology (Alestalo 1971; Stoffel et al. 2010; Stoffel and Corona 2014) can be used to compensate for this difficulty as it is a powerful tool for reconstructing avalanches at annual resolution on decadal and centennial scales (Butler and Sawyer 2008).

In that context, dendrogeomorphology has been used repeatedly to examine relations between snow and weather variables and avalanche activity at locations where little or no historical avalanche data were available and therefore helped to understand better the main drivers of avalanche activity at the local scale. For example, the probability of major avalanche years was associated with mean January snowfall in the western USA (Hebertson and Jenkins 2003) and the French Alps (Corona et al. 2010). High-magnitude avalanche years were significantly correlated with positive snowpack anomalies in the USA (Reardon et al. 2008) and total snowfall in Canada (Dubé et al. 2004). Similarly, Casteller et al. (2011) found a significant correlation between years with large avalanche activity and abundant precipitation during austral winters (May to October) in Argentina.

A major limitation of dendrochronology is that it may underestimate years with natural avalanche activity, in extreme cases by up to 60 % (Corona et al. 2012; Schläppy et al. 2013; Stoffel et al. 2013). Consequently, while complementing generally poor time series of snow avalanche activity back in time, reconstructed series will often remain incomplete in such a way that the relevance of avalanche–climate relationships inferred from tree-ring data is unclear and warrants careful examination.

This paper explores the relevance of tree-ring-derived avalanche records and tests whether dendrogeomorphic data can be reliably used to infer linkages between avalanche occurrences and climate patterns in areas where only little historical information is available. Evaluating avalanche–climate relationship derived from tree rings is difficult because relevant data are scarce. In France, comprehensive avalanche data are available for a long period, as systematic surveys of avalanches have been initiated by foresters in the early twentieth century. In addition, the SAFRAN-Crocus model chain (hereafter referred to as SC) provides valuable reanalyzed daily snow and weather data at various elevations, aspects, and slopes for the 23 French massifs (Durand et al. 1999) for the period 1958/9–2008/9 (Durand et al. 2009a, b).

The aim of this study is therefore (1) to reconstruct past snow avalanche activity in five paths distributed throughout the French Alps using dendrogeomorphic techniques; (2) to define a large set of potential variables from the SC simulations that could explain avalanche activity; (3) to pick the most pertinent variables using a variable selection procedure implemented within a logistic regression framework; (4) to assess statistical relations between snow and weather data and avalanche yearly indices derived from tree-ring data and/or historical archives in the different paths; (5) to discuss the results and draw conclusions regarding the ability of tree-ring data to capture avalanche–climate relations.

Study sites

Study site selection was based on the presence of old-growth forest signs with clear signs of snow avalanche disturbance, easy accessibility, the apparent absence of other mass wasting processes (e.g., landslides, rockfalls, fire), and the presence of avalanche stopping zones within the forest. The choice of avalanche path was done trying to select paths as distant as possible from each other and with a variety of geomorphic characteristics (Online Resource 1) to assure reasonable spatial representation. Five snow avalanche paths were selected in the northern and central parts of the French Alps, namely the *Avalanche des Pylônes* and *Pèlerins* paths near Chamonix-Mont-Blanc (Mont-Blanc massif), the *Ressec* path near Lanslevillard (Haute-Maurienne massif), the *Château Jouan* path near Montgenèvre (Thabor massif), and the *Ourcière* path near La Grave (Oisans massif; Fig. 1). All paths except Lanslevillard were previously used to assess the ability of dendrochronology to document snow avalanche activity by comparing historical observations and tree-ring-derived snow avalanches (Corona et al. 2012; Schläppy et al. 2013, 2014).

Avalanche des Pylônes path

The *Avalanche des Pylônes* path (45°56′ N, 6°51′ E) is located on the S-facing slope of the Arve Valley. Avalanches flow from 1850–1700 m asl through an incised path before reaching the runout extending from 1450 m to 1100 m asl (Online Resource 1). Forest vegetation includes *Picea abies* (L.) Karst. with sparse *Pinus sylvestris*, *Larix decidua* Mill., *Betula pendula*, *Abies alba* Mill.

Pèlerins path

The *Pèlerins* avalanche path (45°53′ N, 6°52′ E) on the NW-facing slope of the Arve Valley is 2 km southwest of downtown Chamonix. Snow avalanches are triggered from a starting zone located between 3600 and 2750 m asl. Most of the avalanches stop in the runout zone at 1500–1100 m asl (Online Resource 1) which is covered by a dense forest dominated by *L. decidua* and *P. abies*.

Ressec path

The *Ressec* avalanche path (45°17′ N, 6°57′ E) on the NW-facing slope of the Arc Valley is located 3 km northeast of downtown Lanslevillard. Snow avalanches are triggered between 3000 and 2300 m asl and generally stop between 2100 and 1700 m asl (Online Resource 1). The runout zone is covered by a dense forest dominated by *P. abies* and *L. decidua* with exceptional *A. alba*.

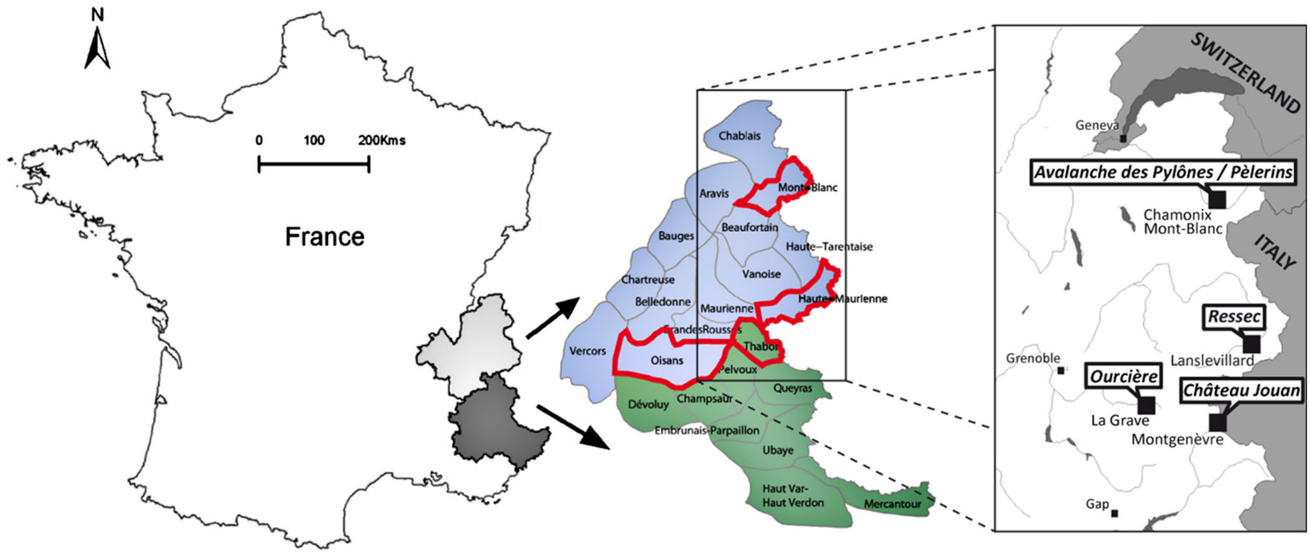

Fig. 1 Location of the five avalanche paths in the French Alps. The French Alps are divided into 23 massifs. The Northern French Alps and Southern French Alps are represented in *blue* and *green*, respectively. The massifs where the studied paths are located are surrounded in *red* (adapted from Castebrunet et al. 2012) (color figure online)

Château Jouan path

The *Château Jouan* path (44°55′ N, 6°42′ E) is located on the N-facing slope of the Durance Valley, 2 km SW of Montgenèvre. The starting zone is located at 2500–2000 m asl and the runout zone extends between 1900 and 1700 m asl (Online Resource 1). The upper part of the runout zone is colonized by shrubs and invasive trees species (e.g., *Pinus mugo* subsp. *mugo*), but *L. decidua* starts to dominate at 1800–1700 m asl.

Ourcière path

The *Ourcière* path (45°02′ N, 6°15′ E) is located on the N-facing slope of the Romanche Valley, 4 km W of La Grave. Most snow avalanches are released from a starting zone located at 2900–1900 m asl (Online Resource 1). Avalanches commonly reach the runout zone between 1800 and 1250 m asl. This area is covered by an open forest built of *L. decidua*.

Data and methods

Dendrogeomorphic analysis and avalanche event identification

The area sampled with dendrogeomorphic techniques was restricted to the lower portions of avalanche paths and their runout zones. Following the recommendations of Corona et al. (2012) and Stoffel et al. (2013), at least 100 trees were sampled at each of the five selected paths (Online Resource 2).

Coring was restricted to *L. decidua*, *P. abies*, and *A. alba*. Characteristic growth disturbances were used to calendar-date the occurrence of past snow avalanches (Online Resources 2 and 3). Selection of trees, sampling design, and sample preparation and analysis followed the procedures described in Stoffel and Bollschweiler (2008). Intensities were assigned to growth disturbances in order to emphasize features that are clearly associated with avalanche activity and to discriminate these from disturbances possibly induced by other factors (Corona et al. 2012; Stoffel et al. 2013). Growth disturbances were classified based on the visual quality of the evidence of reactions within each sample according to the intensity scale presented in Online Resource 3 (Schläppy et al. 2013). The determination of snow avalanche years was based on a visual evaluation of the resulting maps and followed the procedure described by Schläppy et al. (2013) (Online Resource 5.1).

Historical avalanche data

In France, the systematic survey of avalanches was initiated by foresters in the early twentieth century in the "Enquête Permanente sur les Avalanches" (hereafter referred to as EPA). Event occurrence dates as well as various quantitative (e.g., runout altitudes) and qualitative (e.g., flow regime) data (Jamard et al. 2002) are stored in this database maintained by Irstea (Institut national de recherche en sciences et technologies pour l'environnement et l'agriculture).

Locally, the quality of EPA records depends to a large extent on the accuracy of data recording by rangers. Nevertheless, the EPA has repeatedly been found to represent a valuable source of information for larger-scale investigations of avalanche activity and related snow and weather drivers (Jomelli et al. 2007; Eckert et al. 2010b; Naaim et al. 2013).

Historical records corresponding to the five studied paths are by far not the most complete in the EPA chronicles. By contrast, no or very few trees typically colonized the paths with the most complete data series and thus prevented their inclusion in this study. Nevertheless, we assume that the quality of information reported for all events is reliable enough to be compared and/or merged with tree-ring chronologies. Note that for all the historical data, an avalanche year is considered as a year during which at least one avalanche event was reported.

Modeled weather and snow data

In the French Alps, the spatial and temporal coverage of meteorological station network is insufficient to characterize snow and meteorological conditions in starting zones of avalanche paths. Consequently, the primary dataset used for the five sites analyzed in this study consisted of daily simulated snow and meteorological data from the SAFRAN-Crocus model chain (Online Resource 5.2). SAFRAN meteorological data, provided for each massif as a function of altitude, are further projected on various slopes and aspect prior to running Crocus, thereby providing simulated snowpack conditions for representative altitudes, slopes, and aspects within each considered massif.

In this study, we use various daily outputs of these simulations for the four alpine massifs related to the studied paths (i.e., Mont-Blanc, Haute-Maurienne, Thabor, and Oisans massifs; Fig. 1) over the period from 1958/9 to 2008/9. Simulated data for three different elevations (1800, 2400, and 3000 m asl) were considered. The following meteorological and snowpack parameters were used:

- daily precipitation, temperature (minimum, maximum, and mean), maximum wind speed (SAFRAN output);
- for the main aspect (northern, eastern, southern, and western) and a 40° slope, the thickness of surface wet snow and the thickness of surface recent dry snow. These variables are derived from the standard Crocus outputs: The thickness of surface wet snow is taken as the sum of the contiguous wet snow layers characterized by a liquid water content >0.01 %, from the surface, and the thickness of the surface recent dry snow as the depth of the deeper recent snow layer characterized by a dendricity >0.25 (see Brun et al. 1992, for details).

In a given path, we considered only the variables corresponding to the main aspect and mean elevation of the starting zone. For example, in the *Avalanche des Pylônes* path, variables retained were those simulated for the northern aspect at 1800 m asl (Online Resource 1).

Standardized data at annual and monthly timescales

As dendrogeomorphic methods provide data with low temporal resolution, namely the winter during which (at least) one avalanche event occurred, the daily SC outputs need to be smoothed. We chose to explore winter and monthly means by calculating annual (entire winter) and monthly values from December through May SAFRAN and Crocus daily values, i.e., for each year, one annual value and six monthly values. This was justified by the fact that all avalanche events recorded in the historical archives of the five paths referred to these 6 months.

In detail, precipitation values were summed, while temperature, wind, and snowpack values were averaged for each month and for the entire winter. In addition, several composite variables were created with the objective to identify the frequency of occurrence of particular anomalies resulting from extreme meteorological situations: cold waves, warm winter spells, and high-magnitude snowfall. In total, twenty indices (Online Resource 5.3) representing snow and weather conditions were used.

The different variables X_{jt}, where j denotes the (monthly or annual) variable and t the year, were normalized to produce anomaly series as:

$$X_{jt}^{\text{norm}}(t) = \frac{X_{jt} - \mu_j}{\sigma_j} \tag{1}$$

where μ_j and σ_j are the interannual mean and standard deviation of X_{jt}, respectively. The goal of this normalization procedure is to allow intervariable comparison and graphical visualizations and to interpret the respective contribution of each covariate to the interannual fluctuations of avalanche activity. Another advantage is that this choice avoids numerical problems for numerical likelihood maximization in logistic regression models (see below).

Variable selection in logistic regression

Logistic regression is a case of a formal generalization of linear regression concepts referred to as generalized linear models (GLMs). It was used to investigate the relationship between the dichotomous response variable, i.e., the occurrence or non-occurrence of avalanche events in year t, and a set of explanatory variables as:

$$\mathrm{logit}(p_t) = \beta_0 + \beta_1 X_{1,t} + \cdots + \beta_k X_{K,t} \quad (2)$$

where p_t is the probability of an avalanche for the year t, $X_{j,J} \in [1, K]$ represents the K climatic indices used as regressors, β_0 the intercept and β_j the regression coefficients. The logit is simply the log odds ratio:

$$\mathrm{logit}(p_t) = \ln\left(\frac{p_t}{1 - p_t}\right) \quad (3)$$

with an equivalent formulation:

$$p_t = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1 X_{1,t} + \cdots + \beta_k X_{K,t}\right)}} \quad (4)$$

Our calculations were performed under the GLM package of the software R (R Development Core Team 2011).

A specific difficulty was that the total number of potential explanatory variables amounted to 20 snow and weather indices at the annual timescale and up to 120 for the monthly resolved covariates (20 variables calculated over the 6 months from December to May). To choose the best explanatory covariates of avalanche activity from this huge set of potential predictors, we carried out an original selection procedure in several steps within the logistic regression framework.

In the first step, we tested all covariates for marginal statistical significance in the logistic regression, considering p values of $p \leq 0.2$ as small enough to keep a covariate. This relatively low-significance threshold was retained so as to keep enough potential variables for the following steps (see below). Spearman's rank correlation coefficient r was then calculated for all possible pairs of remaining variables. This step was necessary as correlation between explanatory variables can lead to masking effects in an automatic variable selection procedure. For example, fresh snow depth data undoubtedly contain information already given by precipitation. At this stage, among the strongly correlated variables ($r > 0.5$), we kept only the one with the highest marginal significance.

A stepwise regression (e.g., Saporta 2011) was then undertaken with the remaining covariates. This is a variable selection procedure originally designed for linear models but that can also be applied to certain classes of GLMs. With a stepwise procedure, the set of predictive variables retained is selected by an automatic sequence of Fisher F tests. Starting from an initial null *logit* model with no covariates and then comparing the explanatory power of incrementally larger and smaller models, it combines forward selection and backward elimination. Forward selection tests the variables one by one and includes them if they are statistically significant based on the p value of the F statistics, while backward elimination starts with all candidate variables and tests them one by one for statistical significance, deleting any of them that are not significant on the basis of the p value of the F statistics.

The stepwise selection generally led to multiple logistic regression models including less than five covariates, as expected. In some cases (depending on the chronology and path, see below), however, obtained models still had more variables. As our goal was to attain a good compromise between a nearly maximal explanatory power and a restricted number of covariates, we finally kept only models with a maximum of four covariates and with each covariate marginally significant at the 10 % level. This has the advantage to allow a better interpretation of the retained models in terms of physics.

Such multivariate logistic regression models have been established for the three chronology types (dendrogeomorphic dataset, historical dataset, and combined dataset) in the five studied paths, with both the annual and monthly sets of covariates.

Model performance was evaluated with several indicators (Online Resource 5.4) such as the likelihood ratio test, the Wald Chi-square statistic, and the R^2 determination coefficient. Finally, we checked whether modeled high probabilities p_t were indeed associated with events and low probabilities with nonevents. With a 0.5 probability threshold, this turned into calculating the sensitivity, measuring the proportion of correctly classified events, and the specificity, measuring the proportion of correctly classified nonevents.

In a more qualitative investigation, we considered a 80 % threshold to identify years corresponding to the highest snow and weather anomalies and confront them to the actual avalanche observations (Online Resource 4).

Results

Avalanche event chronologies derived from dendrogeomorphic and/or historical data

The focus of this study is limited to the period 1959–2009, for which snow and weather data are available. Tree-ring analysis allowed identification of hundreds of growth disturbances related to snow avalanche impacts in the trees sampled at the five study sites. A detailed presentation of all growth anomalies recorded in the tree-ring records in each path is given in Online Resource 2. Based on the yearly distribution of reacting trees within the runout zone, a total of 19, 8, 12, 7, and 9 avalanche events were identified in the *Avalanche des Pylônes*, *Pèlerins*, *Ressec*, *Château Jouan*, and *Ourcière* paths, respectively (Fig. 2).

Historical data on avalanches (EPA) cover the period investigated in all but one of the studied paths. In the *Avalanche des Pylônes* path, the avalanche survey started during winter 1985–1986. In the five paths, the EPA reports between 8 and 17 years with avalanche activity over the period 1959–2009 (Fig. 2).

By combining the dendrogeomorphic and historical chronologies, the total number of events per path increased to 21, 14, 25, 12, and 19 avalanches in the *Avalanche des Pylônes*, *Pèlerins*, *Ressec*, *Château Jouan*, and *Ourcière* paths, respectively (Fig. 2).

Annual snow and weather explanatory factors of avalanche events recorded in dendrogeomorphic data

Logistic regression models could be established between dendrogeomorphic data and the annual snow and weather covariates sets. For three paths, these included three variables and, and for two paths, one single covariate (Online Resource 4). However, for one path/chronology, the likelihood ratio test was not passed at the 0.05 significance level, indicating that the retained model was not better than the null model. For the four other paths, the test was passed, but corresponding p values remained close to the significance threshold. In addition, for the five paths, the determination coefficient was rather poor (from 0.1 to 0.31; Online Resource 4). Also, their sensitivity was very low (0–47 %), indicating nearly no ability to predict avalanche years. This all suggests that it is not possible to satisfactorily predict tree-ring chronologies with the available annual snow and weather variables, presumably because too few significant variables were retained to discriminate the avalanche/non-avalanche years accurately. Similar deceptive results (not shown) were obtained while relating historical records and composite avalanche chronologies to the annual snow and weather variables.

Monthly snow and weather explanatory factors of avalanche events recorded in dendrogeomorphic data

The monthly covariate sets revealed significant relationships with dendrogeomorphological avalanches data with highly significant ($p < 0.001$) likelihood ratio tests and relatively good R^2 coefficients, ranging from 0.38 to 0.61 (Table 1). The models' specificity was high with rates varying between 87.5 and 97.7 %. Models' sensitivity varied between 42.9 and 78.9 %, but greatly improved with respect to results obtained with annual variables. This means that the models were still generally more effective to characterize years with no avalanche event.

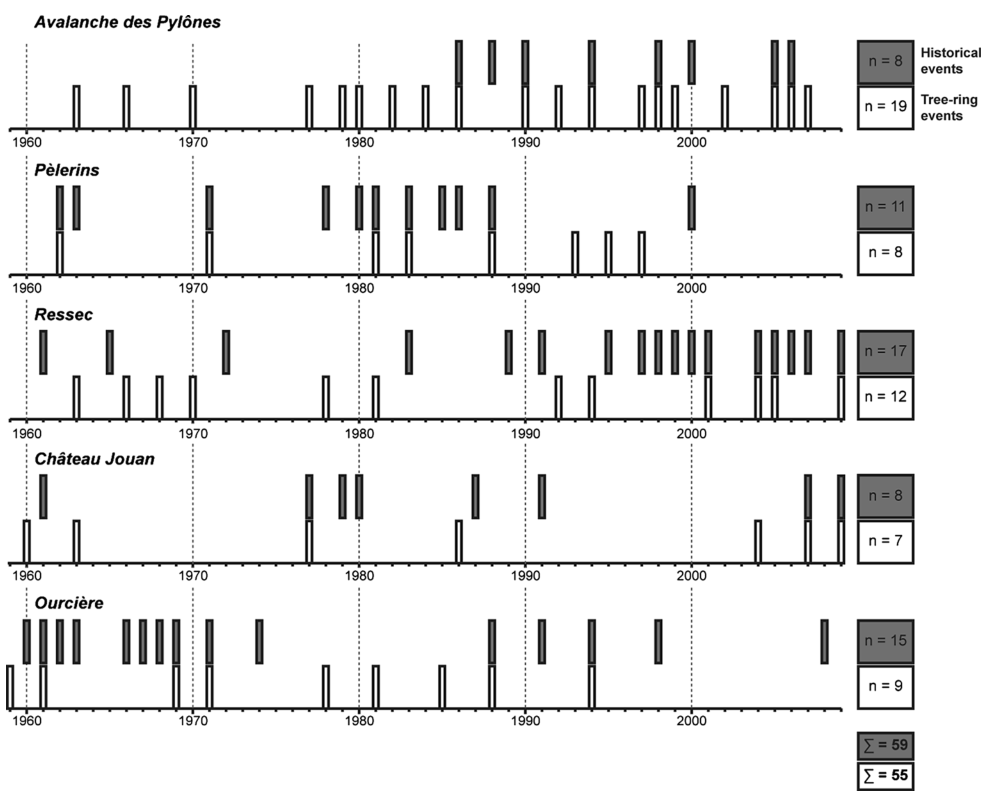

Fig. 2 Snow avalanche years in the five paths. *Gray* and *white* features correspond to avalanche events derived from historical and dendrogeomorphic data, respectively

Most event years corresponded well to strong anomalies in the selected combination of covariates. Thirty-nine out of 55 events (71 %) recorded in the five paths occurred in years for which the respective model exceeds the 80th percentile of its interannual distribution (Fig. 3).

Each model used between 2 and 4 significant covariates (Table 1). They mainly consisted of a combination of precipitation and temperature variables (Table 1; Fig. 3). All except one variable had a positive contribution ($\beta_j > 0$), indicating that higher values imply higher probability of an avalanche year which seems intuitive, at least for precipitation and snowpack variables. Conversely, the temperature variable included in the model related to the *Ourcière* path (*Tmax*_(Jan)) had a negative contribution, indicating that high probabilities of avalanche years are more likely associated with low temperatures in that path, another meaningful result. According to the weighting coefficients (β_j) and marginal correlation coefficients between models and covariates (ρ_j), precipitation and snowpack variables contributed more to the models than temperature variables (Table 1; Fig. 3).

Monthly snow and weather explanatory factors of avalanche events reported in historical data

The five models related to historical data were also based on a small number of covariates, all of them at least significant at the 10 % significance level (Table 2). Note, however, that the intercept in the model related to the *Avalanche des Pylônes* path was insignificant ($p = 0.35$), suggesting that the alternative model without the intercept might be applied to the data as well.

The five models were better than the null model given the high significance of the likelihood ratio test ($p < 0.004$ in all cases) as well as the good R^2 indices (>0.5). Cross-validation classification probabilities indicated that specificity is more than 90 % in all models, while sensitivities ranged from 53.3 to 64.7 % (Table 2). As for models related to dendrogeomorphic data, models better fitted avalanche activity in nonevent years. Nevertheless, the 80th percentile was well exceeded in 58 % of all event years (34 out of 59 events), meaning that most of the events eventually occurred during years with "strong" combinations of snow and weather anomalies (Fig. 4).

Table 1 Logistic regression models $p_t = \sum_{j=1}^{K} X_{jt}^{\text{norm}} \beta_j$ at the path scale for the annual avalanche/non-avalanche years derived from dendrogeomorphic data and the monthly SC covariates

Path name	Explanatory variables $_j$	p value	β_j	ρ_j	R^2	Sensitivity (%)	Specificity (%)	Overall prediction correction (%)
Avalanche des Pylônes	Intercept	0.04	−0.91		0.58	78.9	87.5	84.3
	P_(Feb)	0.00	1.56	0.53				
	FreshSnow(Dec)	0.01	1.91	0.50				
	T_{mean}_(Jan)$_{>\text{mean} + 2\text{SD}}$	0.01	1.13	0.37				
	FreshSnow(Jan)$_{>\text{q}90}$	0.02	1.21	0.42				
Pèlerins	Intercept	0.00	−2.84		0.59	62.5	97.7	92.2
	P_{mean}3j_(Apr)$_{>\text{mean} + 2\text{SD}}$	0.01	1.42	0.60				
	T_{min}_(Mar)$_{<\text{mean-2SD}}$	0.02	1.19	0.61				
	T_{max}_(Dec)$_{>\text{mean} + 2\text{SD}}$	0.06	0.77	0.45				
Ressec	Intercept	0.00	−1.45		0.38	50.0	97.4	86.3
	FreshSnow(Jan)$_{>\text{q}95}$	0.01	1.28	0.80				
	T_{max}_(May)$_{>\text{mean} + 2\text{SD}}$	0.03	0.91	0.54				
Château Jouan	Intercept	0.00	−4.06		0.61	42.9	97.7	90.2
	P_{mean}3j_(Jan)$_{>\text{mean} + \text{SD}}$	0.03	2.05	0.60				
	P_{mean}3j_(Apr)$_{>\text{mean} + 2\text{SD}}$	0.04	1.98	0.58				
	T_{min}_(Apr)	0.03	2.21	0.51				
Ourcière	Intercept	0.00	−1.99		0.53	66.7	95.2	90.2
	P_(Mar)$_{>75}$	0.01	2.53	0.91				
	P_(Apr)$_{>75}$	0.06	0.61	0.18				
	T_{max}_(Jan)	0.06	−1.04	−0.47				

For each explanatory variable retained, X_{jt}, β_j is the weighting coefficient, ρ_j the marginal correlation coefficient between X_{jt}^{norm} and p_t (the regression model seen as a time series), and R^2 the determination coefficient of the logistic regression (Nagelkerke 1991)

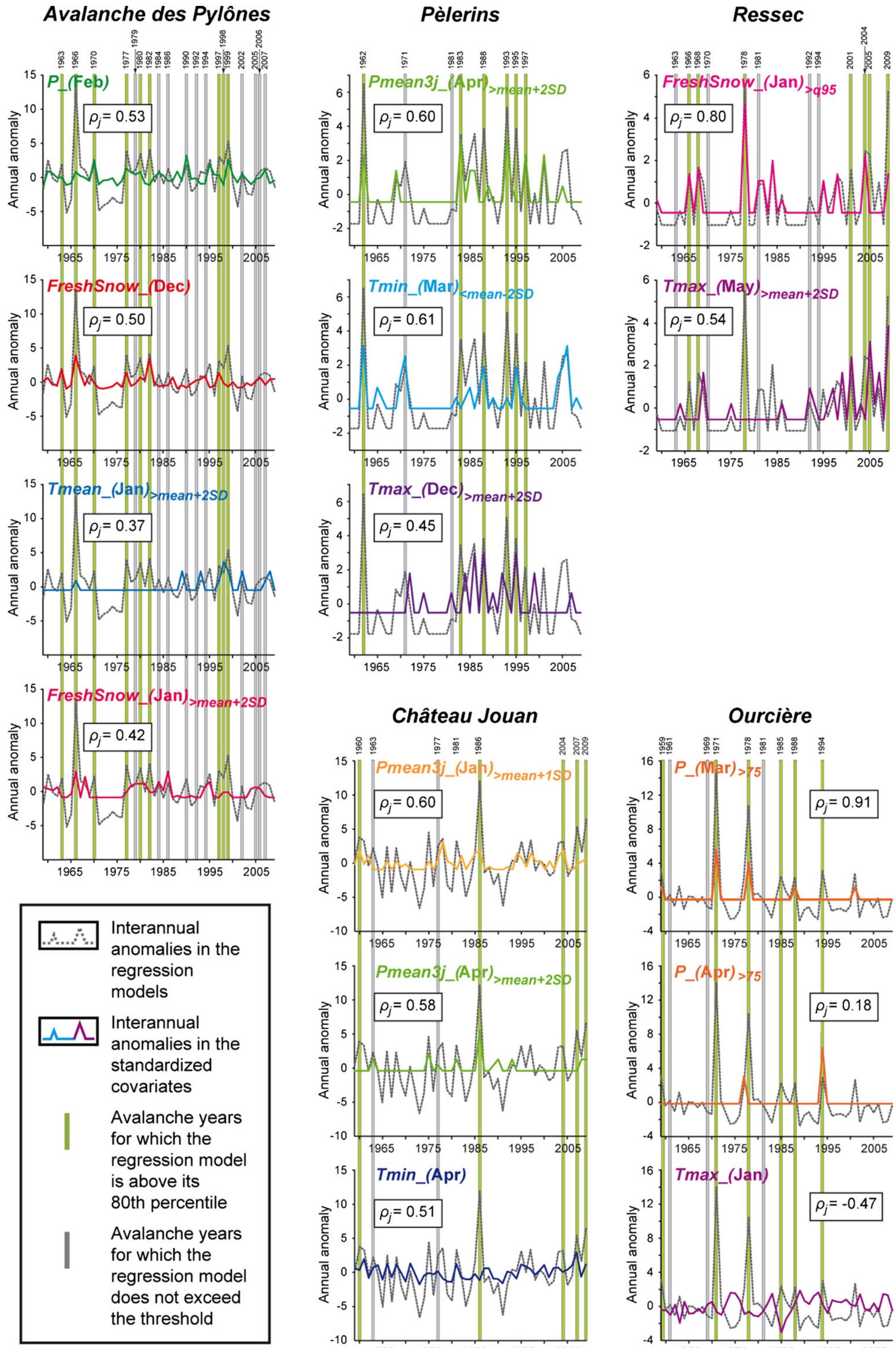

Fig. 3 Interannual anomalies in the covariates retained in the regression models related to avalanche activity derived from dendrogeomorphic data in the five paths. ρ_j is the marginal correlation coefficient between each covariate and the regression model seen as a time series. *Green bands* correspond to avalanche years for which the regression model is above its 80th percentile. *Gray bands* correspond to avalanche years for which the model does not exceed the threshold (color figure online)

Models related to historical data included 2–4 explanatory variables, and most of them represented temperature variables. Snowpack factors were also included in three models, but no precipitation variable was retained (Fig. 4). Note that the model related to the *Ourcière* path also used an additional variable related to wind speed in March (*Vmax*_(Mar)).

Table 2 Logistic regression models $p_t = \sum_{j=1}^{P} X_{jt}^{\mathrm{norm}} \beta_j$ at the path scale for the annual avalanche/non-avalanche years derived from historical data and the monthly SC covariates

Path name	Explanatory variables $_j$	p value	β_j	ρ_j	R^2	Sensitivity (%)	Specificity (%)	Overall prediction correction (%)
Avalanche	Intercept	0.35	−0.55		0.52	62.5	93.8	83.3
des Pylônes	$T_{\max}$_(Apr)$_{>\mathrm{mean}\,+\,1\mathrm{SD}}$	0.05	−2.10	−0.72				
	$T_{\max}$_(Jan)$_{>\mathrm{mean}\,+\,1\mathrm{SD}}$	0.08	−1.41	−0.61				
Pèlerins	Intercept	0.00	−2.38		0.52	54.5	92.5	84.3
	$T_{\max}$_(Jan)	0.01	−2.51	−0.77				
	FreshSnow(Apr)$_{>q95}$	0.01	1.65	0.46				
Ressec	Intercept	0.02	−1.07		0.58	64.7	97.1	86.3
	$T_{\min}$_(Feb)$_{<\mathrm{mean}\text{-}2\mathrm{SD}}$	0.00	1.73	0.42				
	$T_{\max}$_(Mar)$_{>\mathrm{mean}\,+\,2\mathrm{SD}}$	0.04	1.22	0.34				
	$T_{\max}$_(Feb)$_{>\mathrm{mean}\,+\,1\mathrm{SD}}$	0.03	1.07	0.31				
	$T_{\max}$_(Apr)	0.04	1.38	0.51				
Château	Intercept	0.00	−3.43		0.54	62.5	97.7	92.2
Jouan	$T_{\min}$_(May)$_{<\mathrm{mean}-1\mathrm{SD}}$	0.02	1.25	0.57				
	WetSnow_(Apr)	0.02	1.39	0.38				
	$T_{\max}$_(Jan)$_{>\mathrm{mean}\,+\,1\mathrm{SD}}$	0.07	−2.08	−0.77				
Ourcière	Intercept	0.00	−1.61		0.56	53.3	91.7	80.4
	$T_{\max}$_(Dec)	0.00	−1.50	−0.62				
	$V_{\max}$_(Mar)	0.01	1.35	0.57				
	$T_{\max}$_(Feb)$_{>\mathrm{mean}\,+\,2\mathrm{SD}}$	0.08	0.94	0.22				
	WetSnow_(Dec)	0.01	1.44	0.10				

For each explanatory variable retained, X_{jt}, β_j is the weighting coefficient, ρ_j the marginal correlation coefficient between X_{jt}^{norm} and p_t (the regression model seen as a time series), and R^2 the determination coefficient of the logistic regression (Nagelkerke 1991)

Except for the model for the *Ressec* path, variables related to anomalies in maximum air temperature had a highly negative contribution. Hence, high peaks in the model generally corresponded well to sharp declines in these negatively correlated variables, indicating that most of the events were recorded during years where abnormally cold episodes occurred. Noteworthy, marginal correlations (ρ_j) illustrate the preponderant role of temperature variables in comparison with those related to snowpack and wind speed variables.

Monthly snow and weather explanatory factors of events derived from both datasets

While exploring statistical relations between snow–weather data and the chronology containing dendrogeomorphic and historical data, all models retained 2–4 significant ($p < 0.1$) explanatory factors (Table 3). In the models related to the *Avalanche des Pylônes* and *Ressec* paths, the intercept might not be considered given that it is far from the 10 % significance level. According to the likelihood ratio test ($p < 0.003$ in all cases) and R^2 indices, all models were better than the null model. On the other hand, sensitivity ranged from 41.7 to 80 %.

These models were globally less accurate to fit avalanche activity in comparison with the models derived for the dendrogeomorphic or historical chronologies, as illustrated by overall prediction corrections (Table 3). Nevertheless, one in two events occurred in years with strong combinations of snow and climatic anomalies according to the fact that models exceeded the 80th percentile of their interannual distribution in 45 out of 91 events.

Models were composed of a combination of precipitation, temperature, and snowpack variables; they were more complex than the models composed solely of tree-ring or historical data. However, in a similar way as in the models related to dendrogeomorphic data, all but one variable had a positive contribution ($\beta_j > 0$). Only one variable, related to temperature (*Tmax*_(Jan)), showed a negative contribution in the model associated with the *Château Jouan* path (Table 3).

Discussion, conclusion, and outlooks

Methodology and summary of the work done

In recent decades, several studies have explored the link between climate and avalanche activity derived from tree

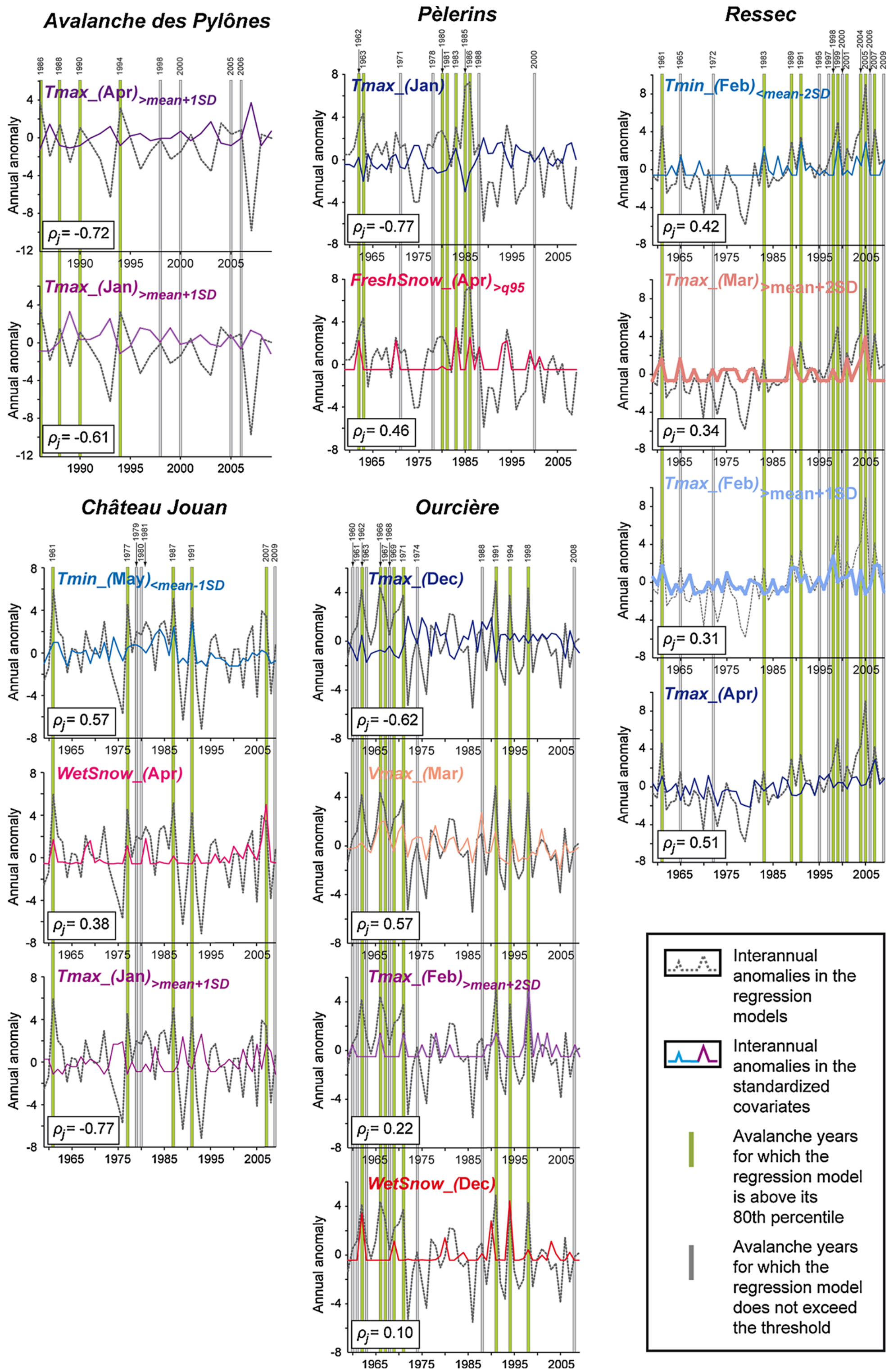

Fig. 4 Interannual anomalies in the covariates retained in the regression models related to avalanche activity derived from historical data in the five paths. ρ_j is the marginal correlation coefficient between each covariate and the regression model seen as a time series. *Green bands* correspond to avalanche years for which the regression model is above its 80th percentile. *Gray bands* correspond to avalanche years for which the model does not exceed the threshold (color figure online)

Table 3 Logistic regression models $p_t = \sum_{j=1}^{P} X_{jt}^{\text{norm}} \beta_j$ at the path scale for the annual avalanche/non-avalanche years derived from both dendrogeomorphic and historical data and the monthly SC covariates

Path name	Explanatory variables $_j$	p value	β_j	ρ_j	R^2	Sensitivity (%)	Specificity (%)	Overall prediction correction (%)
Avalanche	Intercept	0.35	−0.35		0.52	71.4	90.0	82.4
des Pylônes	P_{mean}3j_(Feb)$_{>\text{mean}\,+\,1\text{SD}}$	0.01	1.10	0.65				
	FreshSnow(Dec)	0.01	1.48	0.39				
	T_{max}_(Dec)$_{>\text{mean}\,+\,2\text{SD}}$	0.02	1.34	0.41				
Pèlerins	Intercept	0.00	−1.54		0.58	64.3	91.9	84.3
	P_{mean}3j_(Apr)$_{>\text{mean}\,+\,2\text{SD}}$	0.00	1.46	0.48				
	FreshSnow(Mar)$_{>\text{q}90}$	0.01	1.11	0.48				
	FreshSnow(May)	0.05	1.22	0.47				
	T_{max}_(Dec)$_{>\text{mean}\,+\,2\text{SD}}$	0.07	0.75	0.30				
Ressec	Intercept	0.97	−0.02		0.50	80.0	76.9	78.4
	T_{max}_(Mar)$_{>\text{mean}\,+\,1\text{SD}}$	0.00	1.28	0.71				
	T_{min}_(Dec)$_{<\text{mean}-1\text{SD}}$	0.02	0.94	0.53				
	FreshSnow(Jan)$_{>\text{q}95}$	0.04	1.08	0.37				
Château	Intercept	0.00	−1.53		0.36	41.7	97.4	84.3
Jouan	T_{max}_(Jan)	0.03	−1.04	−0.86				
	T_{min}_(May)$_{<\text{mean}-2\text{SD}}$	0.04	0.93	0.63				
Ourcière	Intercept	0.08	−0.59		0.27	57.9	93.8	80.4
	FreshSnow(Jan)	0.01	0.88	0.86				
	T_{max}_(Feb)$_{>\text{mean}\,+\,2\text{SD}}$	0.08	0.81	0.45				

For each explanatory variable retained, X_{jt}, β_j is the weighting coefficient, ρ_j the marginal correlation coefficient between X_{jt}^{norm} and p_t (the regression model seen as a time series), and R^2 the determination coefficient of the logistic regression (Nagelkerke 1991)

rings and were able to identify various explanatory factors (Hebertson and Jenkins 2003; Dubé et al. 2004; Reardon et al. 2008; Germain et al. 2009; Corona et al. 2010). However, since recent studies highlighted that tree-ring reconstructions tend to underestimate years with natural activity by roughly 60 % (Corona et al. 2012; Schläppy et al. 2013), it still seems highly necessary to evaluate the relevance of using dendrogeomorphic data to infer avalanche–climate relations. With this end in mind, we compared avalanche occurrences documented from different approaches and climate.

Because of the very large number of variables involved in the analysis, it was necessary to implement an original variable selection procedure within the logistic regression framework.

Retained statistical models and outcomes

Results obtained for the five case studies show weak links between annually resolved snow and weather variables and the different dendrogeomorphic or historical avalanche chronologies. On the contrary, clear statistical relations exist between avalanche chronologies and some monthly resolved snow and weather variables. This first important result suggests that annual climate is a signal too smoothed to predict avalanche occurrences at a very local scale. For this, snow and weather variables summing up anomalies at shorter timescales such as intense snowfall or cold/warm spells seem necessary. Given that avalanching is locally a nonlinear, discrete response to recent weather forcing, this result seems consistent with a qualitative interpretation. However, it highlights a first limitation of dendrogeomorphic data for avalanche–climate studies: their low (annual) temporal resolution makes it difficult to identify easily the right intra-annual snow–climate variables, so that an automatic selection procedure such as the one used must be employed.

Even if with monthly climate variables the global evaluation of the different models yielded satisfactory results, one should keep in mind that statistical models do not demonstrate causality but only highlight a coherent evolution of avalanche activity indicators and selected covariates. As a consequence, it is natural that models resulting from a variable selection procedure are not always fully interpretable. This is, for instance, well illustrated by the model related to historical data in the *Ressec* path, where three covariates related to monthly maximum temperature anomalies have been retained to contribute positively to avalanche occurrences (Table 2), a relationship relatively difficult to interpret. On the other hand, the retained variables generally make sense, influencing avalanche release probabilities in rather intuitive ways. Also, for the different chronologies/paths, specificities were found to be higher than sensitivities, meaning that nonevent years are more effectively identified by the models than event years in average. This probably results from the relatively weak proportion of years with avalanche occurrence. Nevertheless, according to the 0.5 probability threshold and the model 80th percentile threshold, almost all events correspond to anomalies in the selected combinations of covariates, with more than one in two events (55 %) related to exceedances of the 80 % threshold (Figs. 3, 4). All these arguments indicate that the relations we have highlighted are arguably not only statistical artifacts and may well represent the predominant drivers of avalanche activity in our case studies.

Discrepancies in terms of retained variables between the models obtained for the different chronologies appear, at first glance, to indicate that dendrogeomorphic data are of limited value for assessing avalanche–climate relations. Indeed, if, on the same path, historical records highlight completely different drivers of avalanche occurrences than tree-ring records, how can this tree-ring-inferred relations be trusted in the case when no other data are available? As said before, in some cases, we cannot exclude that the statistical rather than the physical nature of the links we highlight (one just identifies the most correlated series) may be an issue. However, in what follows, by analyzing in further details the retained model, we also suggest that dendrogeomorphic data may nonetheless contribute to a certain extent to a better understanding of the link between snow–climate and avalanche activity, registering well certain types of avalanches, and less well other types of events. The symmetric conclusion may arguably also be true for medium-quality historical archives such as the one we used (remember that the five studied paths are not the best documented in the EPA chronicle because of site selection criteria related to the presence of forest in runout zones).

Indeed, as corroborated by most explanatory variables retained in the tree-ring models (Table 1; Fig. 3), our results seem to indicate that trees preferentially record events which occur during cold episodes accompanied by heavy precipitation in accordance with previous analyses (Corona et al. 2010). Such meteorological conditions are mainly observed during the coolest winter months. On the other hand, EPA models indicate that avalanche events reported in historical archives are mainly related to temperature anomalies as well as, to a lesser extent, to wind and snowpack anomalies and that these events occurred mostly in late winter.

This seems physically consistent with regard to the specificities of each data type: During severe winter storms, visibility is often bad, and many avalanches occur simultaneously, so that an important proportion of them may be missed by human observation on remote paths or on paths where risk exposure is low. However, such full winter events may be large enough in terms of, e.g., extent or snow volume to affect a significant number of trees and may thus be registered in tree-ring records. On the other hand, during spring, visibility is often better and avalanches tend to be more sporadic. These generally wet snow avalanches are therefore only rarely missed by less busy rangers in charge of observation, whereas their extent may be too small to affect a significant number of trees and may thus not be recorded in tree-ring chronologies.

Dendrogeomorphic data may therefore well contribute to a better understanding of the link between snow–climate and avalanche activity, but only for avalanches occurring in "full" winter conditions. On the other hand, and for the sites investigated, historical archives such as the EPA probably miss some winter events, but record most spring avalanches. The fact that both types of data tend to record avalanche events having occurred in different contexts, and thus presumably with very different characteristics (roughly speaking wet or dry snow avalanches, even if this is certainly not always true) is probably the reason why models resulting from the combined chronology are hard to interpret and do not hive higher specificity, sensitivity, or predictive ability than the models for the separated EPA and tree-ring chronologies. Also, this may be an additional reason to explain why annual variables representing the mean winter climate do not bring enough information into the analysis: they are not able to characterize sub-seasonal climatic contexts with enough accuracy. Hence, combining dendrogeomorphic and historical chronologies in view of refining the study of avalanche–climate relations remains problematic, whereas the combined use of both approaches has been shown to be helpful in the context of risk assessment (e.g., Schläppy et al. 2014).

Spatial variability and overall relevance of our results

Another issue is the strong variability between the five study paths, both in terms of mean activity (in terms of mean number of events per year) and retained generating factors (i.e., the variables in the regression models). Indeed, since weather conditions vary substantially according to path location, the triggering factors of avalanche can logically be very different from one path to another, as illustrated by the different covariates retained in the different models, independently of the type of chronology considered. Moreover, terrain variables are known to influence avalanching since they control slope characteristics, strongly influencing mean activity. This was clearly illustrated in the *Avalanche des Pylônes* path which represents a singular situation in comparison with the other paths. Indeed, its very steep slope coupled with south-facing aspect seem to be responsible for more frequent avalanche releases as suggested by the high number of events ($n = 19$) recorded in the tree-ring series (Fig. 2). Nevertheless, possible explicative terrain variables were not considered in this analysis as the main objective was to evaluate the contribution of dendrogeomorphic data to the understanding of avalanche–climate relations independently of the mean activity of each path.

Also, we have worked with five paths only, which is certainly not enough to draw definite conclusions to the initial question of tree-ring data potential for inferring avalanche–climate links. Hence, further studies using a similar overall framework on more paths and in different climatic and/or geomorphic contexts could definitely be valuable to strengthen (or not) our conclusions.

Taking climate non-stationarity into account

All analyses presented here, including the model fits and variable selections, have been realized under the assumption of stationarity. As a consequence, we did not consider the existing potential of dendrogeomorphic data to inform about long-term climatic evolution and its influence on avalanche activity. This choice was made because event chronologies were too diverse from one path to another, too short, and, more generally, presumably too lacunar (few “ones” among many “zeros”) to infer possible trends in relation to climate change at the scale of a single path.

However, a clear climate control of avalanche activity could be demonstrated in the French Alps (Eckert et al. 2010a, c; Castebrunet et al. 2012, 2014; Lavigne et al. 2015). Using very large datasets, these studies avoided the problem faced in our approach while working at the annual timescale: a climatic signal too smooth to be related to discrete, punctual avalanche triggers at the very local scale. Hence, interesting further work should be performed at the regional scale by pooling as many tree-ring chronologies as possible. This would allow relaxing the assumption of stationarity so as to relate the existing changes to changes in large-scale climate drivers. Then, confronting the results with the mentioned literature could ultimately allow evaluating the contribution of dendrogeomorphic data for the documentation of the response of avalanche activity to climate change.

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