How JMP® Can Help Determine the Type of Surface Collapse Over Abandoned Mines

Yves Gueniffey, PhD, Assistant Professor, École des Mines de Nancy, France
yves.gueniffey@mines-nancy.univ-lorraine.fr

ABSTRACT:

Surface collapse is a major problem that follows many active or abandoned underground workings. Collapses result from roof deformation of underground workings, and/or controlled or uncontrolled rock caving. The uncontrolled rock caving could result in surface instability problems and loss of materials and/or human lives. Over the last century, and as a result of underground-uncontrolled rock caving, major accidents due to surface collapse have been reported in France. Some of these collapses were sudden and violent, happened over a few minutes and up to a few hours, and led to loss of life. Others occurred progressively, within a few days, and with fewer effects on the surface environment. The sudden occurrence of these accidents is of big interest in order to be able to predict the risk induced by abandoned underground mines, especially in areas where we've built cities and where people live. The objective of this presentation is to show how JMP data analysis platforms (Principal Component Analysis, Discriminant Analysis and Partition Modelling) help define criteria of accident rapidity where it is probable to occur according to the site's geotechnical and exploitation properties.

1 INTRODUCTION

The French Lorraine iron ore basin extends over 1700 square kilometers in the eastern part of France and involves more than 150 cities. Figure 1 shows a geographical situation map of the basin. The basin had been worked out since the 19th and 20th centuries. In 1997 the industrial extraction of the deposit came to an end, leaving almost 40 000 km of galleries in the Lorraine underground, a void volume of 3 billions cubic meters.

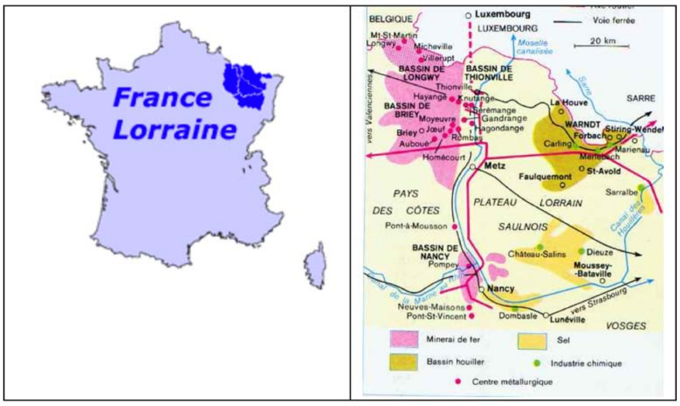


Figure 1. Geographical situation of the Lorraine iron basin

The method of exploitation consisted of rooms and pillars of various shapes followed by integral stooping (Figure 2). In cases where the remained pillars were taken off, surface collapse occurred in a more or less controlled way, and in order to consider surface structures (houses, roads, infrastructure, etc.), the method of exploitation consisted of leaving in place "enough" amount of pillars (varying from 80% to 30%) in order to prevent uncontrolled collapse from occurring.

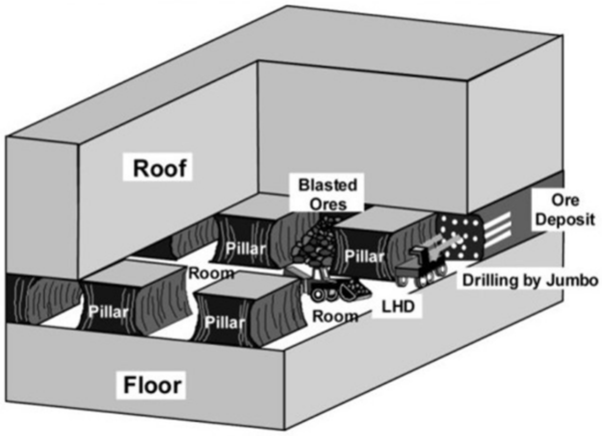


Figure 2. Room and pillar mining.

Unfortunately, the percentage of pillars left in place depended largely on the experience rather than depending on long-term stability analysis.

On numerous occasions during its exploitation, the Lorraine Iron Basin was at the centre stage of uncontrolled subsidence having important effects on the surface. The oldest recorded event goes back in 1902. The most recent one in 2012.

The history of well-known subsidence phenomena across this basin have brought about the distinction of two types: those that happen with sudden surface movement (in a matter of seconds), and those that happen over time (a few days, even months). Some of these events have been to such a scale that the houses have been expropriated because of the extent of the damage.

With the end of mining activity (1997) and the sale of miners' dwellings, the question of subsidence, hitherto an industrial hazard, became an environmental risk. The damage caused by mining, an issue previously addressed privately by the owners, became the responsibility of government services (GEODERIS) when mining concessions were handed over to the State.

This increased concern of regional authority led GEODERIS to try to define for the basin (where geological situations are almost the same) a criterion of discrimination between situations (underground workings) where brutal collapses are likely to happen and others where progressive ones are to be expected.

In 1998, GEODERIS experts have started with a back-analysis of the cases already happened during the 20th century and they finally selected 16 “reference” accidents of unpredicted collapses in the basin.

We performed a statistical data analysis taking into consideration all available information.

With the aid of techniques like Principal Components Analysis (PCA) and Discriminant Analysis (DA), we were able to define such criterion (2000).

Since this first study, GEODERIS experts have identified other areas where subsidence literature searches and archives have been undertaken. Furthermore, several of subsidence phenomena occurred in the years 2000. An update of the base of mining subsidence and collapse was possible. This research has allowed to identify 70 cases, including the 16 reference cases used up to now.

We have then performed a new statistical data analysis, and compared the new results with the old ones (2014).

2 GEOLOGICAL AND GEOTECHNICAL ASPECTS

Tincelin (1959) pointed out that in order to expect a brutal collapse, three geological conditions have to take place. These three conditions are;

1. the existence of a hard rock seam at the roof of the extracted iron bed;
2. the existence of a hard rock seam near the surface;
3. and the existence of an adjacent valley.

According to the geological study of the accidents' areas, GEODERIS experts were not able to prove that these criterions were discriminant due to the fact that in many situations where progressive collapse happened, these three conditions were also present. This fact allowed them to say that there might be some geological conditions that could favour the existence of brutal collapse, but they cannot just rely only on these three conditions for an overall discrimination in the basin.

One of the major problems that experts have faced in working out on the back analysis is that in two adjacent situations, with the same geotechnical and geological conditions, brutal and progressive collapses occurred. This fact led them to conclude that not only geotechnical and geological conditions can discriminate between these two types of collapse, but they have to be coupled with geometrical conditions of extraction (ratio between extracted ore and ore left in place, size of pillars, depth, etc.).

3 FIRST STATISTICAL DATA ANALYSIS (2000)

In 1998, GEODERIS experts have selected 16 “reference” accidents of unpredicted collapses in the basin. Eight of them happened in a sudden and brutal way and led in sometimes to loss of life (brutal), while others happened in a progressive way and led only to the destruction of houses and infrastructures (progressive). They localized and reported any geological, geotechnical, or geometrical aspects over these 16 cases.

3.1 *Data collection and preparation*

Among the collected variables in the subsided zones, experts have chosen these seven measured or observed variables:

- width of rooms (m) *“W_Gal”*;
- depth of the subsided zone (m) *“H”*;
- thickness of exploited seams (m) *“W”*;
- *“C_surch”,* a constant parameter characterizing whether the subsided zone is adjacent to other zones of exploitation (virgin zone, a zone adjacent to a caved zone, and a zone surrounded by caved zones).

The collected variables included also calculated variables that have physical significance:

- ratio between volume extracted and initial volume in place (%) *“Defruit”*.
- Hydraulic diameter of pillars (m) *“Diam_hydr”*.
- maximum stress applied to pillars (MPa) *“Sigma_tot”*
- *“Type”*, the type of observed collapse (Progressive or Brutal).

We have also assigned an ID for each individual.

3.2 *Principal Components Analysis (PCA)*

In order to see the relationships between our seven parameters, we first performed a Principal Component Analysis (PCA). PCA is a multivariate technique of data analysis in which all continuous variables are simultaneously considered. The general purpose of this analysis is first to “X-Ray” the set of original variables, and second to find a way of condensing the information contained in the original variables into a smaller set of new composite dimensions (components) with a minimum loss of information (Hair et al., 1992).

Here, the PCA was conducted on the correlation matrix to overcome the heterogeneity of quantitative variables. We also have used a qualitative variable *Type* to distinguish by colour the two types of collapse on the different plots (red=brutal-blue=progressive).

In a multivariate space of n dimensions, each variable in the model counts for one dimension. The eigenvalues of the correlation matrix might be thought of as the amount of variability that is included in each eigenvector, i.e. the amount of variability included in each component. Depending on the amount of variability that included in each component, we can decide to keep only a limited number of components that include most of the variability of the model.

Our objective of using this type of factor analysis was to try to find from all collected variables, the ones that have significant representation of the population of 16 individuals. This technique allowed us to know which observed/calculated variables are correlated with the type of collapse and though could be used in the discriminant process.

Figure 3 shows the plot of *correlation circle*, or *loading plot*, i.e. projection of the observed variables, over planes defined by "First and Second" components of the PCA.

In the principal component analysis, we can also make a projection of the individuals over the different planes defined by different components. The coordinates of each individual present their values with respect to different principal components. Figures 4 shows the projection of individuals over the factorial plane defines by components 1 & 2.

From these projections over the first, second components, we were able to remark that:

- The first factorial plane or *Score Plot* (1 & 2) include 66,5% of the variability of the model.
- From the projection of individuals over the factorial plane 1 & 2, we can see clearly a visual discrimination between brutal and progressive collapses. This fact led us to concentrate on the factorial plane 1 & 2 in order to extract the variables that could enhance the discrimination between the individuals.
- The three variables *Defruit*, *Sigma_tot,* and *W_gal* seem to characterize the separation between the two types of collapses.

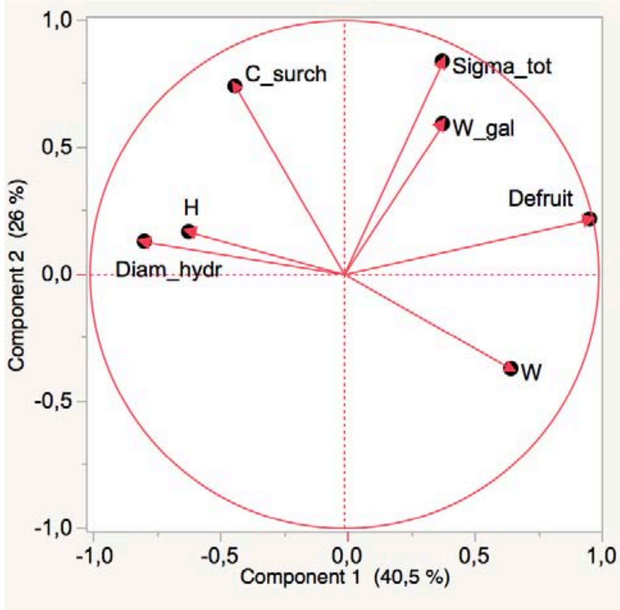


Figure 1. Correlation circle: Factor plot of variables over the factorial plane defined by the first two components of the factor analysis (JMP loading plot)

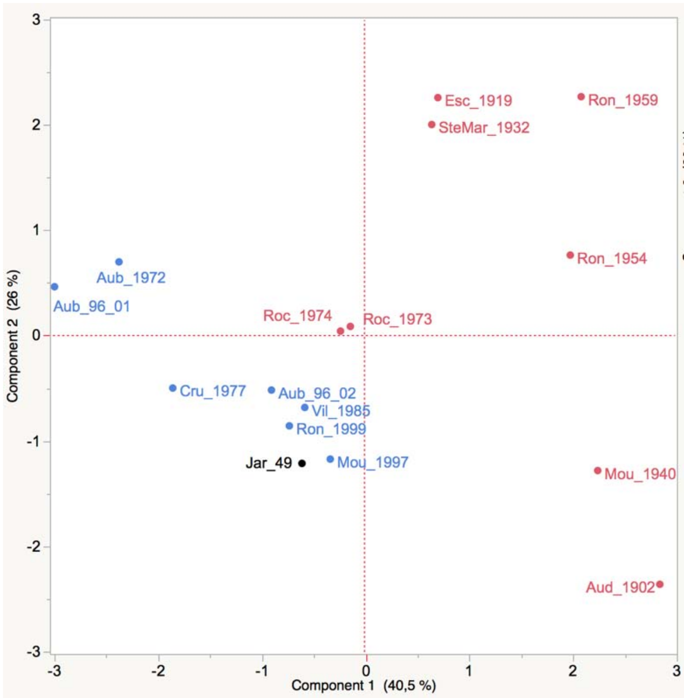
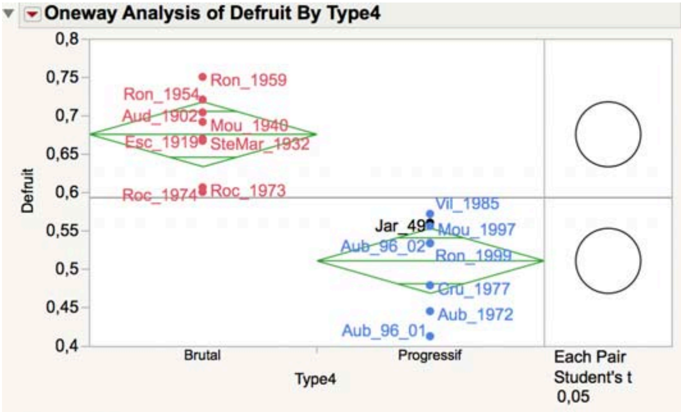


Figure 4. Projection of 16 "historical" collapses over the factorial plane 1 & 2 red=brutal blue=progressive (JMP score plot)

3.3 *Discriminant Analysis*

We wanted to find the best way to distinguish between the two types of collapse. The analysis of variance is the right method to choose the best continuous variable able to do so. We have performed one-way analysis of variance on each of the seven continuous variables, and the three variables that discriminate the 2 types of collapse (α= 5%), are, in descending order of power, *Defruit*, *Sigma_tot,* and *Diam_hydr.* Fig 4 shows the JMP results for *Defruit.*



Excluded Rows 55

Oneway Anova

Summary of Fit

t Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Type4	1	0,10890584	0,108906	34,9450	<,0001*
Error	14	0,04363090	0,003116		
C. Total	15	0,15253674			

Figure 4. One-way Analysis of *Defruit* by *Type*

The Discriminant Analysis (DA) is the appropriate statistical multivariate technique when we want to use the whole set of independent continuous variables "at the same time" to define a discriminant function. Hair et al. (1992).

This technique is also widely used in many situations where the objective is to identify the group to which an object belongs.

In our case, the discriminant analysis is to be used in order to define a discriminant function that separates our population of individuals (collapses) into the two observed groups (brutal and progressive).

As mentioned earlier in the principal components analysis and in the one-way analysis of variance, we were able to define a group of variables (those highly correlated with the first and second components) to be included in the discriminant analysis and that the variable *Defruit* is most likely, the best one to start with.

Discriminant analysis could be performed in a *simultaneous* approach, i.e., all independent variables are considered concurrently, or it could be done in *stepwise* approach, i.e. variables are entered one by one into the discriminant function depending on their discriminating power.

The simultaneous approach is appropriate when, for theoretical reasons, the analyst wants to include all the independent variables in the analysis and is not interested in seeing intermediate results based only on the most discriminating variables. The GEODERIS experts have required such a result: for geotechnical reasons, they wanted to use a discriminant function with all the 7 parameters (continuous variables) they have identified.

3.3.1 *Results of the discriminant analysis*

Figure 5 presents the score summaries resulting of this discriminant analysis. There is no surprise: all the collapses are well classified.

Score Summaries

Source	Count	Number Misclassified	Percent Misclassified	Entropy RSquare	-2LogLikelihood
Training	16	0	0,00000	0,99971	0,00646

Training

Actual Type2	Predicted Count Brutal	Progressive
Brutal	8	0
Progressive	0	8

Figure 5. Score Summaries.

Figure 6 presents a graph of projection of individuals, over the resulting discriminant function Canon(1). As the discriminant function has only one dimension (there are only two groups of collapses), the X axis and the Y axis both plot the same canonical coordinates for presentation purpose only. The two categories of individuals are perfectly discriminated on the graph.

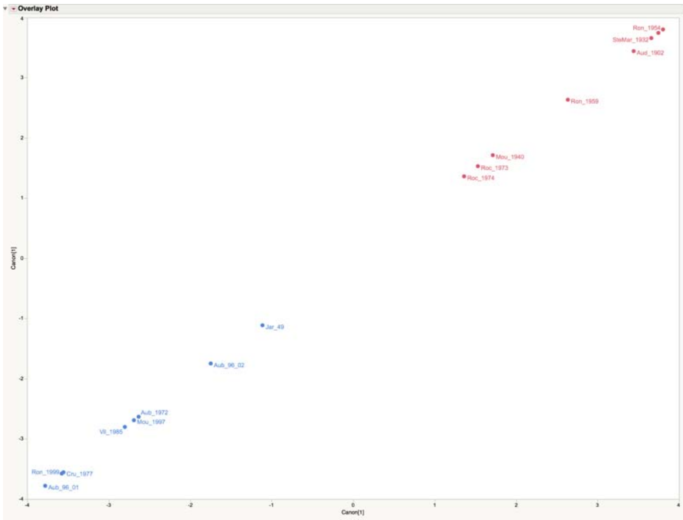


Figure 6. 16 collapses projected over the discriminant dimension.

We were able to define, with the help of site's experts a discriminant function that could be used in the discrimination of new studied zones, or zones of high importance to the society.

This statistical analysis has contributed to the definition of hazard map where one can provide areas of likely to subside in a brutal way and others likely to subside in a progressive way. Figure 7 shows an example of such a map.

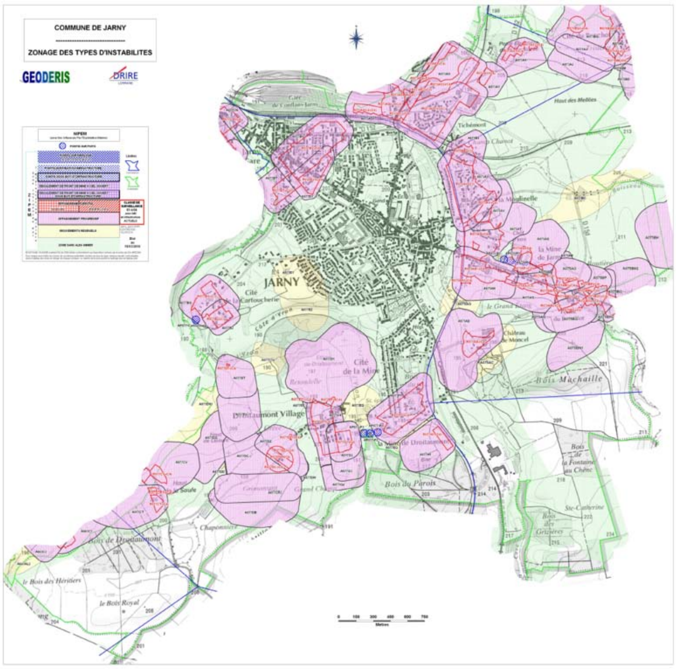


Figure 7. Example of a hazard zones map

4 SECOND STATISTICAL DATA ANALYSIS (2014)

4.1 *Introduction*

Since this first study in 1999, GEODERIS experts have identified other areas where subsidence literature searches and archives have been undertaken. Furthermore, several of subsidence phenomena occurred in the years 2000. An update of the base of mining subsidence and collapse was possible. This 2014 research has identified 70 cases, including the 16 reference cases used up to now. But experts have only identified the type for 31 collapses: the previous 8 as brutal, and 23 as progressive. They were unable to assign a type to the other 39.

We have then performed a new statistical data analysis, and compared the new results with the old ones (2014).

4.2 *Principal Components Analysis (PCA)*

A new PCA is made considering only 31 collapses that we know to be either brutal (8) or progressive (23) as “active” individuals. The other 39 collapses which we do not know the type are taken as “additional” individuals. We use the same 7 parameters (variables) as before.

Figure 8 shows the new *correlation circle*, or *loading plot*, i.e. projection of the observed variables over planes defined by “First and Second” components of the factor analysis. And Figure 9 shows the projection of individuals over the factorial plane defined by components 1 & 2.

From these plots, we are able to remark that:

- The first factorial plane or *Score Plot* (1 & 2) include 66,5% of the variability of the model.
- From the projection of individuals over the factorial plane 1 & 2, we can still see a visual discrimination between brutal and progressive collapses.
- The three variables *Defruit*, *Sigma_tot, W_gal* seem to characterize this separation between the two types of collapses.

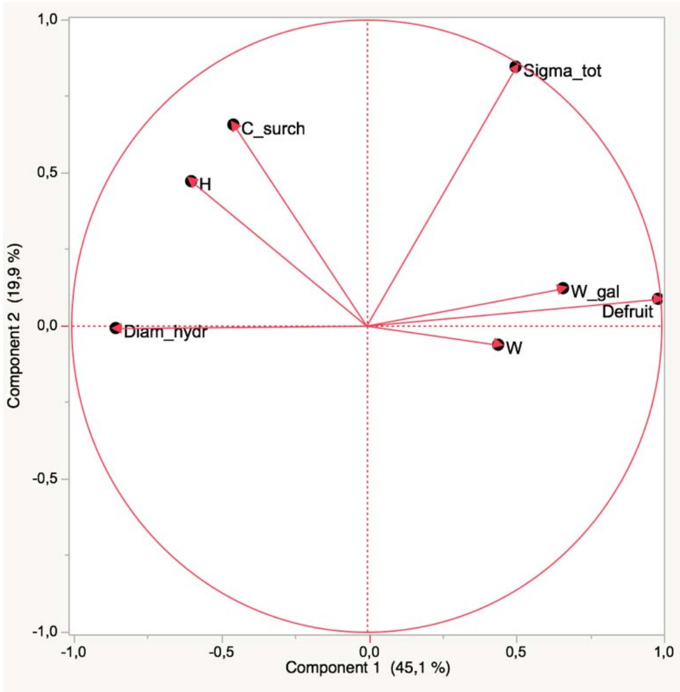


Figure 8. Factor plot of variables over the factorial plane defined by the first two components of the factor analysis (JMP loading plot)

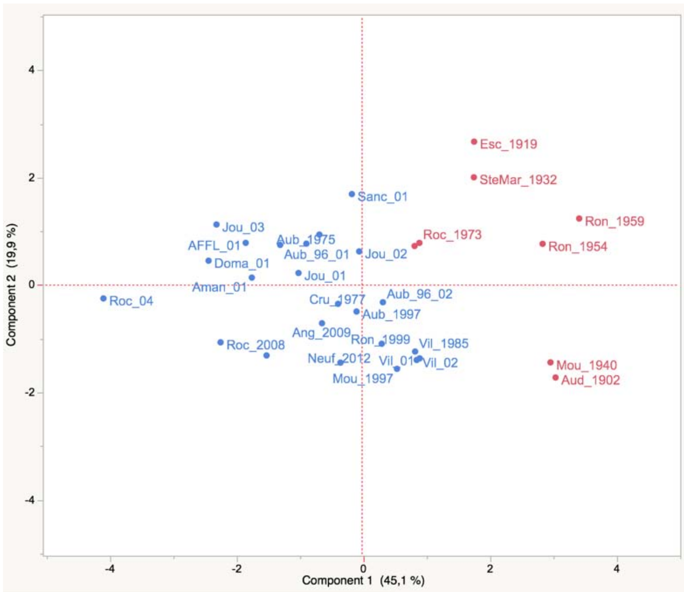


Figure 9. Projection of 31 known collapses over the factorial plane 1 & 2 8 red=brutal 23 blue=progressive (JMP score plot)

JMP don’t give directly the projections of 39 “supplementary” individuals over the factorial plane 1 & 2. But we can save their coordinates over the first two factorial axes, and then use an overlay plot to get the projections of the 70 points over the factorial plane 1 & 2 (Figure 9). So we can have an idea about the type of collapse for the 39 “unknown” individuals (black points).

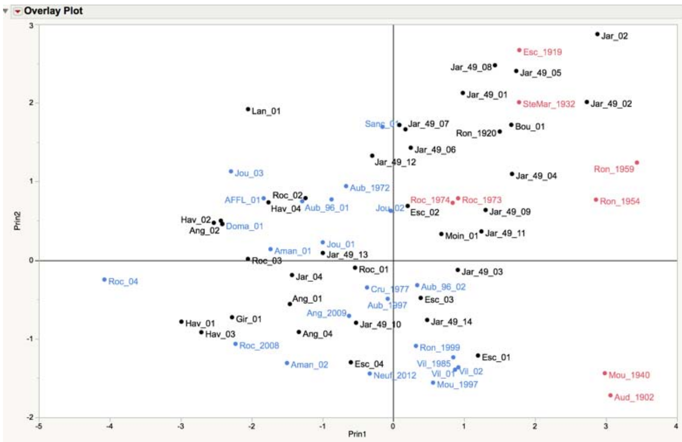
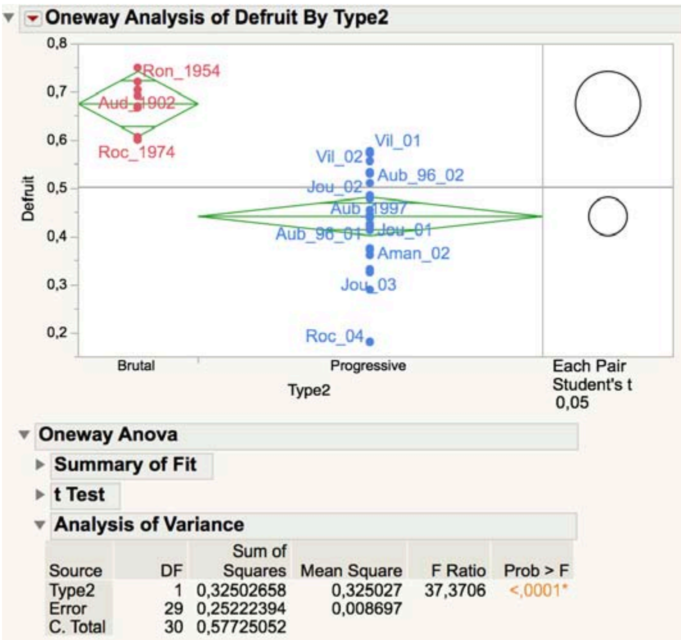


Figure 9. Projection of the 70 collapses over the factorial plane 1 & 2 8 red=brutal 23 blue=progressive 39 black=unknown (JMP score plot)

4.3 *Discriminant Analysis*

We have also performed analysis of variance on each of the 7 continuous variables, still considering only 31 collapses that we know to be either brutal (8) or progressive (23). We find 5 variables that discriminate the 2 types of collapse (α= 5%), in descending order of power, *Defruit*, *Sigma_tot, Diam_hydr, W* and *W_gal.* Fig 10 shows the JMP results for *Defruit.*



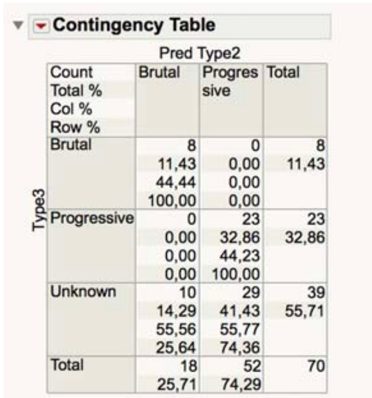
Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Type2	1	0,32502658	0,325027	37,3706	<,0001*
Error	29	0,25222394	0,008697		
C. Total	30	0,57725052			

Figure 10. One-way Analysis of *Defruit* by *Type*

For the same reasons explained before, we have then performed a Discriminant Analysis (DA) to get a discriminant function with all the seven parameters (continuous variables) GEODERIS experts have identified. This DA has been trained on the sample of the 31 collapses whose type is known: either brutal or progressive. So the resulting discriminant function has only one dimension. This new discriminant function is of course different from the first one obtained in 2000, because we used 31 collapses (8 brutal and 23 progressive) to train it. The previous function used only 16 (8+8) cases.

4.3.1 *Results of the discriminant analysis*

Figure presents the group membership resulting of this discriminant analysis. There is no surprise: all the collapses whose type is known are perfectly classified. More interesting, the 39 collapses whose type is initially unknown are now classified: 10 get the brutal type and 29 the progressive one.



Contingency Table

Type3	Count / Total % / Col % / Row %	Pred Type2: Brutal	Pred Type2: Progressive	Total
Brutal	Count	8	0	8
	Total %	11,43	0,00	11,43
	Col %	44,44	0,00	
	Row %	100,00	0,00	
Progressive	Count	0	23	23
	Total %	0,00	32,86	32,86
	Col %	0,00	44,23	
	Row %	0,00	100,00	
Unknown	Count	10	29	39
	Total %	14,29	41,43	55,71
	Col %	55,56	55,77	
	Row %	25,64	74,36	
Total	Count	18	52	70
	Total %	25,71	74,29	

Figure 11. Group membership of 70 collapses

Figure 12 presents a graph of projection of individuals, over the resulting discriminant function Canon(1). As the discriminant function has only one dimension, the X axis and the Y axis both plot the same canonical coordinates for presentation purpose only. The two categories of the 31 individuals whose type is known are perfectly discriminated on the graph. The “black points” refer to the 39 “unknown” individuals.

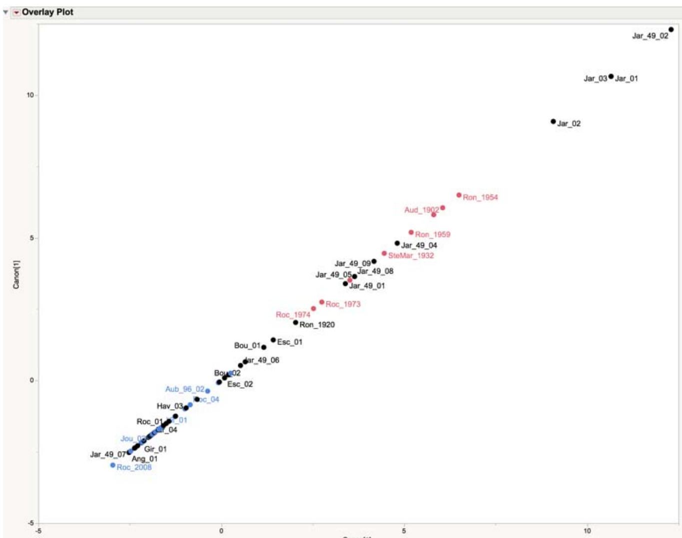


Figure 12. 70 collapses projected over the discriminant dimension.

This analysis of 70 events establishes an operational discriminant function which still mainly uses variables *Defruit* and *Sigma_tot* is not very different from the first function. The results are similar :

- 8 sudden collapses are properly classified as brutal ; 23 progressive collapses are properly classified as progressive.
- 10 of the 39 unknown collapses are classified as brutal and 29 as progressive.

The principle of hazard qualification consists then of combining criteria to characterize the collapses; for instance, geological criteria are used to further examine the 10 collapses classified as brutal by the discriminant analysis. *The final hazard maps are the result of the whole process of expertise*.

5 CONCLUSION: JMP AND STATISTICAL EXPERTISE

In the context of the difficult management of the “Post-Mining” phase, French Authorities have developed a technical and administrative tool: The Mining Risk Prevention Plans (MRPP). MRPP aim to identify the most sensitive areas subject to “post mining hazards” and to define technical and regulation rules able to manage the principles of the future urbanism development on surface (Didier and Leloup, 2005).
According to the French law, experts in charge of the evaluation have to work *given the state of knowledge.* The first question, concerning the existence of potential sources of hazard, is basically relative to the confidence or trust of the experts regarding the data they collected. In the context of MRPP, concerning for example the problems of surface instabilities, the sources of hazard are clearly the old mining infrastructures (underground workings, shafts, etc.).
Experts are limited by the quality of the information they can collect in the field or in archives. They usually have to face problems concerning the reliability of the mining maps (incompleteness, bad adjustment in comparison to surface, etc., cf. Figure 13), the informal nature of several data (oral statements, newspaper articles, etc.) or the difficulty to analyze events that occurred in the past (past collapse that is no more visible on surface at the time of the study, etc.).

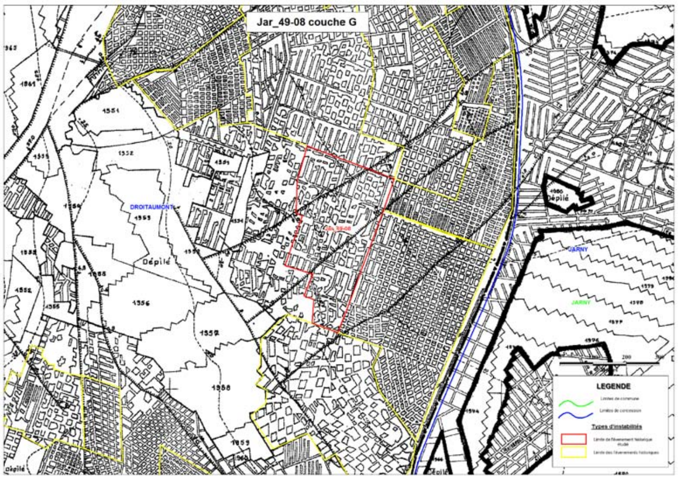


Figure 13. Example of mining map

In this field of applied science and technology where the regime of proof is not the laboratory one (the “true *versus* false” dichotomy is no longer relevant), the statistician is the expert who deals with uncertainty, who explains the results in terms of confidence interval. And he naturally finds his place in the process of expertise alongside his geotechnical colleagues, psycho-sociologists, planners, etc.
That's where JMP expresses all its qualities of decision support tool. Its extreme friendliness allows the statistician to be very reactive in expert meetings and immediately test the assumptions of each other (what if ?).
Statistical analyzes presented here are very simple and can even seem sketchy, but when they are associated with dynamic visualizations (e.g. use of pictures illustrating some points on a factorial plane), they contribute to the enrichment of cross interpretations of experts.

But in fact, when it’s time to assess ‘*how stable the situation is’*, we are talking in terms of risk and acceptance. It is now up to the stakeholders, not just to the experts or the engineers, to decide whether the situation is acceptable or not, and whether uncertainty on the result has to be reduced or not. And a kind of *L’Aquila syndrome* is not so far (Figure 14).

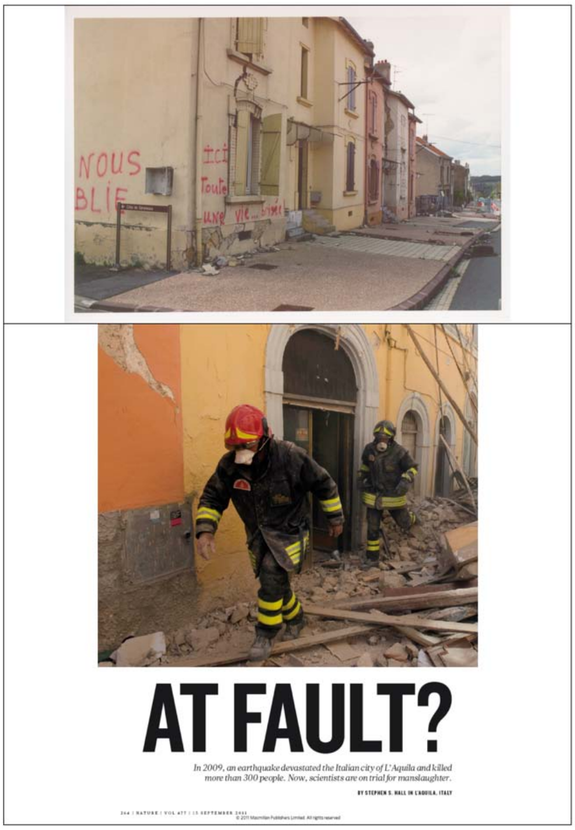


Figure 14. At Fault?

6 REFERENCES

Abbott, A., Nosengo, N., 2014. Scientists cleared of quake deaths. Nature, Vol. 515, 13 November 2014.

Cauvin, M., Verdel, Th., Salmon, R., Didier, Ch. 2006. Mapping expert uncertainties or confidence level in mining risk prevention plans. ECI Conference on geohazards 2006, Lillehammer, Norway.

Didier, Ch., Leloup, J. The MRPP: a powerful operational regulatory tool to prevent and manage post-mining risks. Symposium Post mining 2005, Nov 2005, Nancy, France.

Didier, Ch. The French experience of post-mining management. Symposium Post-Mining 2008, Feb 2008, Nancy, France. ASGA. Vandœuvre-les-Nancy,

Duchêne, F. 2008. Les affaissements miniers dans le bassin ferrifère lorrain: quand le territoire re-politise la gestion du risque. Développement durable & territoires. Dossier 11: Catastrophes et Territoires. (http://developpementdurable.revues.org/7073)

Elshayeb, Y.& Kouniali, S. & Josien, J.-P. & Gueniffey, Y., 2000. Towards the determination of surface collapse type over abandoned mines in the Lorraine iron basin. Eurock 2001 Espoo.

GEODERIS, 2014. Bassin ferrifère lorrain. Liste et caractéristiques géométriques de 70 mouvements de terrains recensés.

Hair, J.F. & Anderson, R.E. & Tatham, R.L. & Black, W.C. 1992. Multivariate data analysis with readings. Third edition. Macmillan Publishing Company.

Hall, S., 2011. At Fault? Nature, Vol. 477, 15 September 2011.

Tincelin, E. 1959. Effondrements spontanés de certains quartiers constatés dans les mines de fer de Lorraine. Rapport École des Mines de Paris.