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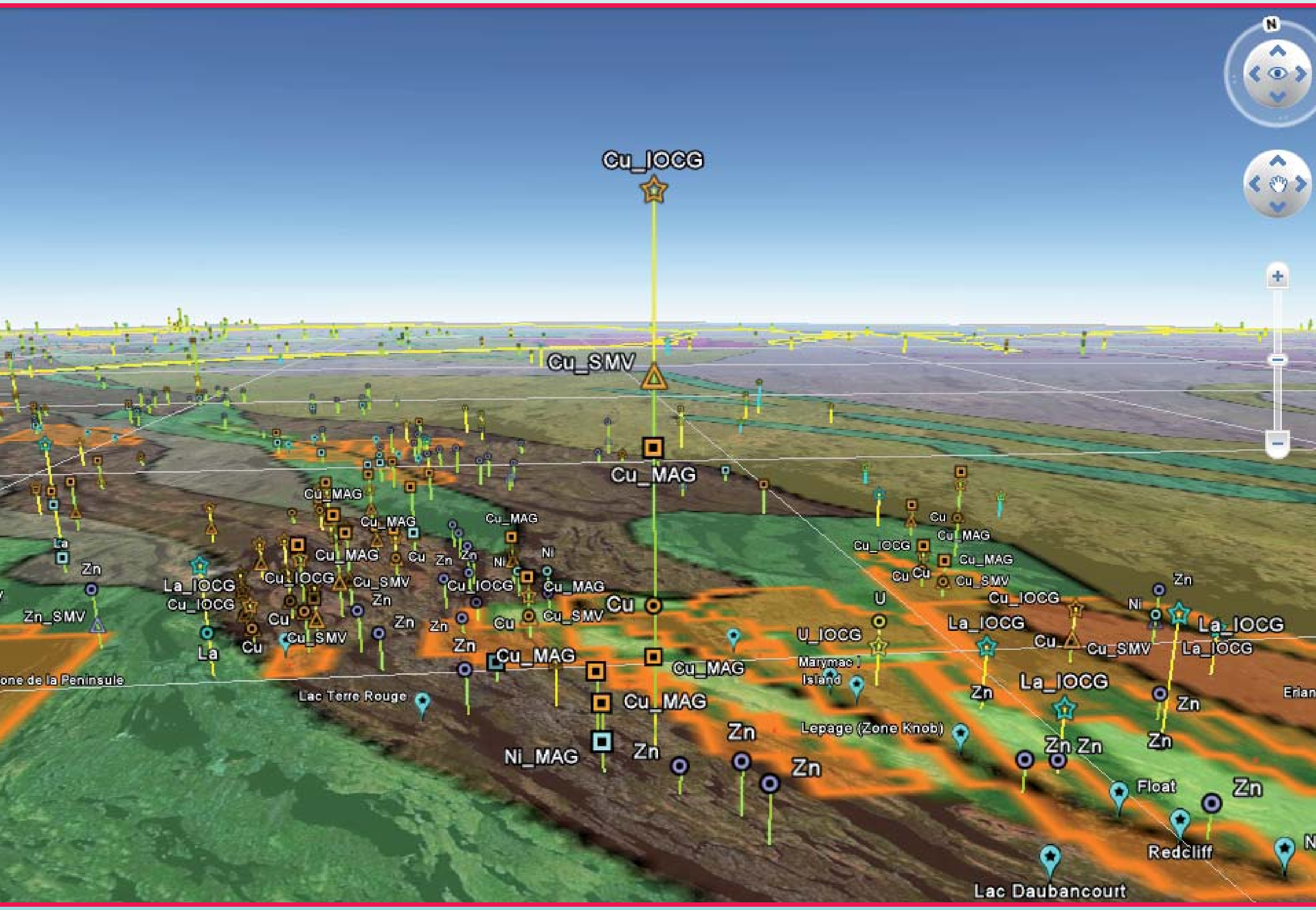
Modelling targets in the secondary environment by the natural break and multivariate spatial regression techniques



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Abstract

This study comprises two parts. The first part presents a method for creating an atlas of anomalous geochemical zones for all types of sediment samples from the secondary environment (lakes, streams, tills and soils) available in the SIGÉOM database. The atlas constitutes a useful land management tool for establishing protected areas, particularly in the under-explored northern parts of the province. The focus is on 11 metals of economic interest: Ag, As, Au, Co, Cu, Li, Mo, Ni, U, Y and Zn. Using a ModelBuilder model, anomalous zones were defined for each element and sample type using a natural break method based on populations from geological domains considered to be relatively homogenous. The favourability of these zones was calculated using the weight of evidence method.

The second part focuses specifically on defining lake sediment targets using a method of multivariate spatial regression. This method is very effective for determining exploration targets using samples that did not initially yield significant anomalous values. It was used to build a database of discrete targets for: 1) a group of five elements (Cu, La, Ni, U, Zn) associated with monometallic deposits; 2) a group of two elements (Cu, Zn) associated with volcanogenic massive sulphide (VMS) deposits; 3) a group of two elements (Ni, Cu) associated with magmatic Ni-Cu deposits; and 4) a group of three elements (Cu, U, La) associated with iron oxide deposits enriched in Cu-U-REE. The present model used a database of 90,844 samples, of which 43,336 were reanalyzed by ICPMS for 53 elements in 2008-2009. The results allowed the samples to be levelled for the following 18 elements: Al, Ba, Ca, Ce, Co, Cr, Cu, Fe, K, La, Mg, Mn, Ni, P, Ti, U, V and Zn.

The digital products accompanying this document comprise: 1) Interpolated grids for the secondary environment in ArcGIS, ASCII or PDF format. The grids integrate lake, stream, till and soil data for 11 (unlevelled) elements from across the province. 2) Polygons of favourable zones determined for nine elements in the secondary environment (Ag, As, Co, Cu, Mo, Ni, U, Y and Zn). These polygons are provided in ArcGIS and Google Earth formats. 3) A folder containing, in ArcGIS format, any of the proposed targets that were unstaked as of October 31, 2009. 4) Multivariate spatial regression targets divided according to metallogenetic context in ArcGIS and Google Earth file formats. 5) Interpolated grids of levelled values for each of the 18 elements used in this study, available in ArcGIS, ASCII and Google Earth formats.

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INTRODUCTION

Study Objectives

The objective of the first part of this study is to produce an atlas of anomalous geochemical zones for all types of samples from sedimentary environments (lakes, streams, tills and soils) available in the SIGÉOM database. It focuses on 11 metals of economic interest: silver, arsenic, cobalt, copper, lithium, molybdenum, nickel, gold, uranium, yttrium and zinc. The analytical results used in the various modelling steps for this first part represent raw and unlevelled data (see the section "Part 2 – Discrete lake sediment targets defined by the multivariate spatial regression method"). Data processing for each element was designed to minimize fluctuations in the values caused by different analytical methods and the different lithological assemblages found in each geological province. This atlas of anomalous geochemical zones constitutes a useful land management tool for establishing protected areas, particularly in the under-explored northern parts of the province. This atlas also has implications for geological exploration because it delineates many areas with elevated potential for discovering new deposits[1].

The second part of the study focuses more specifically on the concept of mineral potential based on the analyzed contents of lake sediments. This approach is identical to the one used by Trépanier (2006) in a study conducted for CONSOREM[2], which defined geochemical domains using this same type of sediment. The study presented various techniques that can be used to distinguish a sample's anomalous component from its regional (typically background) component. Among these techniques, the multivariate spatial regression analysis proved particularly effective in targeting some anomalous zones where samples did not initially show significantly anomalous values. This method was used to build a database of discrete targets[3] for: 1) a group of five elements (Cu, La, Ni, U, Zn) associated with monometallic deposits; 2) a group of two elements (Cu, Zn) associated with volcanogenic massive sulphide (VMS) deposits; 3) a group of two elements (Ni, Cu) associated with magmatic Ni-Cu deposits; and 4) a group of three elements (Cu, U, La) associated with iron oxide deposits enriched in Cu-U-REE. This study also provides raster images for the following 18 levelled elements: Al, Ba, Ca, Ce, Co, Cr, Cu, Fe, K, La, Mg, Mn, Ni, P, Ti, U, V and Zn. An updated version incorporating the results of the ICPMS reanalysis for the Baie-James region will be published in Google Earth format in 2010.

PART 1 – ANOMALOUS GEOCHEMICAL ZONES IN THE SECONDARY ENVIRONMENT DEFINED BY THE NATURAL BREAK METHOD

The total area of protected land in Québec will increase from 8.2% to 12% by 2015[4]. A large portion of the new areas proposed by the MDDEP are in the northern portion of the province where the level of geological knowledge is relatively low. When areas are assigned protected status, staking and other mineral exploration activities are banned, so it is important to assess the mineral potential of these target regions before they are officially designated as protected areas. As such, analytical data from the secondary environment constitute the best source of information for assessing the mineral potential of these little known regions.

The SIGÉOM[5] database contains almost half a million sediment samples from the secondary environment, including lake, stream, till and soil samples (Table 1). The objectives of the first part of this study are to: 1) develop, for 11 elements of economic interest (Ag, As, Au, Co, Cu, Li, Mo, Ni, U, Y and Zn), a province-wide overview of the information stored in the database; and 2) define the anomalous thresholds for each type of sample using populations from geological domains considered to be homogenous.

1- Favourable zones in the secondary environment, as generated by the natural break method, were published in ArcGIS format in GM 64290 in November 2009; they are also available for download in Google Earth format at the following website address: http://www.mrnf.gouv.qc.ca/english/mines/publications/publications-maps.jsp. Both these products are included in the digital data accompanying this document.

2- Consortium de Recherche en Exploration Minérale, Université du Québec à Chicoutimi.

3- The targets are available in digital ArcGIS format or in Google Earth format in the digital data accompanying this document. The Google Earth data are also available for download from the following website address: http://www.mrnf.gouv.qc.ca/english/mines/publications/publications-maps.jsp.

4- Statement made by Jean Charest, La Presse, November 15, 2008.

5- The MRNF's "Geomining Information System" (in French: "Système d'Information Géominière").

Table 1 – Type and number of samples in the SIGÉOM database.

Type	Number
Lake	126 368
Stream	230 362
Till	40 931
Soil	76 036
Total	473 697

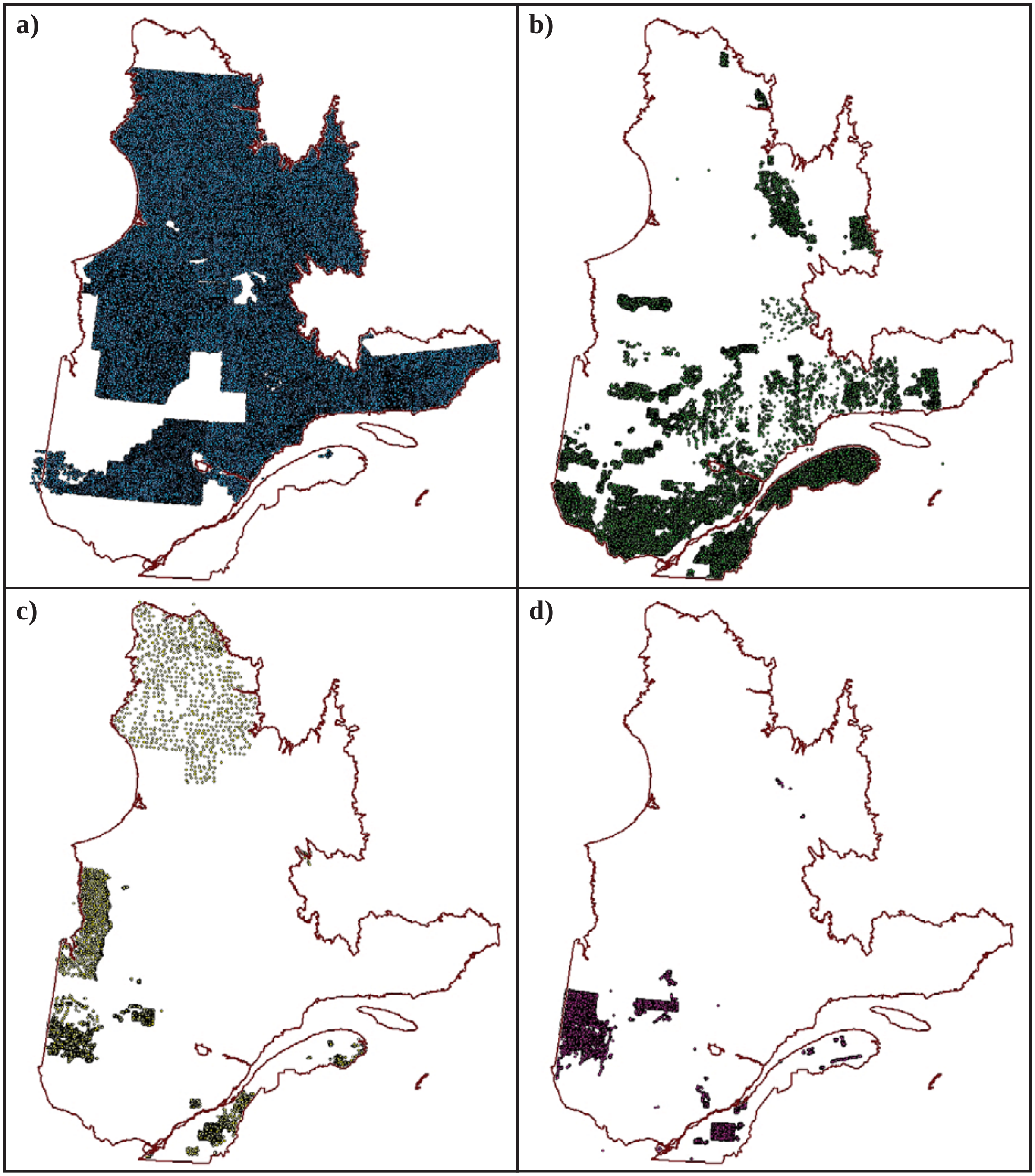

FIGURE 1 – Locations of: **a**) lake sediment samples; **b**) stream sediment samples; **c**) till samples; and **d**) soil samples.

Methodology

The first part consists of four steps:

1. Define geological domains with largely homogenous lithological characteristics.
2. Create a ModelBuilder application for each substance that defines 25 classes of values based on sample type, analytical method, and lithological setting. The goal of the application is to create an image of value classes defined by the natural break method for lake, stream, till and soil samples.
3. Using the raster image of the 25 natural break classes for each element, apply a weight of evidence (WofE) weighting method to determine the effective prediction threshold for mineral deposits containing that element.
4. Convert the predictive classes for each element into vector polygons that define favourable zones in the secondary environment (FZSE) for that particular element.

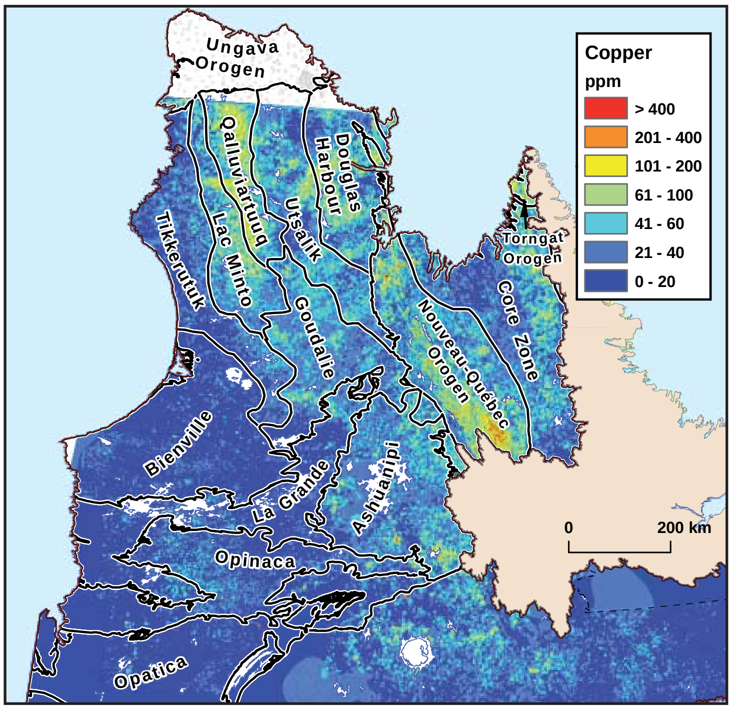

FIGURE 2 – Map of copper in lake sediments from the Far North region (modified from Lamothe, 2009). The influence of geological domains (represented by various subprovinces and lithotectonic assemblages) on the distribution of copper is well illustrated.

Defining homogenous geological domains

Since the goal of the model is to define, for all of Québec, anomalous thresholds for each of the 11 processed elements, it is important that these thresholds be determined using geochemical populations belonging to an area of land with a relatively homogenous lithological and geological setting. As shown in figures 2 and 3, the regional signature for most of the elements in a secondary environment is clearly controlled by the underlying lithological setting. The first step in this part of the study was thus to define coherent geological or lithological blocks corresponding to geochemical populations that we can assume to be distinct. In the case of the Superior and Churchill provinces, the known subprovinces and major geological divisions are, by definition, consistent with the concept of a coherent geological block (Table 2; Figure 3). For the Grenville Province, six assemblages of related lithologies were distinguished[1]. No subdivisions were created for the Appalachian Province or Paleozoic platforms.

1- The compilation by Davidson (1998) was used to determine the lithological divisions. Volcanic rocks were grouped with meta-sedimentary rocks due to their very low volume.

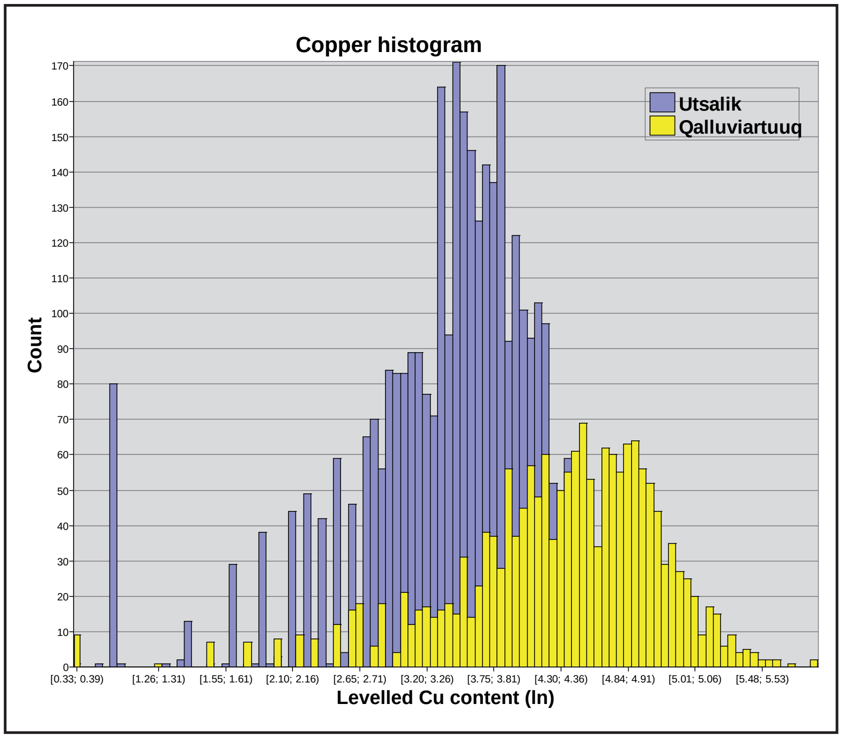

FIGURE 3 - Histogram of natural log values for copper from the Utsalik and Qalluviartuuq domains (see Figure 2) showing that the Qalluviartuuq Domain is relatively enriched in this metal.

TABLE 2 – The geological and lithological subdivisions used for the natural break method.

Province	Geological domains
Paleozoic platforms	St. Lawrence and Hudson Bay platforms
Appalachians	no subdivisions
Grenville	Anorthosite and mafic or ultramafic intrusions – Charnockite – Granitoids and granitic gneiss– Late granite and pegmatite – Syenite and monzonite – Sediments and volcanics
Churchill	Torngat Orogen – Nouveau-Québec Orogen – Ungava Orogen – Core Zone
Superior	Proterozoic sedimentary basins – Abitibi – Ashuanipi – Bienville – Douglas Harbour – Goudalie – La Grande – Lac Minto – Opatica – Opinaca – Qalluviartuuq – Tikkerutuk – Utsalik

Creating a ModelBuilder model

In order to define the classes of anomalous values for each substance, 11 customized ModelBuilder[1] models were created (one per substance). The following set of operations was executed by each model (Appendix I):

1. Using an FGDB database built from SIGÉOM, extract data from the different sample populations in the secondary environment database according to analytical method (excluding water samples). The 473,697 samples are divided into distinct groups according to the analytical method historically used for each element (atomic absorption (AA), neutron activation (NA), plasma emission, ICPMS, or fluorimetry). These subsets are processed separately to avoid grouping together analyses with different detection limits ($CU_{AAlimit}$ = 1 ppm; $CU_{ICPMSlimit}$ = 10 ppb) or different sample preparation methods (CU_{AA} vs. CU_{AN}). Steps 2 to 14 below are sequentially executed for each analytical method available per processed element.
2. Separate each analytical population into 9 subtypes of sediment according to survey type and the nature of the sample (lake, stream1, soil3, till2, etc.; Table 3 and Appendix 1). The chosen classification method was optimized for soil and till samples to avoid creating populations that would be too small to break into 25 classes, as required in step 10.

1- ModelBuilder is an graphical application of ArcGIS that manages models using any of the processing and spatial analysis tools available in the release of version 9.x and 10.

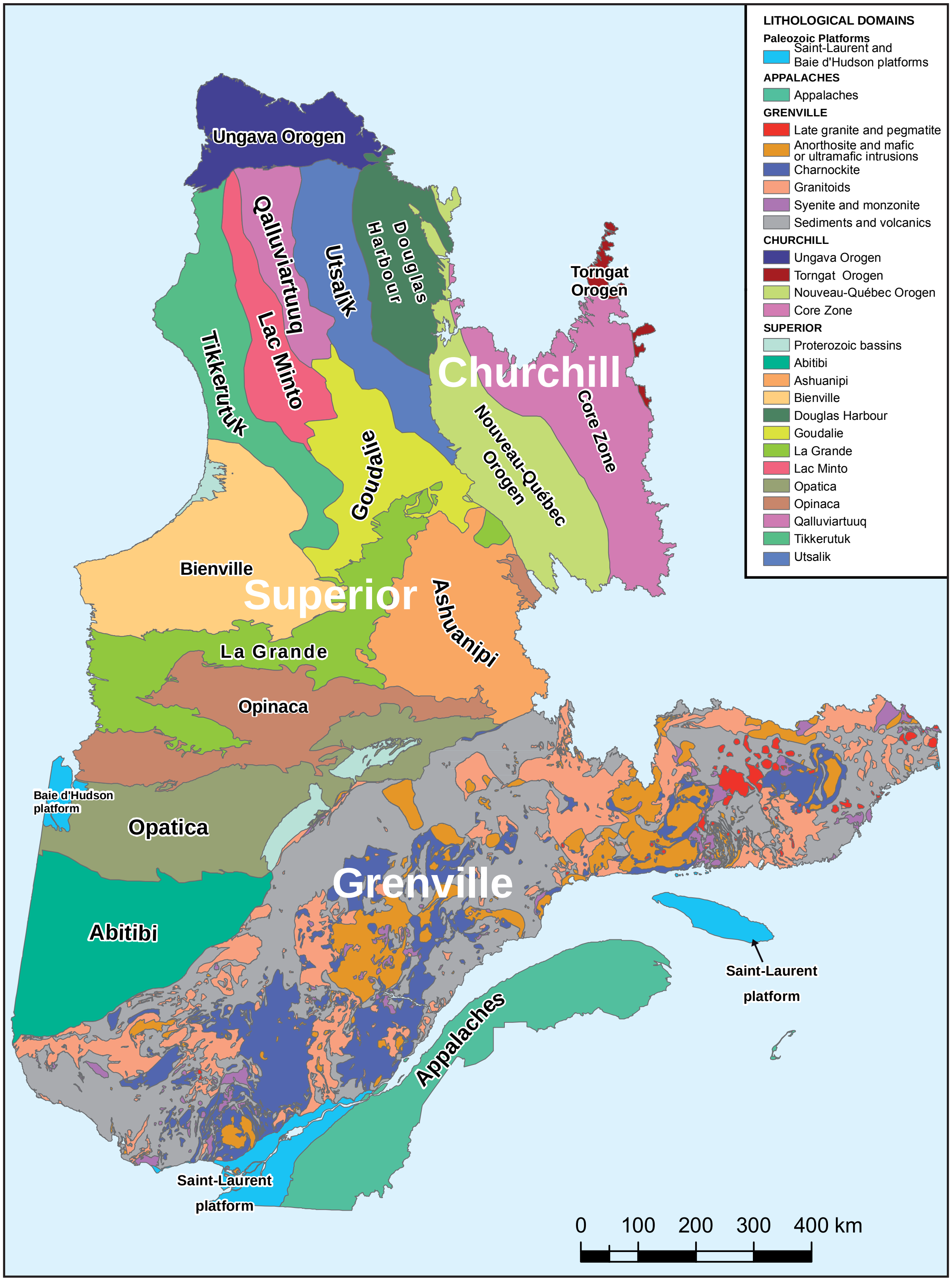

FIGURE 4 - Homogenous geological domains used in the ModelBuilder model.

3. Use the natural neighbour method to interpolate the values for each sample subtype across the province of Québec. Natural neighbour interpolation identifies samples adjacent to the point being assessed and applies a weight that is proportional to the shared surface between them. The application of this technique is local and lends itself particularly well to sample collections with highly variable sampling densities, which is characteristic of the database in question (Figure 1).
4. Apply a distance buffer around the sample points belonging to each subgroup (Table 4) to avoid extending values to unreasonable distances during the interpolation. The distance buffer varies as a function of a substance's mobility and the nature of the sample. Distances for stream and lake samples are estimated using the work of Cameron (1977), one of the rare studies on the dispersion of economic elements in the secondary environment around a mineral deposit. Soil sample values are systematically limited to a distance of 500 m, which is the size of the cells making up the interpolation grid covering Québec. The distances for the till samples are arbitrarily defined as equal to or less than the distances for the stream samples.
5. Produce a map of Québec showing the geochemical values for each analytical method by combining the images created for each sediment subtype into a single image. In the case of overlapping pixels for values from different sediment types, the highest value prevails.
6. Produce a geochemical map for Québec showing raw values for each processed element. During this step, the interpolated geochemical values for all analytical methods are combined into a single image in a way that respects a hierarchy of reliability for the analytical methods[1] (Table 5). For example, all of the pixels taken from the image of the ICPMS geochemical values generated in step 5 are reproduced in the final geochemical map; in the case of a missing ICPMS value, the value of the second most reliable method for the element from Table 5 is used to fill the void in that area; once this exercise is finished for the second most reliable method, any remaining empty pixels will be filled by the third most reliable method for that element, and so on until all analytical methods have been incorporated.
7. Produce a map of percentile classes for raw values combining all sediment subtypes and all analytical methods.
8. Convert the buffered interpolated values generated by step 4 into natural log.
9. Extract the converted natural log values for each group of sediments defined in step 2 and sort by geological domain (Figure 4).
10. Divide the values for each geological domain population into 25 classes using the natural break method (Jenks, 1967). This method produces well-defined natural groupings within a range of values by using the presence of pronounced variations in the values as a basis for defining break points between the classes. In contrast to the percentile or standard deviation methods, classes are not defined by arbitrarily assigned thresholds, but by variations intrinsic to the values of the study population. In the present case, however, the number of classes (25) is arbitrary. The method used for determining the anomalous thresholds dividing the 25 classes is presented in the next section, "Determining effective prediction thresholds".
11. For each of the 9 sediment subtypes defined in step 2, combine the 25 natural break classes representing geological domains to create 9 natural break mosaics for each of the analytical methods.
12. Recombine the 9 sediment groups into four main types (lake, stream, till and soil). The two subtypes of stream sediments (undifferentiated and heavy minerals) are combined to create a single image for the stream sediments. The same process is done for the three subtypes of soil sediment, as well as for the three till groups (Table 3), thus creating a single image for soils and another for tills. In the case of overlap between pixels belonging to different natural break classes within each sediment subtype, the highest value prevails. Four natural break maps, one for each of the main sediment types, are created by combining the pixels for each type according to a hierarchy of analytical methods, identical to the procedure described in step 6.

1- The reliability of each method was evaluated based on the detection limit of the analytical method and the correlation coefficient calculated using groups of samples analyzed by two or more methods, with the assumption that ICPMS is the most reliable of all methods.

13. Create a multisource natural break map for each analytical method by combining the pixels from classes 1 to 25 for the four main types of sediment; in the case of overlap between pixels belonging to different natural break classes, the highest value prevails.
14. Create a natural break map of Québec for each processed element by combining natural break classes for all sediment types and all analytical methods into a single image following a hierarchy of analytical methods identical to the procedure defined in step 6 (Table 5)

TABLE 3 – Classification of analyzed samples as a function of survey type and sediment type.

2.1.3

Subtype	Description
1	Lake sediments
2a	Undifferentiated stream sediments
2b	Stream sediments, heavy minerals
3a	Undifferentiated soil
3b	Soil, A to C horizons
3c	Soil, C horizon; heavy minerals or clay
4a	Till, fine fraction
4b	Till, heavy fraction
4c	Till, light fraction

TABLE 4 – Interpolation distance (in metres) for the 11 processed elements according to sample type.

Type / Element	Lake	Stream	Soil	Till
Ag	2000	1000	500	1000
As	3000	1000	500	1000
Au	2000	1000	500	1000
Co	7000	5000	500	4000
Cu	7000	5000	500	4000
Li	6000	4000	500	3000
Mo	6000	4000	500	3000
Ni	8000	6000	500	4000
U	8000	7000	500	5000
Y	6000	3000	500	2000
Zn	7000	5000	500	4000

Determining effective prediction thresholds

Each raster image per sediment type for each of the 11 elements generated in step 12 consists of pixels assigned a value from 1 to 25 as determined by the natural breaks, which represent progressively increasing classes of values that take into account analytical method and geological context. But how do we determine the threshold at which natural break classes can be used as reliable indicators for the presence of nearby mineral deposits?

To answer this question, the 4 natural break grids (lakes, stream, till, soil) for each of the 11 processed elements were validated using the weight of evidence method (Spiegelhalter, 1986; Bonham-Carter *et al.*, 1988; Lamothe, 2009).

The process can be illustrated using the example of copper in lake sediments. The weight of evidence method is a spatial analysis technique used to calculate the probability of a spatial association between the various classes of a geological parameter and the locations of known deposits[1]. This probability of association is expressed by a contrast value (C) that is less than or equal to zero if the association is negative or nil. The stronger the association, the higher the C value. It is generally acknowledged that a value of $C \geq 1.5$ signifies that the association is probative (predictive). In the present study, a minimum contrast value of 1.8 was used to lend more credibility to the anomalous thresholds.

1- The reader is referred to Lamothe (2009) for a more complete description of the method.

TABLE 5 – Order of integration for the various analytical methods used for the 11 processed elements. ICPMS analyses take precedence over all other methods in all cases. (Codes for the analytical methods: **AA** = atomic absorption; **NA** = neutron activation; **CO** = colourimetry; **FL** = fluorimetry; **XRF** = X-ray fluorescence; **ICPMS** = Inductively Coupled Plasma Mass Spectrometry; **PL** = plasma emission; **FA** = fire assay)

Method / Element	AA	NA	CO	FL	XRF	ICPMS	PL	FA
	Rank	Rank	Rank	Rank	Rank	Rank	Rank	Rank
Ag	2	5	3			1	4	
As	3	2	4			1	5	
Au	4	2				1	5	3
Co	2	4	5			1	3	
Cu	2	4	5		6	1	3	
Li	2	4				1	3	
Mo	2	3	5		6	1	4	
Ni	2	6	5		4	1	3	
U	4	3	6	2		1	6	
Y		4			3	1	2	
Zn	3	4	5		6	1	2	

As shown in the example for copper (Table 6), a contrast value was calculated for each class of each sediment subtype (see Table 3) for all 11 processed elements. When all the subtypes for a particular sediment type are predictive, their images were combined into a single image by retaining the pixels of the most predictive subtypes in order to keep, at most, 4 sets of generated targets (lake, stream, soil or till). After the combining process, a new contrast calculation was performed on the resulting image. For copper, this meant that stream sediments 2a and 2b (see Table 3), both of which are predictive according to the initial contrast calculation, were combined into a single grid by retaining the pixels of the file with the better contrast value (Figure 6). The same approach was also adopted for soil subtypes 3a, 3b, and 3c. In the case of tills, only the heavy fraction image (subtype 4b) was retained because the contrast values for the two other subtypes are too low.

Calculating contrast values using the WofE method made it possible to determine, for most of the processed elements, which sediment types have natural break classes that represent reliable indicators of proximal mineralization (Table 7). Only two substances (lithium and gold) did not demonstrate a positive association with known deposits. In the case of lithium, there are too few known deposits (32) to perform a reliable calculation of the predictivity of the natural break classes. The case of gold is different because there are 3,193 known gold deposits in Québec. Even though the contrast values calculated for natural break classes 24 and 25 for lake sediment samples are relatively high (Table 8), they are nonetheless below the threshold of 1.8 established at the onset. The very low mobility of gold in the secondary environment (Trépanier, 2001) is probably responsible for this result. In fact, unless the lake sediment sample is very close to the mineralization, there is little chance that gold values will be above the detection limit for traditional analytical methods (atomic absorption, plasma emission, etc.). It is also possible that many elevated gold values for the various sediment types are, in fact, a nugget effect unrelated to mineralization, which would negate the benefit of calculating a contrast value.

Following the weight of evidence assessment, the pixels for the predictive classes for all 24 datasets (Table 7), including all sediment types considered predictive for the 11 substances, were converted into polygons.

Creating favourable zones and targets for each element

The integration procedure in steps 12 and 13 (Appendix 1 and the section "Creating a ModelBuilder model") retains the cells with the highest values for the natural break classes when several types of sediments are combined. Despite this, however, it is possible that some of the pixels belonging to the higher classes will include low values for the element being assessed. In fact, if the processed population includes relatively few samples from a single geological domain (for example, a hundred soil samples from Opatica), it is very possible that the highest class in the range of values will nonetheless consist of relatively low values. A zone of class 25 soil in the Opatica could thus be less relevant than a class 25 zone in the Abitibi that was established using a population of several thousand samples and is likely to represent significantly higher values.

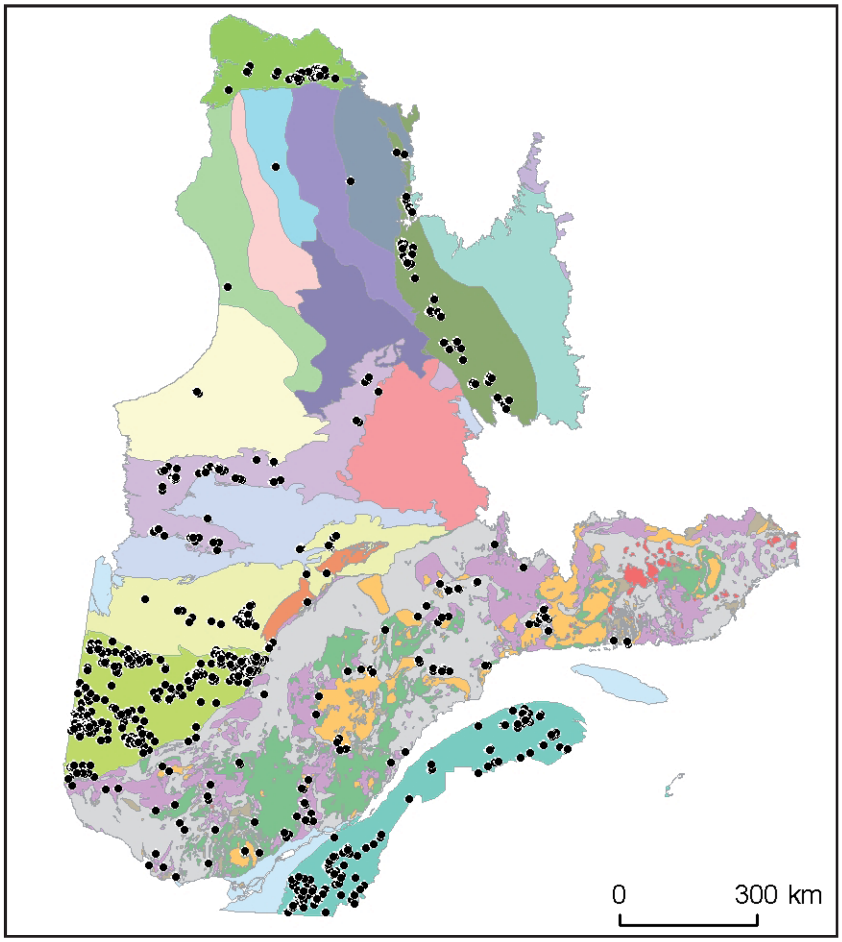

FIGURE 5 – Locations of the copper deposits used to determine the effective prediction thresholds for the natural break classes for lake, stream, till and soil copper grids across Québec. This group of deposits does not include mineral showings, which generally produce only a moderate footprint in the secondary environment.

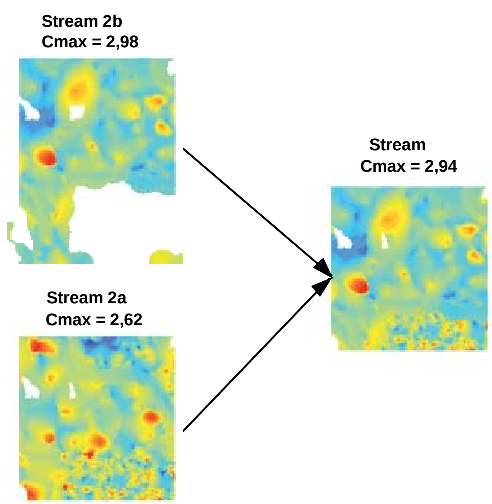

FIGURE 6 – Combining pixels for the two prediction subtypes for stream samples into a single grid. All pixels belonging to the more predictive subtype (heavy minerals in stream sediments) are retained during the integration.

The last step in the modelling process therefore consists of retaining only those polygons (created using favourable pixels) for which the highest values for a given element are clearly anomalous, and this for each of the 24 datasets created (Table 7). A threshold above which values are considered anomalous was established using a quantile-quantile diagram applied to the highest values recorded in the polygons for each of the 24 datasets. Figure 7 presents examples of the four quantile-quantile diagrams displaying the highest polygon values for the lake, stream, soil and till datasets for copper. In each case, it is possible to define a threshold (expressed as a Cu value) from which a significant change in slope occurs. The polygons with maximum values above this threshold were retained and constitute the targets provided in the digital data accompanying this report.

TABLE 6 – Weight of evidence method: calculated contrast values or the natural break grid for copper for each of the 4 sediment types. When all subtypes of a sediment type are predictive, the grids for each subtype are combined into a single grid while retaining the pixels of the more predictive subtypes in order to minimize the number of generated target types. Grids for the two stream subtypes (2a and 2b, Table 3), both of which are predictive, were grouped together into one single grid by assigning priority to type 2b cells because they have greater predictivity. The same priority-driven integration procedure was applied to the three soil and till grids. Grids with insufficient predictivity were not taken into account when generating targets. The classes in yellow correspond to contrast values (C ≥ 1.8) that are high enough to be considered predictive for the presence of copper deposits.

Lake																									
Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Area_km²	1885	5501	11013	17155	25513	35452	45910	56642	67884	77303	84804	89338	89729	86834	81170	73463	62974	51862	41287	31856	22546	15227	8586	3817	1428
No_Points	0	0	6	19	10	7	8	14	17	16	16	29	36	49	38	24	39	31	39	35	25	20	14	6	5
Contrast			0,17	0,90	-0,17	-0,87	-1,00	-0,65	-0,64	-0,84	-0,94	-0,38	-0,15	0,22	0,01	-0,37	0,31	0,27	0,76	0,91	0,91	1,07	1,28	1,23	2,04
Stream																									
Area_km²	14076	7198	9950	13258	17062	21099	25151	28696	30789	31015	30679	28425	25468	22501	20197	17223	13643	10831	7764	5741	3876	2450	1497	1029	483
No_Points	4	2	14	16	25	18	34	30	28	34	57	51	39	32	33	21	37	24	31	17	26	19	15	30	10
Contrast	-1,80	-1,80	-0,17	-0,33	-0,13	-0,69	-0,22	-0,49	-0,64	-0,44	0,12	0,09	-0,09	-0,16	-0,02	-0,32	0,52	0,30	0,91	0,59	1,43	1,57	1,79	2,94	2,56
Soil																									
Area_km²	33	72	110	170	211	238	262	328	342	377	385	394	394	406	358	311	290	280	262	212	139	118	82	51	18
No_Points	1	0	0	2	0	6	3	2	3	7	5	3	5	4	6	4	2	0	2	7	4	7	1	3	6
Contrast	0,79			-0,20		0,62	-0,23	-0,89	-0,51	0,29	-0,10	-0,66	-0,12	-0,39	0,18	-0,11	-0,76		-0,65	0,91	0,74	1,55	-0,16	1,51	3,60
Till (heavy fraction)																									
Area_km²	217	655	1095	1341	1684	1841	2090	2406	2468	2509	2374	2289	2114	1809	1557	1410	975	734	580	431	302	237	168	108	58
No_Points	0	0	0	0	0	0	1	1	2	3	1	1	2	7	5	6	2	1	1	1	1	1	0	1	1
Contrast							-0,97	-1,12	-0,43	-0,01	-1,11	-1,07	-0,26	1,31	1,07	1,39	0,55	0,12	0,36	0,67	1,03	1,27		2,07	2,71

TABLE 7 – Sediment types for which the highest natural break classes are considered to be reliable indicators of proximal mineralization for the processed elements. In all, 24 datasets demonstrated a predictive ability and were converted into polygons.

Element	Lake	Stream	Soil	Till
Ag	√	√	√	√
As	√	√		
Au				
Co	√	√		
Cu	√	√	√	√
Li				
Mo	√	√		
Ni	√	√		
U	√	√		
Y	√	√		
Zn	√	√	√	√

TABLE 8 – Contrast values for the natural break classes for gold in lake and stream sediments. Although the higher classes are clearly anomalous, their contrast values remain below 1.8, which was established as the effective prediction threshold.

Lake																									
Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Area_km²	289925	36297	32698	37649	90428	40625	41350	38262	34466	29703	24502	19295	14601	19653	27088	12188	10516	7724	4421	3015	1962	1241		1277	282
No_Points	150	18	14	18	121	21	20	36	35	21	17	19	13	32	22	17	17	9	4	1	0	3		5	1
Contrast	-0,53	-0,43	-0,58	-0,47	0,68	-0,39	-0,46	0,24	0,32	-0,06	-0,08	0,28	0,18	0,81	0,08	0,63	0,78	0,45	0,19	-0,82		1,18		1,66	1,56
Stream																									
Area_km²	22119	3298	2264	1780	17294	2776	1869	7391	1720	1755	1887	1099	911	875	738	686	476	412	397	309	275	938	166	131	95
No_Points	84	10	7	7	53	22	13	9	11	9	12	13	14	9	10	17	4	5	10	7	5	9	2	1	2
Contrast	-0,33	-0,48	-0,46	-0,21	-0,56	0,53	0,38	-1,46	0,29	0,07	0,29	0,93	1,20	0,78	1,06	1,70	0,57	0,94	1,70	1,58	1,35	0,71	0,93	0,46	1,50

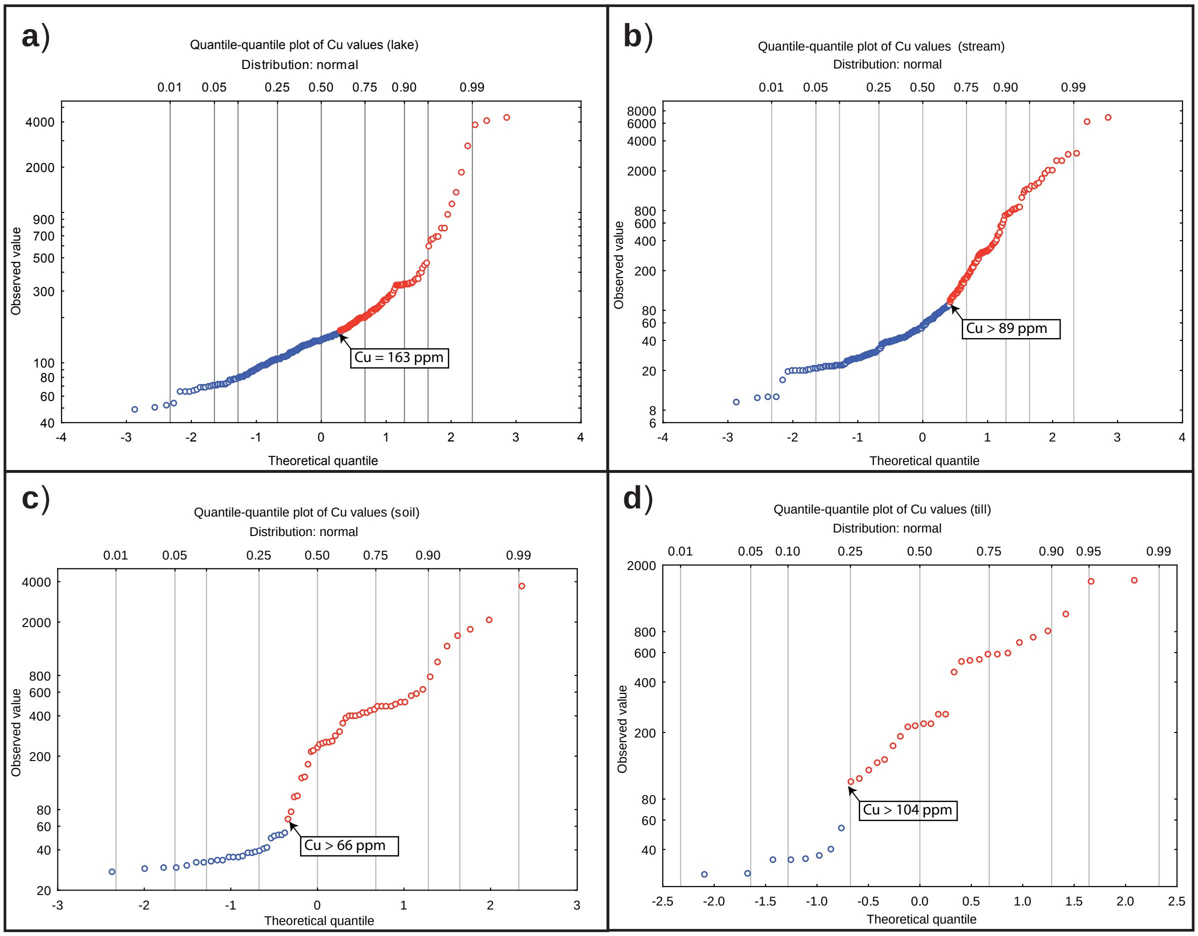

FIGURE 7 – Determination of copper's anomalous threshold value for defining favourable zones for the 4 types of sediments. In each case, a quantile-quantile diagram was produced by using the highest measured copper value for each polygon within a set of favourable zones. The gently sloping rectilinear portion (in blue) at the bottom of each diagram indicates a normal range of values (for example, between 0 and 163 ppm for the lake sediment samples). In each case, a break in the slope indicates the anomalous threshold above which polygons are retained..

Discussion of results

The method used in this first part allowed statistically anomalous zones to be defined according to sediment type, major geological subdivision, and analytical method. The following points should be noted:

1. This approach aims, above all, to assist with land management, notably during the creation of protected areas, by defining favourable zones across the entire province for a group of 9 substances. In the context of mineral exploration, the approach presented in the second part of this study is more appropriate for some of these substances (Cu, Ni, U and Zn).
2. The ModelBuilder modules developed for this study produce images showing the distribution of substances in the secondary environment across Québec according to their raw values and percentile classes, as well as their classification into one of 25 classes by the natural break method. These modules could easily be adapted for other elements, as needed.
3. The model subdivides the entire sample set based on analytical method and other attributes. If levelling was not performed between different survey types, this approach relies on the premise that analytical differences are relatively small for a single method. However, in the case where values are relatively low for a given substance, it is highly possible that analytical differences are amplified, an effect that would be revealed by examining the raw value and percentile class images, especially in the example of copper (see the percentile class PDF image for copper in the digital products accompanying this report). In the case of relatively high values, these differences are generally less pronounced.

4. The decision to prioritize one analytical method (notably ICPMS) over other methods preferentially affects the integration of some data. For example, in the La Tuque and Baie-Comeau areas, there is some overlap between lake sediment samples reanalyzed by ICPMS and stream sediment samples analyzed by atomic absorption or plasma emission. Because the last two methods are less accurate than ICPMS and thus "lower priority", only the lake sediment data were integrated into the final image, except in the cases of Ag, As and Au, which have shorter lake interpolation distances that permit stream sediment information to be inserted as infill data.
5. Large favourable zones for base metals probably reflect lithological signatures; for example, the nickel- or zinc-rich zones in the Labrador Trough likely reflect magmatic and sedimentary signatures respectively. These zones are therefore not necessarily related to significant mineralized occurrences of these metals. Nevertheless, the overlap of spatial regression targets for nickel and zinc (see the next section) confirm the elevated economic potential for this area.

PART 2 – DISCRETE LAKE SEDIMENT TARGETS DEFINED BY THE MULTIVARIATE SPATIAL REGRESSION METHOD

The functionality of the natural break method relies on the hypothesis that all mineralization produces a significant enrichment of indicator elements in the secondary environment. However, if the enrichment is only local and weakly developed, the natural break method would not be able to target this type of mineralization. The multivariate spatial regression method is an interesting alternative useful to define local-scale noise and study any significant variations therein.

We can assume that the value for each lake sediment sample potentially consists of two fractions: a geochemical component of lithological or environmental origin, and an anomalous component from nearby mineralization. The objective of the model presented here is to separate these two components, not just at the level of sample populations but rather at the level of individual sample values.

Trépanier's (2006) spatial regression model was developed using an analytical database of 75,610 samples that were levelled using the survey carried out in 1997 as part of the Far North project, which analyzed 44 elements by plasma emission or neutron activation techniques (Trépanier, 2007). The present model uses a database of 90,844 samples of which 43,336 samples were reanalyzed for 53 elements by ICPMS[1] in 2008-2009, the results of which were used to perform the levelling.

Methodology

The multivariate spatial regression method was developed by Sylvain Trépanier (2006) using the "Geographically Weighted Regression" concept presented in Fotheringham *et al*. (2002). The basic principle is that it is possible to evaluate an element's content in a given sample using the other elements present in other samples from the immediate vicinity. The objective is to predict the concentration of the element by presuming it is entirely the result of the surrounding lithological contribution. If the measured value of the element in the sample is significantly higher than the predicted value, the **residual value**[2] can be explained by the presence of mineralization. This prediction is calculated by a multivariate spatial regression equation that uses a certain number of analyzed elements in the samples as independent variables[3], and the element of interest as the dependent variable. The regression equation is a mathematical equation resembling the following:

Dependent variable   Independent variable   Constant

$$Cu_{predicted} = 0.7*Al + 0.1*Ba - 0.2*Ca + 1.08*Ce + 0.07*Co - 0.2*Cr\ldots + 2.4$$

Coefficient

1- Inductively coupled plasma mass spectrometry.

2- In statistics, the residual is the difference between a predicted value and a measured value.

3- Variables used to predict the values of another (dependant) variable in a model. Also known as predictors in a regression model because the values of those variables allow us to know the value of a dependant variable with a certain degree of accuracy.

In this equation, the copper value is predicted using elements other than copper, which are generally representative of the lithological contribution from the proximal environment. Each element is associated with a regression coefficient representing the effective contribution of this element in the prediction. If the correlation between the element of interest and the independent variable is strong, the coefficient will be positive and high; when weak, the coefficient will be negative. The constant at the end of the equation represents the expected value for the element of interest if all independent variables are nil. The elements selected to define the neighbouring lithological contribution are: Al, Ba, Ca, Ce, Co, Cr, Cu, Fe, K, La, Mg, Mn, Ni, P, Ti, U, V and Zn. These elements were selected because they are present in many surveys and their analytical quality is good.

Multivariate spatial regression allows specific regional geochemical signals to be determined for each sample. Spatial regression analysis[1] uses a grid of points spaced 20 km apart and calculates a series of regression coefficients for 17 of the 18 elements listed above (the element of interest being left out of these calculations). The coefficients are established using the population of samples lying within a 20-km radius (Figure 9, Table 9) to avoid variations caused by structural control[2]. In a second step, the predicted values for the element of interest and the residual for each sample are calculated by using the coefficient values for the closest regression point on the grid. At least 20 samples are necessary to perform the calculation[3]. To avoid the possibility of large variations in the measured values introducing errors into the coefficient calculations, the values for all variables are converted to natural logarithm.

The conditions for this processing method are as follows:

1. The samples must all be of the same type (lake, stream, till or soil). Only lake samples were processed for the present report (see Figure 1a), and thus the Ungava Orogen, Abitibi, southern Grenville, St. Lawrence Platform and Appalachians are not covered by this approach.
2. The lake sediment samples must have been analyzed for all 18 elements used in this method. Of a total of 118,610 samples, only 90,844 satisfy this condition (Figure 10).
3. Values for the 18 elements used in the spatial regression calculation must be levelled between the various sampling surveys (and/or the sets of reanalyzed samples) to avoid gaps caused by different analytical methods or variations in detection limits.
4. A minimum of 20 samples around each reference point in the regression grid (20 km x 20 km) is required to perform the regression coefficient calculation.

Levelling of the elements

The levelling for each of the 18 elements was done using the GSL module developed by Sylvain Trépanier in Visual Basic.NET language, and the method is based on the work by Daneshfar and Cameron (1998). As a first step, lake sediment samples are grouped according to survey. One survey (generally the most recent) is chosen as the reference survey and the values of the other surveys are then adjusted (levelled) to it. During a similar study by CONSOREM in 2005 (Trépanier, 2007), the Far North lake sediment survey served as the reference survey. In the present work, a collection of about 50,000 lake sediment samples from the Churchill and Grenville provinces, which the MRNF reanalyzed by ICPMS in 2008-2009, were regrouped into a single project and used as a reference set for levelling the other projects. In addition to using a different reference survey, our study differs from CONSOREM's work by including 4,357 new samples collected east of Val-d'Or in 2008 (Labbé, 2009), as well as 336 new samples taken from the Lac Amariton (22F/16) and Lac Georgette (22G/13) areas in 2008. The levelling procedure closely follows the approach described in Trépanier (2007). The reader is invited to consult this document for a complete description of the procedure. It also explains why certain elements (Ag, Au, etc.) cannot be levelled by this technique. Finally, it should be noted that all values were converted into natural logarithm (Ln values) before levelling.

1- The calculation is made using a .NET module developed by Sylvain Trépanier for CONSOREM.

2- In order to realistically calculate the lithological contribution, only those samples falling with a resonable perimeter should be considered. Some models using experimental variograms developed by Trépanier (2006) demonstrated that, in the context of the Far North survey, the influence of a lithology's structural orientation on the values of lake sediment samples is only noticeable beyond 45 km (Figure 8), and thus a radius of 20 km was assigned for sample selection.

3- This minimum cut-off means that samples along the periphery of the group of 118,610 samples shown in Figure 10a have not been processed.

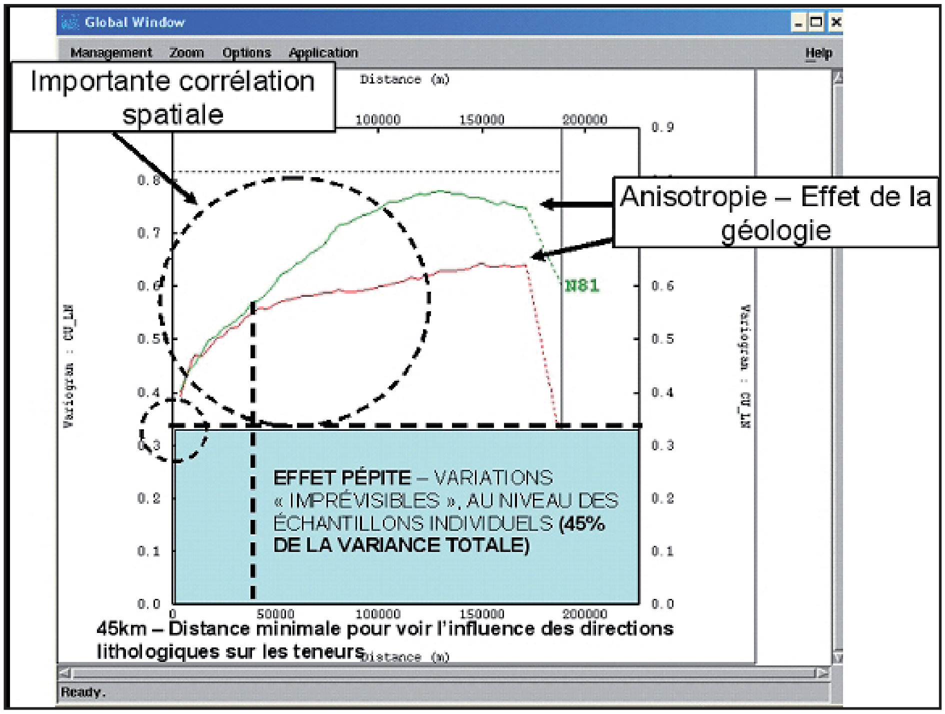

FIGURE 8 – Anisotropic experimental variogram for copper in the Far North lake sediment survey (Trépanier, 2006).

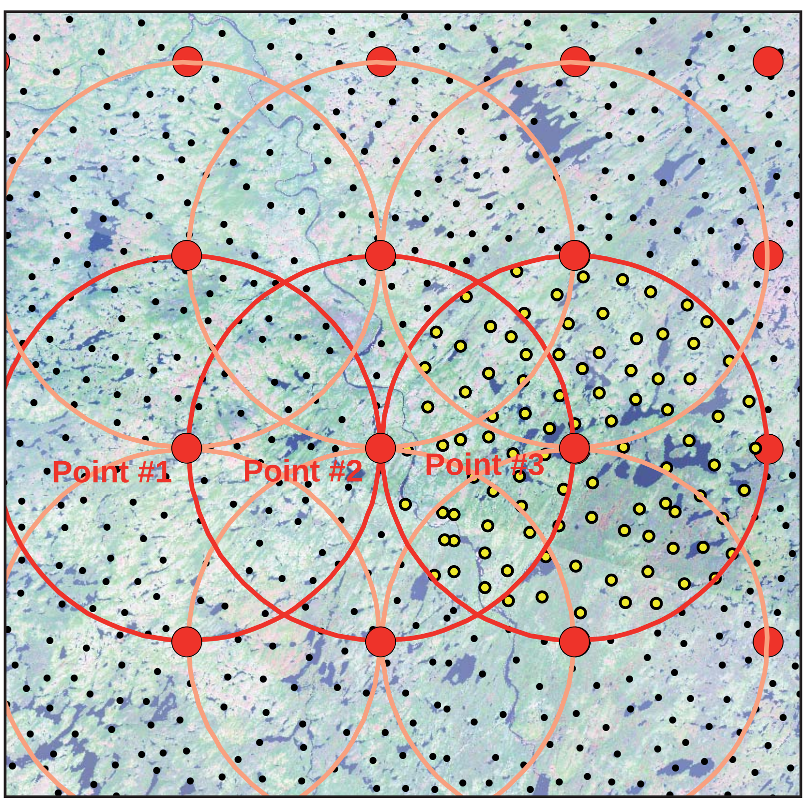

FIGURE 9 – Example of a spatial regression coefficient calculation. A grid of reference points spaced 20 km apart is first created. All samples within a 20-km radius around each reference point (point #3 in this example) are then selected and the coefficient for each independent variable is calculated using this population.

TABLE 9 – Spatial regression coefficients for the independent variables needed to calculate the predicted copper value for point #3 in Figure 9. The calculation uses 99 samples located within a 20-km radius around the point. The R2 variable is a statistic that describes the model's performance (83.7% of the variation in copper values for the samples around point #3 is predicted by the model). The B variable corresponds to the model's error constant, which would be the value for copper if all the independent variables were nil. The coefficients will be used to calculate the predicted copper value in the samples closest to the reference point, within a 20-km radius.

R2	AL_NIV	BA_NIV	CA_NIV	CE_NIV	CO_NIV	CR_NIV	FE_NIV	K_NIV	LA_NIV
0.83721	0.27692	0.00964	0.16965	-0.28440	-0.40742	-0.22522	-0.06527	-0.38453	0.45207
MG_NIV	**MN_NIV**	**NI_NIV**	**P_NIV**	**TI_NIV**	**U_NIV**	**V_NIV**	**ZN_NIV**	**B**	**N**
0.08091	-0.00682	0.85661	-0.06151	0.21140	0.03863	0.15325	0.15230	-1.49455	99.00000

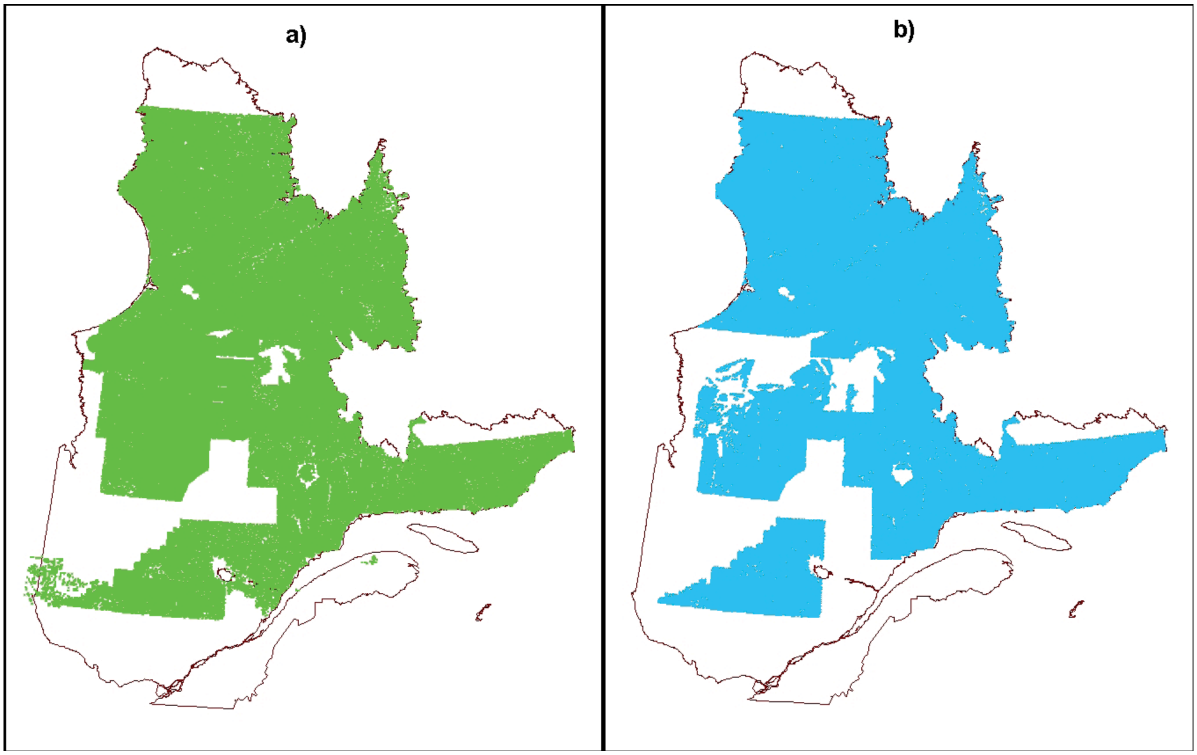

FIGURE 10 – Lake sediment surveys: **a**) survey coverage from 1957 to 2008 (118,610 samples); **b**) areas covered by samples analyzed for the 18 elements successfully used and processed by the spatial regression method (90,844 samples).

Multivariate spatial regression analysis of selected groups of elements

The general method of multivariate spatial regression provides a means of assessing the degree to which a particular value is anomalous for a given sample. In the present study, as in the study of Trépanier (2007), 5 elements (Cu, La, Ni, U and Zn) were tested by spatial regression. A sample collected near a monometallic deposit containing one of these 5 elements should theoretically be enriched in that element compared to the background contribution from surrounding lithologies.

But what about the very common scenario of polymetallic deposits, such as volcanogenic massive sulphide (VMS), magmatic Ni-Cu, or Cu-U-REE[1] IOCG[2]-type deposits? Aside from the element being processed by the general method, enrichment in any of the other elements in the sample will cause an increase in the predicted value of the element being processed and, consequently, a reduction in the residual anomaly. By removing any elements typically enriched in a specific type of deposit from the set of independent variables, it is possible to calibrate the calculations and enhance the geochemical signal of the targeted element within a specific metallogenic context.

1- Abbreviation for Rare Earth Elements

2- ***I**ron **O**xide **C**opper **G**old*: a class of deposits that includes major iron, copper and gold (and sometimes uranium) deposits. Charac-terized by an abundance of rare elements, phosphorous, fluorine, and iron oxides.

Four different metallogenic families were selected for this study[1] (Table 10):

1. monometallic deposits;
2. volcanogenic massive sulphide deposits;
3. magmatic Ni-Cu deposits;
4. IOCG-type Cu-La-U deposits.

From among the 18 available levelled elements, the ones most likely to be locally enriched near mineralization were therefore removed from the modelling to enhance the geochemical signal of the targeted element within the context of a specific metallogenetic setting (Table 11). For example, in the case of VMS deposits, the elements Cu, Fe and Zn are likely to be simultaneously enriched in a processed sample, so these were removed from the treatment for VMS settings when calculating the residual values for Cu and Zn.

TABLE 10 – Independent variables used for each element processed by spatial regression. The elements are grouped into four families by metallogenic context.

Element	Independent variables	Removed variables
Monometallic deposits		
Cu	Al, Ba, Ca, Ce, Co, Cr, Fe, K, La, Mg, Mn, Ni, P, Ti, U, V, Zn	Cu
La	Al, Ba, Ca, Ce, Co, Cr, Cu, Fe, K, Mg, Mn, Ni, P, Ti, U, V, Zn	La
Ni	Al, Ba, Ca, Ce, Co, Cr, Cu, Fe, K, La, Mg, Mn, P, Ti, U, V, Zn	Ni
U	Al, Ba, Ca, Ce, Co, Cr, Cu, Fe, K, La, Mg, Mn, Ni, P, Ti, V, Zn	U
Zn	Al, Ba, Ca, Ce, Co, Cr, Cu, Fe, K, La, Mg, Mn, Ni, P, Ti, U, V	Zn
VMS-type Cu-Zn deposits		
Cu Zn	Al, Ba, Ca, Ce, Co, Cr, K, La, Mg, Mn, Ni, P, Th, Ti, U, V	Cu, Fe, Zn
Magmatic Ni-Cu deposits		
Ni Cu	Al, Ba, Ca, Ce, K, La, Mn, P, Ti, U, V, Zn	Ni, Cu, Cr, Co, Fe, Mg
IOCG-type Cu-U-REE deposits		
Cu La U	Al, Ba, Ca, Co, Cr, Mg, Mn, Ni, P, Ti, V, Zn	Ce, Cu, Fe, La, U

Target determination and validation

One of the more important advantages of this method is that it eliminates environmental variations that influence the geochemical signature of certain elements. Kerr and Davenport (1990) and Trépanier (2006) demonstrated that variables such as lake depth and loss on ignition display a direct correlation to Zn, Cu, Pb, Ni, Co, Ag, Mn, As, Mo and Fe values (Figures 11a and 11b). If lake depth or sediment composition (clay, organic matter) constitute enrichment factors for some metals of economic interest, then the presumed direct relationship between a higher value and the presence of nearby mineralization could be called into question. However, as shown by Figures 11c and 11d, the calculated residual value does not display any correlation with lake depth or loss on ignition (Trépanier, 2006). As a result, the anomalies calculated by spatial regression are independent of environmental variables.

Because this approach uses values converted to natural logarithm, spatial regression analysis can generate high residual values even when an element's measured concentration in a sediment sample is low. For example, some of the samples in Figure 12 with less than 5 ppm Cu display residual values above the 99th percentile for the entire set of calculated residual values for lake sediments in Québec. The intensity of the residual anomaly alone is thus insufficient to define a target, and it is therefore also necessary to determine a threshold for measured values that would be of interest to mineral exploration. The definition of these thresholds must satisfy two criteria to maintain the study's credibility: 1) the number of proposed targets must remain within reasonable limits, on the

1- These families are identical to those established in the study by Trépanier (2006).

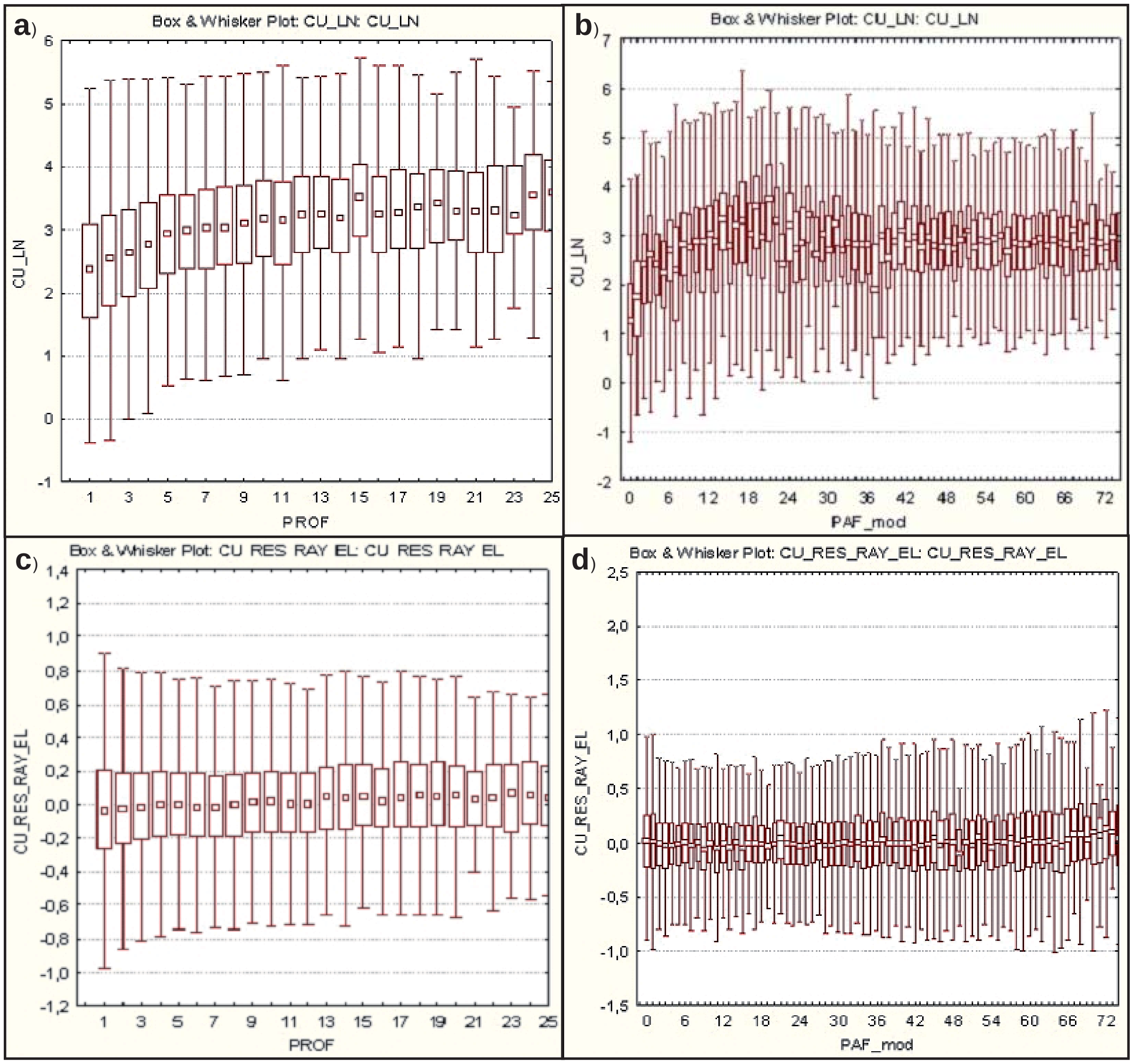

FIGURE 11 – For all sediment surveys across Québec: a) the relationship between raw copper values (CU_LN) and lake depth (PROF); b) the relationship between raw copper values and loss on ignition (PAF_mod); c) the relationship between residual values for copper (CU_RES_RAY_EL) and lake depth; and d) the relationship between residual values for copper and loss on ignition. (Trépanier, 2006)

order of several hundred targets per metallogenic setting; and 2) the predictivity of the results must be greater than what would be attained using a standard method of target definition.

To satisfy the first of these two criteria, only those samples with calculated residual values above the 99th percentile are retained, resulting in 909 samples (R_{99th}) for each of the metallogenic settings. To satisfy the second, three groups are created from each of the 12 sets of spatial regression analyses (Table 10):

1. a group of samples with values equal to or greater than the mean calculated from natural logarithm values (Ln values) for all lake sediments ($R_{99th+Mean}$);
2. a group of samples with values equal to or greater than one standard deviation above the mean, as calculated from Ln values for all lake sediments (R_{99e}+1sd);
3. a group representing a standard method of target definition, comprising 909 samples for which the levelled values for the processed element are above the 99th percentile for the population of lake sediment samples (EL_lev_{99th}).

The predictivities of the three test groups were calculated using the weight of evidence method (see the section "Determining effective prediction thresholds"). Buffer zones, as multiples of 1,000

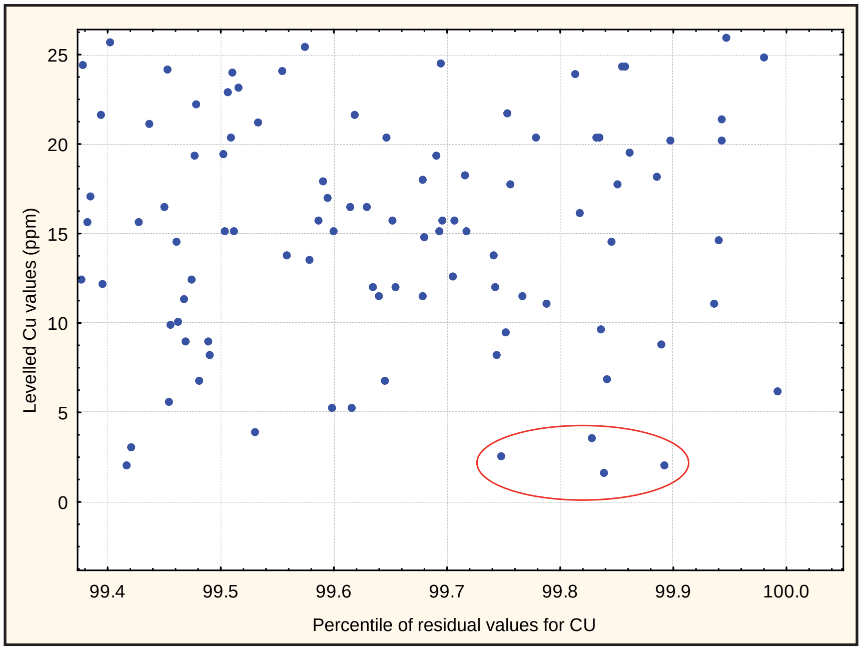

FIGURE 12 – Spatial regression analysis can generate high residual values even when the concentration of the processed element in the sample is low. In this example for copper, values below 5 ppm display residual values above the 99th percentile for all calculated residual values for lake sediments in Québec.

TABLE 11 – Tested elements for the four families of metallogenic settings. Presented for each element is the number of deposits that contain the element and belong to the metallogenic family in question. Test groups with the best predictivity (in yellow) were used to define targets. When the number of deposits was too low to perform prediction tests, the "R_{99th}+1sd" test group was used.

Element	Number of deposits	Contrast value within a 1000-metre radius			Number of targets
		EL_lev_{99th}	$R_{99th+Mean}$	$R_{99th+1sd}$	
Mono-element deposits					
Cu	420	2.11	2.76	3.11	498
La	Insuff.				286
Ni	113	2.28	3.23	3.86	297
U	185	2.24	2.56	2.81[1]	516
Zn	482	2.3[2]	1.35	1.20	909
VMS-type Cu-Zn deposits					
Cu	165	0.95	1.72	2.15	493
Zn		0.96	2.12	2.29	432
Magmatic Ni-Cu deposits					
Ni	453	2.95	2.81	3.29	459
Cu	324	2.60	2.40	2.93[3]	408
IOCG-type Cu-U-REE deposits					
Cu	Insuff.				568
La	Insuff.				527
U	Insuff.				575

metres, were generated around the samples belonging to the three test groups. A control group was created for each element, consisting of deposits belonging to the same metallogenic setting (Table 11). Contrast values (see the section "Determining effective prediction thresholds") were calculated using the weight of evidence method for each buffer zone. For clarity, only the contrast values for the first 1,000-metre zone of each of the three groups are presented in Table 11. Except in rare instances, these values are always the highest and represent the best indicators of a group's predictivity. Table 11 shows, in almost all cases, that predictivity values obtained from the "R_{99th}+1sd" test group are higher

1- For monometallic uranium, the threshold was raised to 2 standard deviations to reduce the number of targets to less than 600.

2- In the case of monometallic zinc, the predictivity of spatial regression targets was systematically lower than that for samples with levelled zinc values above the 99th percentile, even after raising the threshold for spatial regression targets to several standard deviations above the mean. The targets provided are those determined by the 99th percentile of the levelled value.

3- The threshold was raised to 1½ standard deviations for samples processed for Cu within a magmatic Ni-Cu context to ensure that the predictivity of spatial regression targets is higher than the predictivity of samples with levelled copper values above the 99th percentile.

for all elements. The only exception is for monometallic Zn, in which case the group of 99th percentile levelled zinc values (EL_lev$_{99th}$) displays the best contrast value. Despite performing several selection tests using various thresholds for residual values combined with various thresholds for zinc values, the "EL_lev$_{99th}$" test group provides the best predictivity. The inability of spatial regression to effectively target monometallic Zn deposits is probably due to the fact that the immediate surroundings for this type of deposit are enriched in Cu and/or Fe. Indeed, we can demonstrate that the correlation index for these metals with Zn doubles (0.21 to 0.43) at distances less than 20 km from the 482 deposits used in the study. This systematic increase of the Cu and Fe content in lake sediments around Zn deposits leads to an overestimation of the predicted Zn value during the regression calculation, as well as an underestimation of the residual value for monometallic Zn.

When the number of deposits was too low to perform predictivity tests, it was assumed that the "R$_{99th}$+1sd" test group provided the best predictivity and was therefore used to define targets. This was the case for La (monometallic deposits), as well as Cu, La and U (IOCG context) (Table 11).

Examples of results for several known deposits

Two examples are presented to illustrate the effectiveness of enhancing values for economic elements using the multivariate spatial regression method for a given metallogenetic setting.

The first example presents two overlapping spatial regression targets for copper and zinc in a VMS metallogenic context for the Lac Heslin area (NTS 23L14, Figure 13). The lake sediment sample taken 1 km south of a group of four mineralized bodies constituting the Coulon deposit (indicated resource of 3.675 Mt at 3.61% Zn, 1.27% Cu, or inferred resource of 10.085 Mt at 3.92% Zn, 1.33% Cu)[1] contains 80 ppm copper (levelled value[2]). This value places the sample in the 92.6th percentile of copper values for all lake sediment surveys in Québec. The residual value of +0.995, calculated according to the approach defined for VMS-type deposits (see section "Multivariate spatial regression analysis of selected groups of elements") places this sample in the 99.7th percentile for all calculated residual anomalies for copper within a VMS context. The zinc analysis reveals a less pronounced although nonetheless significant difference, moving from the 99.3th percentile to the 99.9th percentile. It should be noted that the residual value for copper in the context of monometallic deposits—that is, without zinc and iron being removed from the independent variables (Table 10) is only +0.679, which places it in the 98.9th percentile and thus too low to constitute a target.

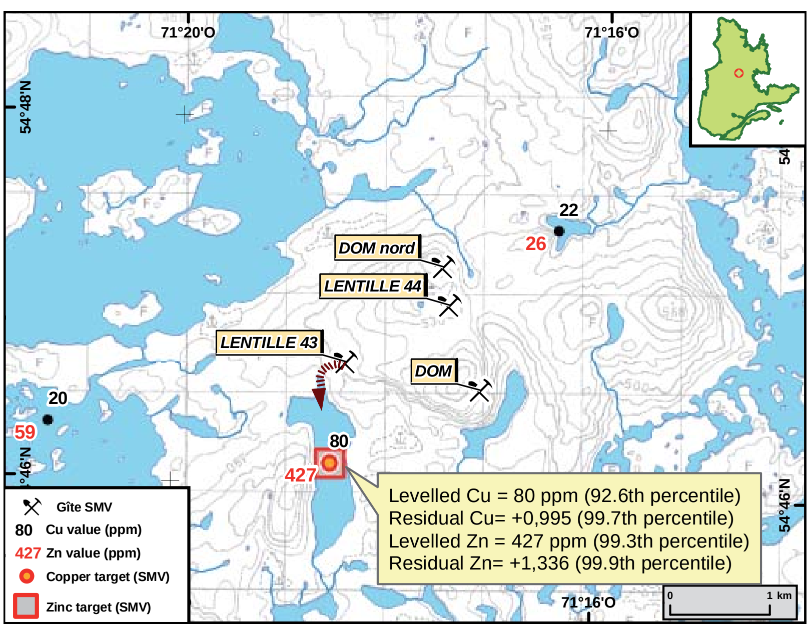

FIGURE 13 – Spatial regression targets for copper and zinc within a VMS metallogenetic context near the Coulon deposit.

1- Virginia Gold Mines press release of April 4, 2009.

2- Original value before levelling: 67 ppm.

The second example (Figure 14) presents mineral showings and deposits for the Gayot property in the Lac Chavamond area (map sheet 23M11). The high nickel value in the lake sediment sample 1 km northwest of the deposits is 101 ppm (98.2th percentile). The residual value for nickel in the context of magmatic-type Ni-Cu deposits is +0.952 and represents a move into the 99.5th percentile. In contrast, at the same location but in the context of monometallic nickel deposits that is, without copper, cobalt, chromium, iron and magnesium being removed (Table 10) the residual value is only +0.333, which places it in the 95.3th percentile and thus too low to constitute a target. It should be noted that in the same area, approximately 7 km west of the previous target, a new copper target was also identified within a magmatic Ni-Cu context, and in this case there is no known proximal mineralization.

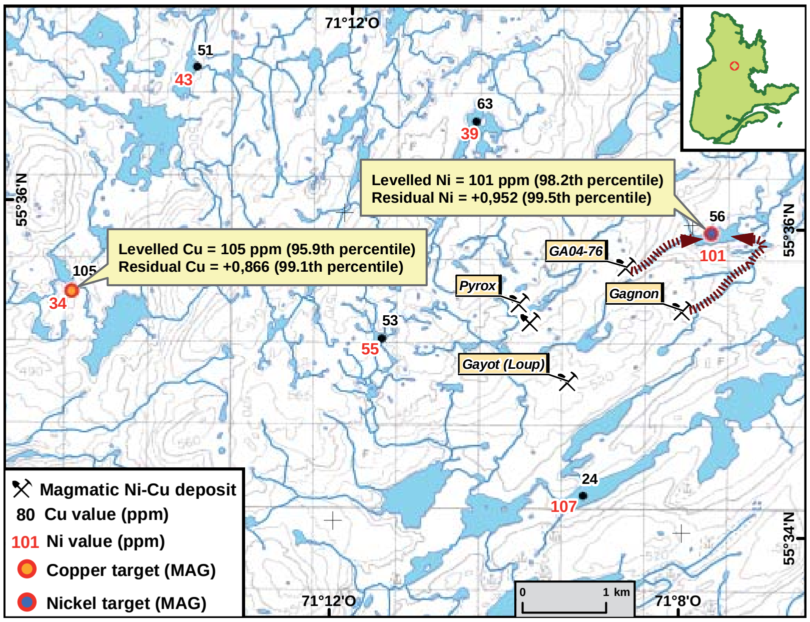

FIGURE 14 – Spatial regression targets for nickel and copper within a magmatic Ni-Cu context (MAG) near the Gayot property.

CONCLUSION

Lake sediment targets generated by spatial regression analysis are clearly more predictive than targets based on levelled value percentiles. In addition, such targets are insensitive to environmental factors, which add a degree of uncertainty regarding the primary or secondary source of measured values for certain metals in a lake sediment sample. Although less predictive, targets generated using value percentiles are nonetheless valid. However, in contrast to targets generated by multivariate spatial regression, some may be the result of secondary enrichment unrelated to a mineralized source.

The multivariate spatial regression method was improved using a variogram study that examined the behaviour of zinc and copper in the 1997 MRNF survey, which was mostly located in the Ungava Peninsula (Trépanier, 2006). On the basis of the variograms, it was determined that a 20 km radius around the samples, without any preferential orientation, was large enough to include a representative number of samples while ensuring they were not influenced by compositional variations caused by the regional geological structure (see section 3.1). However, it is likely that variograms for the same elements in the Nouveau-Québec Orogen will provide distinctly different results, notably due to the significant topographic control and the dominant major structure of the orogen oriented NW-SE.

The proposed approach in this part of the study is of particular interest to the mineral exploration industry. Other metallogenic settings could be used to generate new targets in areas like the Nouveau-Québec Orogen (volcanogenic exhalative sulphides) or the Baie-James region (Cu-Au-Mo porphyry-type deposits). On the other hand, the discrete nature of the targets makes them difficult to use in terms of provincial land management. A single isolated target would probably not be considered important enough to regard that part of the province as having significant economic potential.

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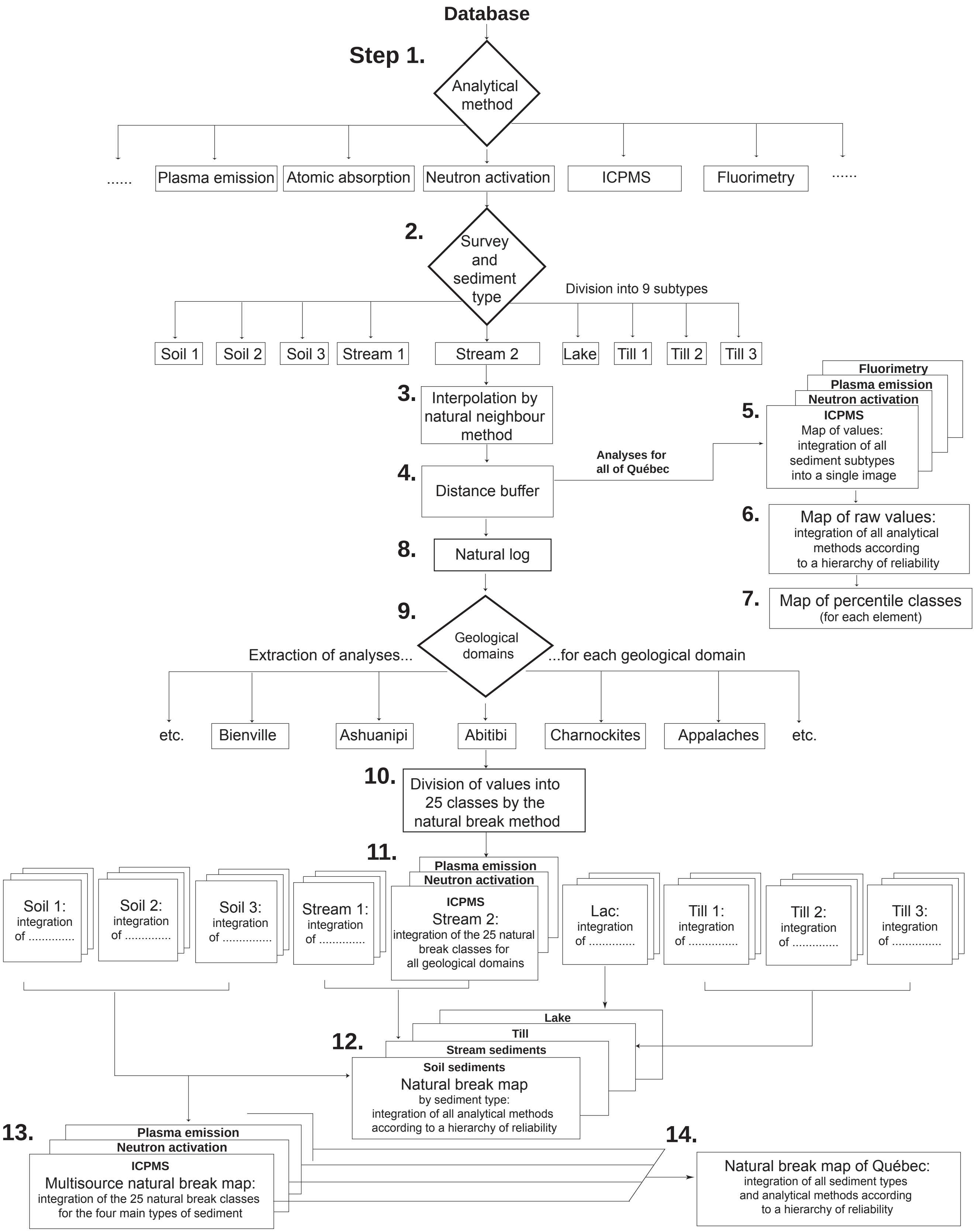
APPENDIX 1

Flowchart of the steps involved in creating a ModelBuilder model, adapted to each substance.



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