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A Global System for Avalanche Risk Assessment

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Abstract—Several decision-support methods exist to assist ski touring practitioners in their choice of the safest possible route to take. This paper proposes approaches to solve two different challenges presented by decision-support methods: 1) the description and assessment of the parameters used in the methods and 2) the combination of the parameters into a final result. Specifically, this paper focuses on recent avalanche observations. Indeed, this parameter is a particularly effective indicator of the current danger level and is considered in several decision-support methods but is not well formalized yet. The developed process, based on unsupervised statistical analysis and machine learning methods, evaluates both the weather trends and the criticality of different areas. It aims to positively impact and improve the assessment of this parameter in the existing methods. Further, this paper presents a global system based on fuzzy logic and developed to combine all parameters into a final result. We have constructed this system in collaboration with a domain expert and applied it to the CRISTAL approach, one of the existing decision-support methods, whose final result is the vigilance mode to adopt when practicing ski touring.

Index Terms—Decision-support system, Avalanche risk evaluation, Clustering, Unsupervised methods

I. INTRODUCTION

Avalanches cause each year a large number of victims among people practicing recreational activities in mountain regions. In the majority of cases, practitioners are the triggering cause of the avalanche that bury or carry them away. Two concepts relate to avalanche accidents: “danger” and “risk”. In 2008 Statham [18] presented clear definitions for both concepts. Avalanche danger corresponds to a potential source of damage. In contrast, avalanche risk relates to a specific subject (called *element at risk*), e.g., a skier. Thus, risk evolves in direct correlation to when the subject move, as its exposition to the danger changes: this is the case for a group of skiers in avalanche terrain. For this reason and in contrast to risk management concerning infrastructures, in the case of mountain sports it is not possible to intervene to reduce the danger but solely to decrease the risk for the subject. Towards this, practitioners themselves can act on their exposure and vulnerability to reduce risk. For example, in the route they choose.

To address this problem, since the 1990s several decision-support methods have been developed [9]. These methods propose decision-aiding tools for practitioners, who in this setting become decision-makers on the field, to combine multiple observations and parameters they can rely on to assess their situation and take themselves a risk-based decision [10].

Most of the existing methods ask the user to fill in many parameters and the system takes a decision. These methods require too much information, so they are rarely used. The method developed in this paper is derived from the automation of risk assessments, a technique that originates from the design science methodology [7]. The goal of this paper is to improve the decision-support methods with few parameters. These are composed of two levels: 1) the description and estimation of the parameters used in the process and 2) the combination of these parameters into a final result. This process generates two needs: 1) To work on the definition of each parameter and give a framework for their assessment. In this paper we argue that automating their evaluation can reduce the biases that users are likely to introduce when the concepts remain qualitative or imprecise. 2) To combine the parameters in a global system to output a single final decision-support result. Most existing methods produce “Go” or “Do not go” decisions or travel recommendations as output. This parameters combination can either be based on statistics or co-developed with a domain expert. In this second case, the aim is to generate a system of rules to explicit the link that there exist between the main parameters of the method and the output. The new risk parameter assessment process constitutes the design artifact that solves the problem of eliminating human estimation biases in risk assessments. To address both research questions, we make propositions at two different levels of a decision-support method: describe the parameters used and combine them through a set of rules.

The rest of the paper is structured as follows: Section II focuses on the *Recent Avalanche Observation* parameter, a key parameter for risk estimation as it captures clear signs of avalanche danger. The goal of this paper is to allow an automatic assessment of this parameter by identifying, at the French Alps scale, which areas have the same danger level as the one where an avalanche just occurred. For this purpose, we use clustering methods. In Sections III and IV we present both steps of a process dealing with this parameter. Towards this, this paper aims to formalize and define an expert decision-support system merging several previously assessed parameters, such as the *Recent Avalanche Observation* parameter that this paper deals with. For this purpose, we establish expert rules by interviewing a domain expert. Finally, Section V develops the combination of several parameters into a final result in the case of one specific decision-support framework: the CRISTAL approach [5].

II. THE *Recent Avalanche Observation* PARAMETER

Within the range of parameters used in decision-support methods, we focus in this paper on the *Recent Avalanche Observation* parameter because the release of an avalanche is a clear sign of avalanche danger. Indeed, in avalanche risk assessment, avalanche observations are a particularly effective indicator of the current danger level and direct evidence of snow instability [10]. Avalanche observations are one of the input parameters of several decision-support methods [10]. This parameter has to assess where similar conditions as those leading to the observed avalanche are likely to be encountered. Until now, this factor remains considered as a warning sign and is never quantified or measured in the existing methods [9]. For example, the Obvious Clues Method [11] remains vague by solely considering "Avalanches in the area in the last 48h" but not formalizing the boundaries of the area to consider.

Regarding this parameter, the main objective is to identify which areas are likely to encounter similar conditions. Thus, thanks to a recent avalanche observation, it is possible to identify areas that are supposed to present the same danger level as the one where the avalanche occurred. Whereas we can consider several parameters to estimate the notion of similar conditions, the paper focuses on the amount of accumulated snow during the last 24 hours. Most researchers are interested in the internal snowpack variability at various scales [17] but experts consider the snowpacks overload as one of the main criteria causing natural avalanches. For this reason, this paper focuses on the geographical variability of the snow overload due to recent precipitations. Then, the main objective is to identify which French Alps areas are likely to receive similar amounts of fresh snow, according to different weather trends. It is equivalent to studying the variability in rainfall conditions at lower altitudes, where the density of automatic measuring stations is higher. The proposed work in this paper aims to improve the assessment of the *Recent Avalanche Observation* parameter included in several decision-support methods.

While two locations may encounter the same rainfall conditions under a given weather trend, they may behave differently. Moreover, some areas may be affected by several weather trends. Thus, when observing a new natural avalanche, it is necessary to estimate the current weather trend of this specific day to know which area makes sense for the given observation. That is why, regarding the *Recent Avalanche Observation* parameter, it is useful to:

- 1) Determine the different weather trends according to the location of the main rainfall totals. To that aim, we develop a multilevel clustering process presented in Section III.
- 2) Carry out, for each trend, the areas associated with different levels of criticality related to the overload. And then estimate the situation of a given day in order to use the parameter in practice in global systems. Section IV describes both needs.

III. A MULTILEVEL CLUSTERING PROCESS FOR WEATHER TRENDS DETECTION

We develop a multilevel clustering process to detect the main weather trends (according to rainfall totals) that affect

a given area. We are working on data that contains 12 years of rainfall measurements recorded hourly during the winter season. These measurements come from 90 EDF-DTG's¹ automatic measuring stations spread across the French Alps.

The specific objective of the multilevel clustering process is to classify days that are similar in terms of the location of the main rainfall totals. This way, it outputs the major weather trends affecting a given mountain area.

We present a classification approach that 1) outputs, after several steps, the main weather trends affecting an area, 2) enacts an automatic process that does not require any parameter refinement nor specification, 3) does not require any expert assistance, and 4) is generic enough to be transferable to other areas. For this purpose, we focused on unsupervised methods and used classical methods of statistical analysis and machine learning: Principal Component Analysis (PCA) [16], Hierarchical Classification (HC) [15], and K-means [8] [21] successively, and then, to finalize the result, we use Affinity Propagation (AP) [6].

The studied dataset includes 12 years of winter season measurements, where each entry corresponds to a day. Each day contains 90 variables corresponding to the 24 hours sum of rainfalls over the 90 measuring stations. To process unsupervised classification methods on the whole dataset (i.e., 1455 days) leads to classifying days according to the total amount of new rainfalls instead of the location of the main rainfall totals. That is not the result we aim to obtain, as we are looking for clusters that identify the location of the main rainfall totals. Experiments have shown that working on smaller datasets that contain fewer days (e.g., one year instead of 12 years) leads to clusters that capture the location of the precipitations rather than focusing on the total amount of rainfalls. For this reason, we split the initial dataset into 12 separated data subsets, each one corresponding to a winter season. This reduces the size of these data subsets to 121 or 122 individuals (i.e., days) according to the winter season.

The developed process starts with these 12 data subsets in input and applies two levels of clustering to give as output the main trends that affect the studied area. Sections III-A and III-B describe both levels. The first one aims to detect all the existing trends, whereas the second one expects to output only one final cluster for each detected trend.

Figure 1 illustrates the multilevel clustering process applied to the data we study.

A. First level: PCA \rightarrow HC \rightarrow K-means

The first level of clustering consists of three methods used in sequence to obtain a clustering result [14]. It processes the following sequence on the 12 data subsets individually: PCA \rightarrow HC \rightarrow K-means. It aims to classify similar days according to the location of the main rainfall totals. As each weather trend corresponds to a different location of the main rainfall totals, the objective of this level is to detect, as clusters, a maximum of distinct weather trends.

¹Électricité de France, French electricity production and supply company

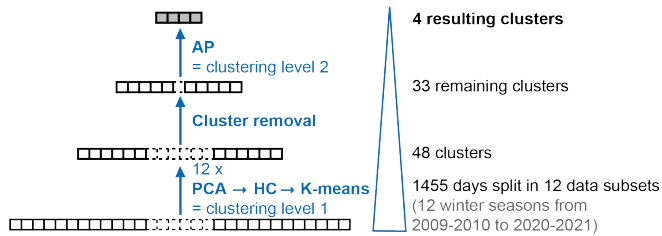


Fig. 1. Schematic and applied representation of the multilevel clustering process

During this first level, each method has a specific role.

First, PCA aims to reduce the data dimensionality while preserving most of the variation of the original data points. This way, it reduces the problem dimension, simplifies results in interpretation after classification, and removes a part of the included noise in the data subset due to the nature of the studied phenomenon. PCA is the most widely used dimensionality reduction technique. It transforms the 90 variables into a reduced number of principal components. Each component corresponds to a linear combination of the initial variables. The first components only are truly informative as they contain most of the variability. We select three principal components as they contain most of the initial variability (from 84.5% to 90.5% according to the data subset) and are well explainable. The first one corresponds to the opposition between dry and wet days, and the second and third components correspond to North / South and East / West oppositions.

Then, HC and K-means are run in sequence to take advantage of both methods. As we do not know the expected number of clusters and do not want to presume it, we use HC to automatically extract the most appropriate one for the given data subset. HC creates clusters by aggregating elements two by two. During the successive iterations, the method creates from $x - 1$ clusters to a sole cluster (which contains all the x individuals). We use the euclidean distance and Wards criterion [19], which minimizes the loss of between-clusters inertia when aggregating two clusters. To set the number of clusters, we keep the partition with the biggest relative loss of inertia. Then, as during HC's iteration, when an individual is misclassified, it remains so until the end, we use K-means to improve the classification and refine the result. Indeed, during K-means iterations, individuals can move from one cluster to another. K-means is thus consolidation of the HC's result. Processing K-means after HC makes it possible to avoid a random initialization:

- the number of clusters is estimated by HC,
- the initial starting centroids are set to the centers of the gravity of HC's clusters.

Thus, using K-means and HC in sequence allows the development of a generic process transferable to other areas (e.g., on Swiss Alps data) without requiring any input expert knowledge. HC suggests generating between three and seven clusters according to the data subset. Applying K-means with

this k number of clusters, the first level clustering process finally outputs 48 clusters from the 12 data subsets.

The stepwise classification process (PCA → HC → K-means) does not always detect all the trends included in the dataset it processes. That means that here, some trends effectively contained in a data subset may remain undetected. For this reason, it is essential to process this sequence on several data subsets to increase the possible detection of all the existing trends. Here is the interest to consider 1455 days, split into 12 data subsets. Conversely, the sequence sometimes detects several clusters corresponding to the same trend, i.e., clusters with differences in intensity (high or low rainfall total quantity) but all impacting the same areas.

In addition, the sequence also detects clusters that correspond to the days with very few or no rainfalls. As we are working in the context of avalanche risk, there is no interest for these clusters as they do not correspond to an important enough overload to impact the snowpacks stability and generate avalanche activity. Consequently, we set aside these clusters before the second level of clustering. Thus, for the second level of clustering, it remains 33 clusters.

To summarize, at the end of the first level of clustering (i.e., at the end of the PCA → HC → K-means sequence) processed on each given data subset, there may be both missing trends and trends detected multiple times. By processing this sequence on 12 data subsets, we solve the problem of missing trends by increasing the possibility for each one to be detected at least once. Conversely, it increases the number of trends that are detected several times. In the end, the multilevel clustering process has to output only one cluster per trend. That is why we process the second level of clustering.

B. Second level: AP

The second level of clustering aims to merge all the results of the first level into a final global one. So the second level of clustering outputs only one final cluster for each detected trend. The second level aims to classify the former clusters (the ones resulting from the first level) that are similar, i.e., that correspond to the same trend, whatever the intensity of the rainfalls. Clusters' centroids are not directly taken as new individuals for the second level because the values on the three components given by PCA are in a specific referential given by the calculation of the PCA on each data subset independently. Coming back to all the initial 90 variables (precipitations amounts) makes it possible to have a common referential.

For this clustering level, we decide to use the AP method [6] as it neither requires setting the number of clusters nor choosing an initial set of points. This algorithm considers each individual as a potential exemplar and uses a similarity matrix between all the individuals two by two to obtain clusters. The AP's unsupervised version set by default the median value of the similarity matrix for the preference value of the algorithm. If, as mentioned in the literature from other fields [13] [6], it usually gives too big of a number of clusters, it is not the case at this stage. We tried to use AP directly after PCA at the first level clustering (instead of HC and K-means),

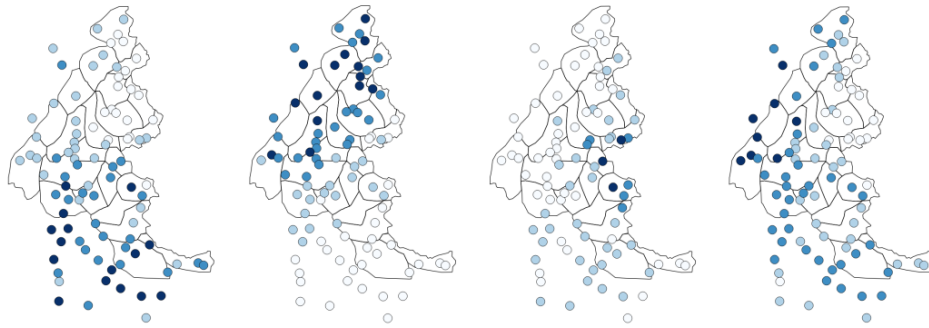


Fig. 2. Visualization of the four resulting clusters and the location of their areas mainly affected by rainfalls (from white to dark blue points: no or very few rainfalls to high rainfall totals)

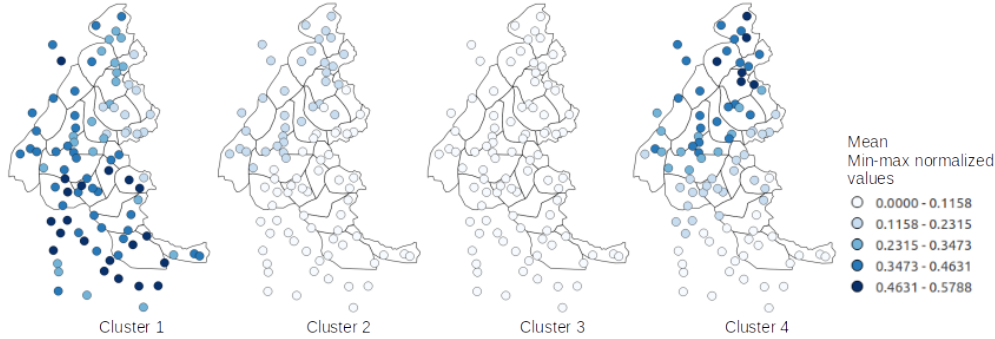


Fig. 3. Clustering (PCA \rightarrow K-means) on the entire dataset (i.e., 12 winter seasons), with $k=4$

and we effectively got too many clusters. But here, as we are working on preprocessed data (the individuals processed here are means obtained from the first level of clustering), the preference value fixed by default gives an appropriate number of clusters as output. In AP, the higher the preference value is, the lower is the number of final clusters. The ratio between the preference value and the maximum value of the similarity matrix is approximately 40% at this second level, whereas it was approximately 1% when using AP at the first level clustering. Thus, the preference value is at this stage considerably increased. This difference explains the former observation. We conclude that AP with the preference value set by default outputs a correct number of clusters to satisfy the objective of this second level of clustering.

The second level of clustering finally outputs a single cluster per weather trend. It correctly returns all the detected weather trends spotted during the previous level. As a result, the multilevel clustering process provides four final clusters that correspond to four weather trends (Figure 2).

We presently know that four different meteorological trends may be detected in the 12 winter seasons dataset. Let us see which result gives K-means algorithm directly leads on the three main components extracting by PCA on the whole dataset (i.e., 12 winter seasons), with a random initialization and $k = 4$. It only detects two different trends. Clusters 1 and 4 (Figure 3) correspond to these two trends (with the same range of intensity). And, one of these trends appears three times with three different intensities (see clusters 2, 3, and 4 on Figure

3). Thus, applying K-means on the entire dataset does not give an optimum result (as solely two out of the four possible trends are detected, and as a sole trend is given several times). It emphasizes that the multilevel clustering process produces better outputs.

IV. ASSESSMENT OF THE CRITICAL AREAS ASSOCIATED WITH A SITUATION

The multilevel clustering process finally gives a first idea of the rough areas that are mainly affected by rainfalls according to each detected weather trend (Figure 2). At this stage, to define and be able to assess the *Recent Avalanche Observation* parameter as presented in Section II, it is necessary to assess distinct levels of criticality of the different areas for each trend. Then, it determines the influencing zone of an avalanche observation. Areas will be more or less *critical* according to the total amount of new rainfall they receive, i.e., according to the new overload (as rainfalls are presently the only parameter we consider to estimate the notion of similar conditions in the multilevel clustering process).

A. Areas' criticality assessment due to overload according to each trend

The objective is to determine, for each trend, the areas that are more or less critical according to the new rainfall amount they received. Areas associated with high rainfall totals will be the most critical, whereas areas that received the fewest rainfall totals will be the less critical for a given trend.

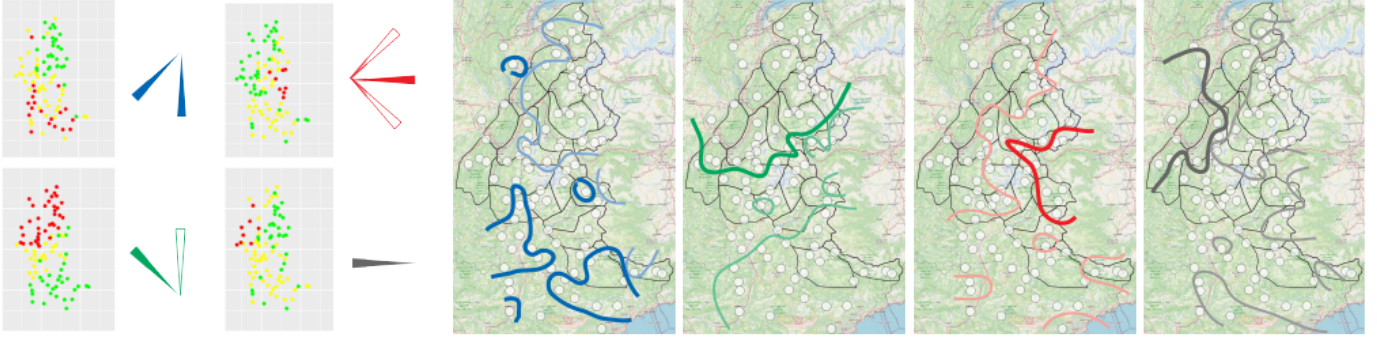


Fig. 4. Visualization of area's criticality according to the four detected trends. left: clustering results among the 90 measuring stations (three levels of criticality: red, yellow, and green), and wind direction (main direction and associated directions); right: location on a map of the associated areas for each trend (blue, green, red, gray)

For this purpose, we apply a clustering method to the 90 measuring stations spread over the French Alps. We identify, by extension, the areas that receive similar precipitations. In this section, the individuals to classify are the measuring stations. There is a sole variable for each clustering: the variable is the centroid of the final cluster obtained by the multilevel clustering process. We process the clustering four times to extract areas' criticality for the four final trends.

As we know the number of clusters we are looking for, we directly use the K-means algorithm. We expect three clusters as output for each trend in order to identify three level of criticality: *high*, *intermediate*, and *low*. We initialize K-means with $k = 3$ and let a random initialization of the initial centroids. We run K-means 100 times with the random initialization and keep the result which maximizes the ratio: $\frac{bSS}{tSS}$, where bSS is the between-clusters sum of squares, and tSS is the total sum of squares.

By applying the K-means algorithm on each of the four detected trends separately, we obtain three gradual zones for each trend. Figure 4 illustrates the results. We identify each trend thanks to the dominant orientation of the wind that induces it: 1) most impacted area located in the southern part of the French Alps that corresponds to a flux mostly coming from South or South-West directions, represented in blue; 2) most impacted area located in the northern part of the French Alps that corresponds to a flux coming from North-West, represented in green; 3) most impacted area located in the eastern side of the French Alps that corresponds to a flux coming back from the East, represented in red; 4) most impacted area located in the western part of the French Alps that corresponds to a flux coming mostly from the West, affecting, the pre-alpine massifs, represented in gray.

B. Automatic estimation of the situation

The determined areas above directly intervene in the description of the *Recent Avalanche Observation* parameter. To fill it, for a given recent avalanche observation, the system has to determine the situation which is in progress (i.e., the trend associated with the day that leads to avalanching). Thus, the zoning of the corresponding trend will be the one that makes sense for the situation to assess.

To estimate the corresponding trend, we calculate the distance between the day and each of the four detected trend. We consider an euclidean distance, based on the 90 available values associated to the trend and the 90 measures recorded for the given day. We then affect the day to the closest trend. This way, for a given day, the user knows which are the most critical areas, according to the meteorological situation (Figure 4: red means high criticality, yellow means intermediate criticality, and green means low criticality). Thus, thanks to the meteorological conditions (i.e., the rainfall totals on 90 stations for a given day), the process estimates the trend and the zoning of the more or less critical areas.

As we only studied rainfalls in the multilevel clustering process and as we only take one day here into consideration, this assessment is valid for natural avalanches, as 1) overload induced by new precipitations is the main parameter that induces natural avalanches, and 2) these avalanches are spontaneous and generally trigger just after a new overload (1 day). To transfer this assessment to all possible types of avalanches 1) the multilevel clustering process (Section III) should include other variables (like temperature and wind) to analyze the weather conditions, and 2) the assessment of the trend that leads to avalanching should consider here several days as more complex evolutions lead to accidental avalanches. Both assumptions are possible follow-ups to the work presented in this paper.

Then, depending on the location of the observed avalanche, the criticalities associated with the different zones may be worsen. Thus, the location of the observed avalanche has to be taken into account. Indeed, the avalanche did not necessarily occur in the most critical area (i.e., the red one). If the avalanche occurred in the other ones (yellow or green), that means that the conditions in the other areas are sufficient to cause avalanches. In this case, they must themselves be associated with high levels criticality. The other zones, which are already considered more critical based on the meteorological conditions, are then at least as critical, and the initially lower criticality zones must also be made worse. Thus, the criticality levels of the three colored zones are maintained or increased according to the location of the avalanche observed :

- If the avalanche occurred in the red zone, the sole criticality of the red zone is *high*, the yellow one stays *intermediate*, and the green one *low*.
- If the avalanche occurred in the yellow zone, both the criticality of the yellow and red zones are *high* and the green one will be *intermediate*. Both yellow and green zones are worsen.
- If the avalanche occurred in the green zone, the criticalities of the three zones are *high*, as even the zone with the lowest precipitations led to an avalanche.

Finally, only one final value will be given to the *Recent Avalanche Observation* parameter, according to the destination of the user. The parameter receives thus a criticality level which depends on 1) the trend that leads to the avalanche, 2) the location of the avalanche, and 3) the location where the user plan to go.

We can now obtain the *Recent Avalanche Observation* parameter using a rigorous and transparent approach. Such proposed approach is generic enough to be then associated with most of the existing decision-support methods of the literature [9]. Section V presents a global system that uses this parameter and combines it with several others. We apply this development on the CRISTAL approach.

V. GLOBAL SYSTEM: APPLICATION TO THE CRISTAL APPROACH

Within the range of existing decision-support methods [9], the CRISTAL approach [5] has a particularity: CRISTAL provides, at the decision-making stage, concrete choices which are consistent with the carried out analysis. CRISTAL is indeed built on three steps: detection, analysis, and decision. The formalization of the last two steps allows going beyond the "all-or-nothing" result proposed in most methods. CRISTAL outputs four gradual vigilance modes associated with appropriate behaviors to adopt during the practice. These four vigilance modes are: *relax*, *suspicious*, *alert* and *gamble*. CRISTAL relies on a reduced number of parameters. Duclos [4] is indeed talking about "*simple, measurable and debatable indicators*". These parameters are: 1) *Danger level of the avalanche bulletin*, 2) *Slope angle*, 3) *Recent Avalanche Observation*, 4) *Temperature rise, Thawing*, 5) *New overload*, and 6) *Weak layer*. CRISTAL relies thus on six danger indicators, which have to be checked as a priority to determine which of the four vigilance modes is the most appropriate to the situation. Earlier works are the foundations of these six parameters [11] [12]. In 2012, thresholds and values were proposed to estimate the parameters [4]. They were then considered too simplistic by Duclos, who decided to revert to a qualitative version of the six parameters in 2018 pending more precise formalization work. The work described in this paper is part of this evolution.

We specifically deal with the CRISTAL's danger detection phase. The CRISTAL approach helps users find the most appropriate behavior according to the assessed situation and reduces the surprise effect. Thus, CRISTAL aims to make people aware of the danger based on tangible indicators. In

addition, the way to output the vigilance mode according to the six parameters is not formalized yet. For these reasons, CRISTAL illustrates well the work presented in this paper: this method requires to describe all the needed parameters and then combine them into a final vigilance mode.

When applying this work to the CRISTAL approach, the *Recent Avalanche Observation* parameter relies on sub-parameters, such as the number of observed avalanches, their size, and their location. The process presented in sections III and IV allows to set automatically the criticality value of the *Location* sub-parameter.

The *Danger level* of the avalanche bulletin is one of the six parameters of CRISTAL. As it already corresponds to a coarse-grained assessment of the avalanche danger and is not a parameter that acts on the danger level (as others do), we decide to let it aside. We finally combine the five remaining parameters (and consequently their sub-parameters).

We propose a global system based on two aggregation levels to improve the CRISTAL detection phase. Indeed, to be consistent with the first objective of the CRISTAL approach, which was to combine only a small number of parameters, we decide not to aggregate all the emerging sub-parameters at once. Both aggregation levels are as follow:

- A first aggregation level to combine the sub-parameters (relative to one main parameter) into the corresponding parameter. That means the global system requires five first aggregation levels conducted in parallel.
- A second aggregation level to combine the five parameters and obtain the output vigilance mode.

Figure 5 presents the principle of the global system. It emphasizes especially the second aggregation level.

Both aggregations are built in the same way and by following the same method for their development. We present the method we follow, illustrated on the basis of the second level.

1) List all the possible values the parameters can take. We collaborated with the expert for this work. The number of values associated with each parameter differs depending on the parameter considered. It indeed depends on the expert's ability to differentiate more or fewer nuances on each of them. Here, we assigned 3 or 4 gradual levels of output values for each parameter on the following model: *low*, *moderate*, *considerable*, and *high*. We highlighted three possible values for the *Slope angle* parameter, four for *Recent Avalanche Observation*, three for *Temperature rise, Thawing*, three for *New overload*, and four for the *Weak layer* (Figure 5).

2) Extract expert rules to combine the parameters with their different possible values and output a final result. First, we stated the simplest rules as they contain no ambiguity. They often correspond to the extreme ones. For example, in case each of the five parameters takes the value *low*, then the output vigilance mode is *relax*. Conversely, if all five parameters are set to *high*, the output vigilance mode is *gamble*. In addition to these extreme rules, we also stated the rules that lead to extreme output (i.e., *relax* or *gamble* vigilance modes) as they contain very little ambiguity. For example, if the *Slope angle* parameter is *low*, experts know that no avalanche may

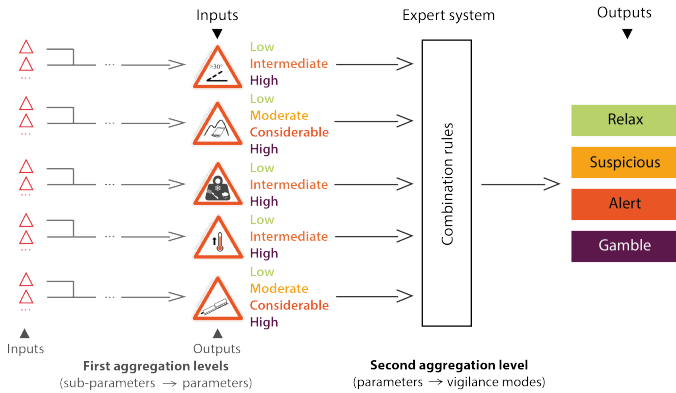


Fig. 5. Schematic representation of the global system

be triggered. In this case, whatever the values set to other parameters, the output is *relax*. Then, according to the possible values highlighted by the first step, we can calculate the total number of combinations: $3 \times 4 \times 3 \times 3 \times 4 = 432$. All the remaining rules are finally stated to consider the 432 possible combinations.

Then comes the additional step of testing and validating the system in the field: does the global system give the same output values as those that an expert would estimate for given conditions? If necessary, we will slightly change the rules to better match the expert's way of thinking.

Thus, we formalize and make explicit an expert process that allows the transition from the six parameters of CRISTAL to the four vigilance modes. We may use fuzzy logic [1] [3] [20] to generate a more flexible system, i.e., a system that outputs intermediate situations instead of a sharp and unique vigilance mode. It will make it possible to improve the management of the output's gradualness. It will, in addition, make it possible to keep some room for customization for the users. Indeed, the automatization in assessing the parameters (as is the case here with the *Location* parameter) reduces the flexibility available to users but the fuzzy system output membership degrees to the four vigilance mode, which leaves the user a final margin of interpretation and the choice in the final decision. We used the jFuzzyLogic library [2] to implement the fuzzy global system. A clear example of stated rules is expressed below using the FCL language [2]:

```

IF P2 IS Intermediate AND
    P3 IS Moderate AND
    P4 IS Low AND
    P5 IS Intermediate AND
    P6 IS Moderate

```

```

THEN Vigilance Mode IS Suspicious

```

where P2 to P6 correspond to the five input parameters combined by the system.

According to the obtained vigilance mode, the method advises the user, for the decision step, to avoid, reduce or also change the itinerary. Thus, a behavior to adopt on the field corresponds to each vigilance mode. A practical example illustrates this assessment by describing the analysis and decision steps (see Figure 6 to follow the global process in

the case of this example). If the global system outputs the *Suspicious* vigilance mode according to the terrain, snow, and weather monitored parameters, then the analysis phase of the system asks him to assess if he can avoid the danger or not. If yes, by avoiding the danger, he stays in the *Suspicious* vigilance mode (Figure 6-a). Avalanche is only possible close by his planned route. Else, if he can not avoid the danger, he has to assess if he can take mitigation measures. Whatever his answer, his state of mind has to change, and he will enter at least in the *Alert* vigilance mode. Indeed, if he takes mitigation measures to reduce the risk, he will be in the *Alert* vigilance mode (Figure 6-b), else, he will move to the *Gamble* vigilance mode (Figure 6-c) and have to change his project as identified signs indicate that avalanche is possible on the planned route and he can neither avoid it nor reduce the risk.

Then the following example illustrates, in addition, the benefits of a fuzzy system. We first remember that in *Suspicious* mode, one will try to avoid the danger, in *Alert* mode, to reduce the risk. Thanks to the different membership degrees obtained in the output of a fuzzy system, for example, 0.8 for the *Suspicious* mode and 0.2 for the *Alert* mode, the skier will be more on his guard than a skier only in the *Suspicious* mode. He will, therefore, take some extra precautions to consider reducing the risk and thus avoiding any surprise effect. Else, if he deems it necessary, he may also reiterate the process by reassessing the parameters that played a major role in the process in order to clarify the result.

VI. CONCLUSION

In this paper, we deal with the description of the parameters included in a decision-support method and the combination of its parameters into a final result. We applied our work to CRISTAL, which is an approach that supports users to go toward a good decision in avalanche risk assessment. This approach relies on six main parameters. All these parameters are presently qualitative in CRISTAL and they thus have to be broken down into sub-parameters to be clarified. That generates groups of sub-parameters. All sub-parameters are combined group by group to estimate the main parameters. Similarly, the parameters are then combined to output the final result of the global system.

First, this paper presented the description and automatization of the sub-parameter *Location* from the parameter *Recent Avalanche Observation* of CRISTAL approach. We focused, in this work, on this particular parameter as it is direct evidence of snow instability and a clear sign of avalanche danger. The developed process results in a precise solution to assess the value set to the sub-parameter when using it in the global system. Its automatization reduces the biases that a user can introduce when he estimates the sub-parameter without any precise guidelines or framework.

To formalize this sub-parameter, we developed a generic and transferable multilevel clustering process to extract the main weather trends affecting an area. Indeed, a sole level of clustering on the entire dataset does not capture the different trends (based on the location of the rainfalls), whereas working

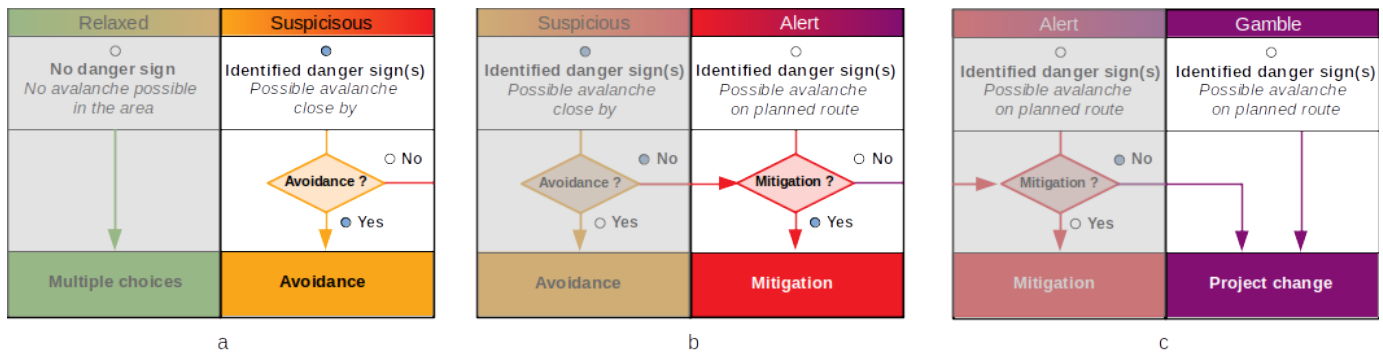


Fig. 6. Decision-making stage: concrete choices consistent with the analysis

on subsets does. The multilevel clustering process makes it possible to work on data subsets and merge the results. This clustering approach may be useful for a range of applications that depend on weather context factors, even for other scales and locations. It may also be useful for other applications for which working on a large dataset or on smaller subsets does not detect clusters with the same characteristics (as it is the case here with the *intensity* and the *location* of the precipitations). Then, we assessed the criticality level of different areas according to each detected weather trend. To make a correct assessment of the parameter, the process analyzes a targeted day and the location of recently observed avalanches. Thus, this paper proposes a first approach to quantify the size of the area to consider when observing a new avalanche in the field. This area corresponds to the one that encountered similar conditions as the one which was avalanching, and it, therefore, corresponds to a high danger level area. This work leads to a rigorous and transparent approach to assessing this parameter. Moreover, the approach is generic enough to be used in conjunction with the other decision-support methods.

Finally, all the parameters of CRISTAL are organized and combined to give a final result. This paper described the formalization and the elucidation of the way to go from the parameters of CRISTAL to the four vigilance modes.

A follow-up to this work is to make the developed assessment of the sub-parameter *Location* valid in the case of accidental avalanches.

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