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Soil Quality Assessment from Areas of Great Mining Interest Using the Grey Clustering Method

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***Abstract*—Mining is one of the most important activities in Peru, although controversial because it is currently highly criticized for generating environmental liabilities that mostly contain a high content of metals which contaminate the different environmental components such as water. , soil, air, biodiversity and social among others, for the study and analysis of the soil in a specific area we will use the grey clustering methodology, which determines, based on the grey systems and it should be noted that for this analysis it was also used as a reference the parameters defined by the Kelley Directives, a clustering coefficient through various calculations and with these define the level of soil contamination in 5 sectors located in the communities of Michiquillay and La Encañada. With the calculated grey clustering coefficients, it was determined that, of the five sectors, only the Michiquillay sector presents a slight level of contamination, and the other sectors are in uncontaminated soils, at least for the parameters that were selected. Mining activity, the authorities in charge of measuring the environmental impact in the sector, can proceed to investigate and infract if the permitted limits are exceeded and these have not been correctly remedied. The results of this study could be an important contribution for the analysis of soil contamination and the impact on the same of future mining projects that are developed in Michiquillay and La Encañada communities studied, how much the natural conditions of the soils have changed after the operation of the mine.**

***Keywords*—Grey Clustering, Grey Systems, Mining Activities, Soil Quality.**

I. INTRODUCTION

Guaranteeing the safety and sustainability of mining operations is a frontier for scientific research, non-effective policymaking can obstruct or slow down sustainable development [1]. Social impact Assessment (SIA) and Environmental Impact Assessment are the main studies needed to approve mining projects. Mining operations require the depletion of natural resources, which needs to be executed in a responsible way. Mining produces loads of unwanted material which, if this is not conserved in a proper and responsible way, could produce land or water pollution [2].

In addition to this, governments must improve people's quality of life to avoid any possible conflicts[3].

Most of the methods that have been developed to identify pollution, cannot be used with limited data, and usually require several variables to get accurate results [4]. Grey systems work with poor information and small samples. Some countries may have difficulties with the implementation of these methods because some tools require high environmental monitoring development[5]. Grey clustering (GC) is based on a grey system theory, and it is used to qualify objects or indicators based on a grey number whitening weight function[6]. This specific method is useful to study the uncertainty of a system. Data previously taken can also be unified [7].

The case study took place in the Michiquillay and La Encañada peasant communities. This study was made for a possible mining project, which takes place in La Encañada district, Cajamarca state. The activity was done under the PLANEFA (Annual environmental evaluation and control plan) framework and had twelve monitoring spots. These spots were distributed in four ground sectors: MichiquillayMisceláneo Roca (Mq-R), QuinuayocSogoron (Qy-So), SogoronMisceláneo Roca (R-So), Michiquillay (Mq) and Wetlands [8].

The main objective of this study is to evaluate the ground in which Michiquillay mining operation will take place. This objective will be reached by using the parameters contained in the Peruvian law. These parameters will be used to qualify each defined area with a contamination level, so the company is able to take action for the contaminated areas in order to prevent permanent ground damage.

The paper development will be organized as follows. Section two describes the grey clustering method and how it is applied for the determination of metals and metalloids. Section three shows the case study description, which explains where the study will take place and presents the analysis. Section four presents the case study and methodology results and discussion. Finally, conclusions will be presented in section five.

II. METHODOLOGY

The grey clustering methodology is determined according to the order grey correlation matrix or the whitenization functions to determine the grey numbers of some observation parameter, in this case the dual parameter, which can be divided into several categories [9]. A clustering is considered as a collection that belongs to the same observation class of objects. According to the above division, grey methodology can be divided into white and grey weight function cluster analysis and grey cluster analysis.

The grey clustering methodology is used to simplify more complex systems, with different parameters, making their evaluation uniform. The advantages of this analysis are that it standardizes the evaluation criteria for different parameters of the studied samples and with a relatively simple calculation, it will be possible to obtain more useful and detailed information on the sample according to clustering [10].

The steps followed by the grey clustering analysis method are [11][12]:

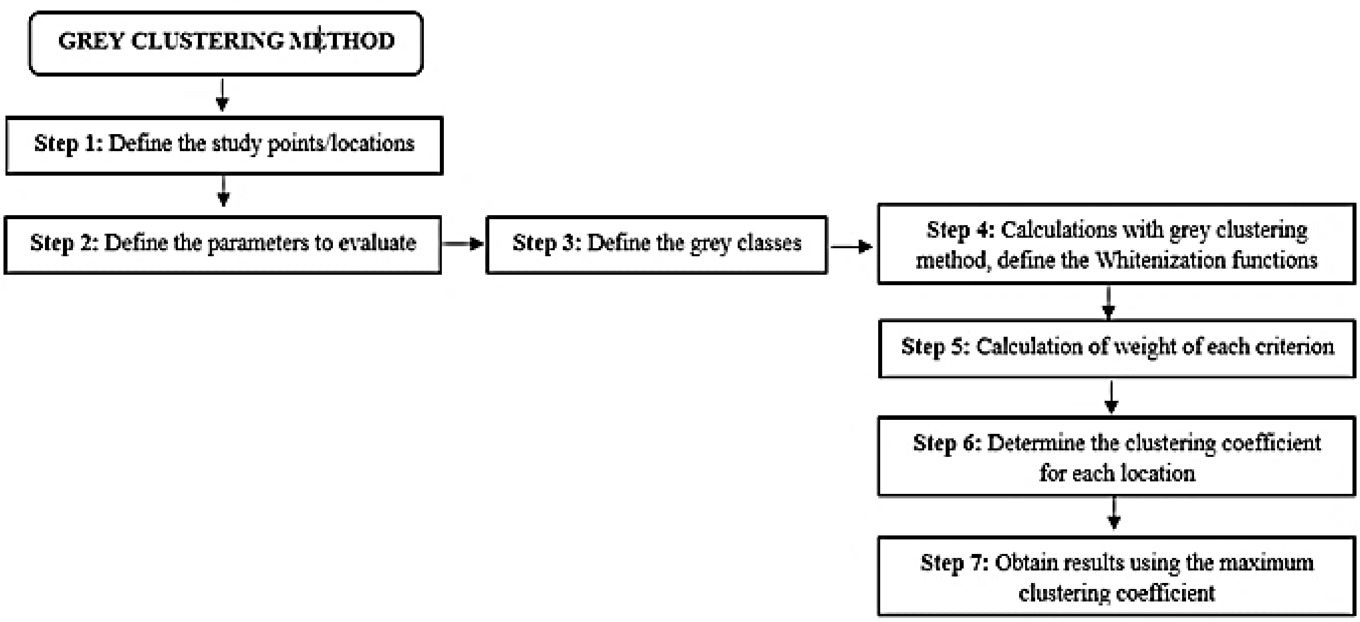

Fig. 1: Flowchart of the Grey Clustering Analysis Method steps

A. Step1

First, the study points must be identified, and the data from these points must be correctly characterized and ordered.

B. Step 2:

The study points will be determined in the database on which we are basing ourselves, in this case they can be environmental quality studies of a certain area or national pollution measurement reports, it is from these data that we will extract the parameters that will be evaluated by grey clustering.

C. Step 3

With the defined parameters, local and international standards or regulations will be sought with which we can classify these parameters, for example, in this case we will use the Kelley directives used for the evaluation of soil quality in the European Union. These classification criteria will be called λi, they will be how many classification levels we have, these classification levels are called grey classes. To define the evaluation values by parameters, the midpoints of the ranges of the directives will be taken.

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D. Step 4:

Depending on the number of grey classes, and the central points defined, the whitenization functions can be determined, determined by f, where j will represent the chosen study points and k the number of grey classes that have been chosen, these functions are the following:

$$fj1(xij) = \begin{cases} 1 & ,x \in \left[0;\lambda_j^1\right] \\ \frac{\lambda_j^2 - x}{\lambda_j^2 - \lambda_j^1} & ,x \in \left[\lambda_j^1;\lambda_j^2\right] \\ 0 & ,x \in \left[\lambda_j^2;+\infty\right] \end{cases} (1)$$

$$fjk(xij) = \begin{cases} \frac{x - \lambda_j^{k-1}}{\lambda_j^k - \lambda_j^{k-1}} & ,x \in \left[\lambda_j^{k-1};\lambda_j^k\right] \\ \frac{\lambda_j^{k+1} - x}{\lambda_j^{k+1} - \lambda_j^k} & ,x \in \left[\lambda_j^k;\lambda_j^{k+1}\right] \\ 0 ,x \in \left[0;\lambda_j^{k-1}\right] U \left[\lambda_j^{k+1};+\infty\right] \end{cases} (2)$$

$$fj5(xij) = \begin{cases} \frac{x - \lambda_j^4}{\lambda_j^5 - \lambda_j^4} & ,x \in \left[\lambda_j^4;\lambda_j^5\right] \\ 1 & ,x \in \left[\lambda_j^5;+\infty\right] \\ 0 & ,x \in \left[0;\lambda_j^4\right] \end{cases} (3)$$

Whitenization Functions for 5 grey classes[13].

These functions can be used in general for different amounts of grey classes, only the index numbers should be adjusted, since it should be considered that λi represents each grey class and that the subscripts will depend on the parameter and the value of the midpoint that should be used.

E. Step 5:

The weight of each criterion or grey class, λ, will be calculated, where λ is the mean value taken in the data that was considered, as in this case are the Kelley directives for the parameters, k is the function number a which is evaluated and j the evaluated point.

The calculation of the weights can be done by consulting experts to have a subjective weight, by means of the harmonic mean method or the Shannon entropy method, to have an objective weight and arithmetic mean, the latter when there is a high uncertainty, in our case, the harmonic mean method was used:

$$n_j^k = \frac{\frac{1}{\lambda_j^k}}{\sum_{j=1}^{m} \frac{1}{\lambda_i^k}} (4)$$

F. Step 6:

The clustering coefficients will be calculated for each evaluated point, using each weight, which can give us an evaluation scope for each grey class, evaluating all the parameters, to determine a result for each evaluation point. This will be found by multiplying each weight by the value obtained for each point according to the corresponding grey class and parameter, and then these values will be added to obtain the coefficient.

G. Step 7:

Continuing with the grey clustering methodology, the highest coefficient found per evaluated point will be the result, that is, the gray class in which the maximum coefficient is located will be the classification that our point has[14].

III. Case Study

A. Context

The case of study was carried out in the rural communities of Michiquillay and La Encañada near the mining project, which is in an exploration stage. 120 demonstrator points distributed in the 4 soil units were studied and these demonstrator points were consolidated based on the EIA-sd of 2009 and the modified one of 2013. Each demonstrator point had the parameters that would be analyzed, and these analyzes were carried out by ALS LS Perú S.A.C and TYPSA S.A (accredited by the National Quality Institute - Inacal).

EXPLORING RESEARCH AND INNOVATIONS

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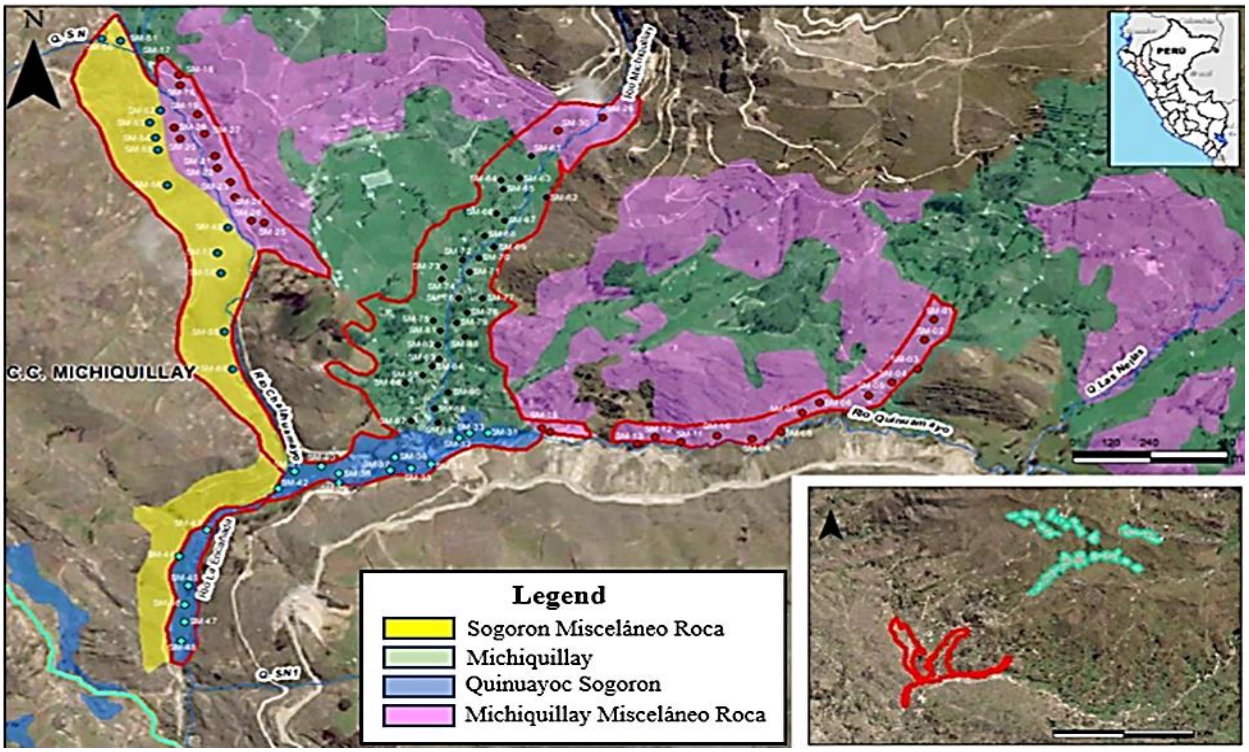

Fig. 2: Location of soil sampling points [8]

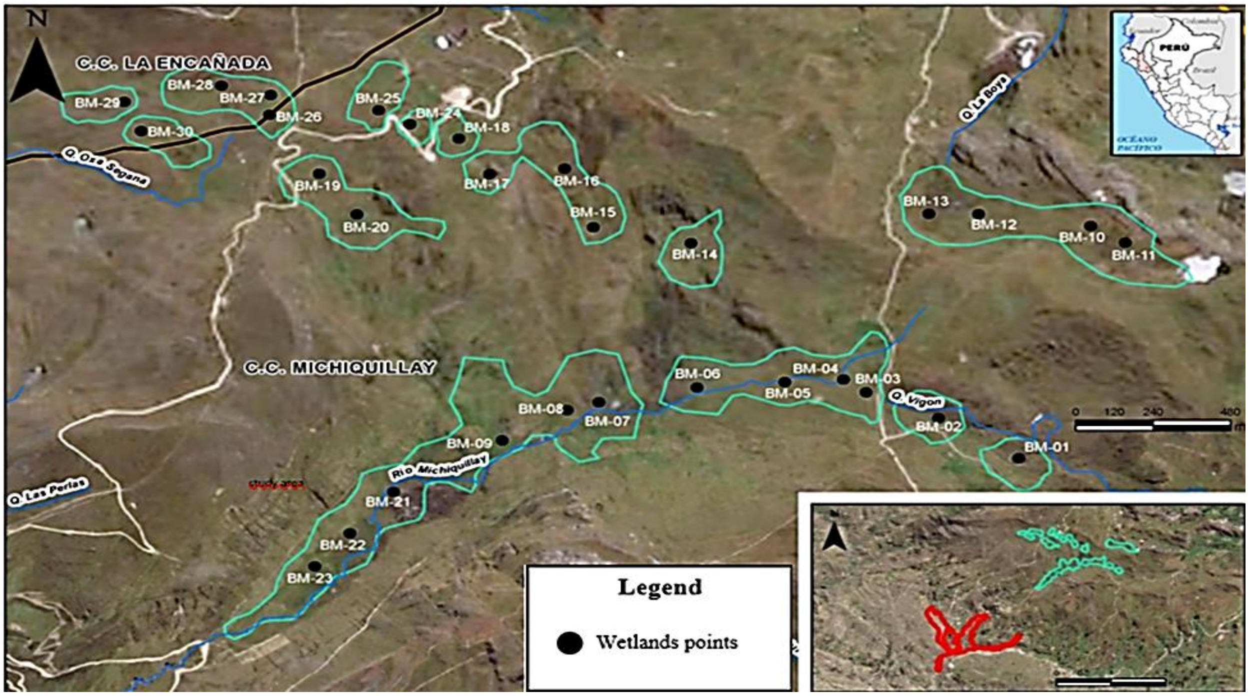

Fig. 3: Location of wetlands sampling points [8]

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In these areas, the Michiquillay type porphyry copper deposit is registered, which has content of different metals such as molybdenum and copper. For a correct development of the mining project, it is necessary to know the natural conditions of the soil and its content of metals and metalloids before mining activities begin.

B. Case of Grey Clustering

For the analysis of this study, we are basing ourselves on the grey clustering methodology that will be developed in different steps.

Step 1: As a first step we will be defining 5 sectors as the object of study as shown in table 1 and we will also consider the figures 5, 6, 7, 8 and 9 that would indicate the data obtained from each sample for each sector.

TABLE I.
NAME OF EACH SECTOR

Sector 1	**MichiquillayMisceláneo Roca**
Sector 2	**QuinuayocSogoron**
Sector 3	**SogoronMisceláneo Roca**
Sector 4	**Michiquillay**
Sector 5	**Wetlands**

Sampling results for each sector:

Sector 1: MichiquillayMisceláneo Rock

TABLE II.
SAMPLING RESULTS FOR SECTOR 1 [8]

Element	n	Minimum	Median	Half	P95	Maximum	Variance	Standard deviation
Cr	30	2	25.7	25.57	42.46	48.7	90.31	9.503
Cu	26	11.3	24.15	27.52	55.05	68.7	210.83	14.52
Pb	22	9.7	18.05	18.7	26.01	32.7	29.32	5.415
Mn	29	26.3	625	642	1052	1397	80883.36	284.4
Ni	26	9.4	20.05	21.13	29.08	31.8	31.23	5.588
Zn	30	3.1	98.9	124.2	265.9	326	5741.09	75.77

Sector 2: QuinuayocSogoron

TABLE III.
SAMPLING RESULTS FOR SECTOR 2 [8]

Element	n	Minimum	Median	Half	P95	Maximum	Variance	Standard deviation
Cr	18	6.8	13.25	16.19	28.01	32	50.1	7.078
Cu	18	56.6	688.9	745.4	1596	1898	270920.3	520.5
Pb	18	5	26.45	30.29	63.23	73.6	243.3	15.6
Mn	18	283	666.2	956.4	1943	2654	364453.7	603.7
Ni	18	7.8	11.95	13.87	22.97	25.6	27.69	5.262
Zn	15	40.3	167	168.7	295.4	308.1	4588.708	67.74

Sector 3: SogoronMisceláneo Rock

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TABLE IV.
SAMPLING RESULTS FOR SECTOR 3 [8]

Element	n	Minimum	Median	Half	P95	Maximum	Variance	Standard deviation
Cr	12	14.1	28	28.88	36.65	37.2	46.06	6.787
Cu	11	12	18.7	19.33	28.1	30.2	32.8	5.727
Pb	12	9.2	16.5	16.56	21.83	22.1	11.58	3.403
Mn	12	322.9	470.9	505.4	721.5	771.3	16666.81	129.1
Ni	12	12.5	19.7	19.64	26.18	26.4	26.5	5.148
Zn	10	37.5	59.85	60.24	76.72	80	171.61	13.1

Sector 4: Michiquillay

TABLE V.
SAMPLING RESULTS FOR SECTOR 4 [8]

Element	n	Minimum	Median	Half	P95	Maximum	Variance	Standard deviation
Cr	21	3.8	9.1	9.162	13.6	16.4	10.1	3.178
Cu	30	62.6	559.4	809.7	1948	2112	342810.3	585.5
Pb	30	15.8	27.75	31.92	56.07	71.7	187.69	13.7
Mn	30	52.2	662.3	723.7	1410	1495	178337.3	422.3
Ni	30	2	8	10.3	26.64	30.6	82.14	9.063
Zn	29	52.8	216.7	221.6	493.4	524.8	16307.29	127.7

Sector 5: Wetlands

TABLE VI.
SAMPLING RESULTS FOR SECTOR 5 [8]

Element	n	Minimum	Median	Half	P95	Maximum	Variance	Standard deviation
Cr	30	3.3	9	8.75	13.77	18.6	12.6	3.548
Cu	20	3.8	17.5	18.5	40.8	44.6	139.9	11.83
Pb	29	16.9	64	66.97	150.5	170.3	1906	43.65
Mn	30	15.3	206	963.5	5490	7721	3663396	1914
Zn	27	2.1	91.4	102.9	300.3	311.9	8053.268	89.74

Step 2: As a second step we will determine which parameters to choose. The parameters chosen for the analysis, which will be samples to determine the initial characteristics of the area, are described in Table 3.

TABLE VII.
ANALYZED PARAMETERS

PARAMETER	CRITERIA	NAME
Cr	C1	Chrome
Cu	C2	Copper
Pb	C3	Lead
Mn	C4	Manganese
Ni	C5	Nickel
Zn	C6	Zinc

With the parameters already determined, we would proceed to separate these data by each sector as shown in the next table.

TABLE VIII.
VALUES OF THE MEAN PRESENCE OF THE CHOSEN PARAMETERS, BY SECTOR, IN MG/KG

Sector	C1 Chrome	C2 Copper	C3 Lead	C4 Manganese	C5 Nickel	C6 Zinc
1	25.57	27.52	18.7	642	21.13	124.2
2	16.19	745.4	30.29	956.4	13.87	168.7
3	28.88	19.33	16.56	505.4	19.64	60.24
4	9.162	809.7	31.92	723.7	10.3	221.6
5	8.75	18.5	66.97	963.5	20	102.9

Step 3: As a third step we will define the grey classes, the quality levels, the standards, and the legislation that should be followed.

For this work, the Environmental Quality Standards (ECA) for soil (D.S. N°011-2017.MINAM) and the Kelley directives (for the classification of contaminated soils) will be used for the analysis of the case with Grey Clustering[15][16]. In Figure 6 we will have the Kelley directives used for each criterion thus defining the gray classes.

TABLE IX.
KELLEY GUIDELINES FOR CLASSIFICATION OF CONTAMINATED SOILS [16]

Parameters	Uncontaminated soils	Pollution (mg/kg dry soil)			
		Light	Medium	Hight	Very Hight
Chrome	0 - 100	100 - 200	200 - 500	500 - 2500	> 2500
Copper	0 - 100	100 - 200	200 - 500	500 - 2500	> 2500
Lead	0 - 200	200 - 500	500 - 1000	1000 - 5000	> 5000
Manganese	0 - 500	500 - 1000	1000 - 2000	2000 - 1%	> 1%
Nickel	0 - 20	20 - 50	50 - 200	200 - 1000	> 1000
Zinc	0 - 250	250 - 500	500 - 1000	1000 - 5000	> 5000

TABLE X.
GREY CLASSES DEFINED

S1	Uncontaminated Soils (SNC)
S2	Light Pollution (CL)
S3	Medium Pollution (CM)
S4	Hight Pollution (CA)
S5	Very Hight Pollution (CMA)

TABLE XI.
DISTRIBUTION OF GREY VALUES CLASSES ACCORDING TO KELLEY DIRECTIVES, BY DEFINED CRITERIA

CRITERIA	GREY CLASSES				
	S1 (SNC)	S2 (CL)	S3 (CM)	S4 (CA)	S5 (CMA)
C1	50	150	250	1500	2750
C2	50	150	250	1500	2750
C3	100	350	750	3000	5250
C4	250	750	1500	6000	10500
C5	10	35	125	600	1075
C6	125	375	750	3000	5250

*Step 4:*As a fourth step we will determine whitenization functions. First, it is necessary to transform the values of the data tables (the table of grey classes shown just before and then the table with the data obtained from the sectors points studied) to values without dimensions[17].

TABLE XII.
VALUES OF THE MEAN PRESENCE OF THE CHOSEN PARAMETERS, BY SECTOR, IN MG/KG

Parameters (mg/kg)	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5
C1	25.57	16.19	28.88	9.16	8.75
C2	27.52	745.40	19.33	809.70	18.75
C3	44.76	30.29	16.56	31.92	66.97
C4	642.00	956.40	505.40	723.70	963.50
C5	21.13	13.87	19.64	44.63	20.00
C6	124.20	168.70	60.24	221.60	102.90

As a result, we obtained the next two tables:

TABLE XIII.
DISTRIBUTION OF GREY VALUES CLASSES ACCORDING TO KELLEY DIRECTIVES WITHOUT DIMENSIONS

Grey Classes - Without dimensions					
Parameters	**SNC**	**CL**	**CM**	**CA**	**CMA**
C1	0.053	0.160	0.266	1.596	2.926
C2	0.053	0.160	0.266	1.596	2.926
C3	0.053	0.185	0.397	1.587	2.778
C4	0.066	0.197	0.395	1.579	2.763
C5	0.027	0.095	0.339	1.626	2.913
C6	0.066	0.197	0.395	1.579	2.763

TABLE XIV.
VALUES OF THE MEAN PRESENCE OF THE CHOSEN PARAMETERS, BY SECTOR WITHOUT DIMENSIONS

Real data - Without dimensions					
Parameters	**Sector 1**	**Sector 2**	**Sector 3**	**Sector 4**	**Sector 5**
C1	0.027	0.017	0.031	0.010	0.009
C2	0.029	0.793	0.021	0.861	0.020
C3	0.024	0.016	0.009	0.017	0.035
C4	0.169	0.252	0.133	0.190	0.254
C5	0.057	0.038	0.053	0.121	0.054
C6	0.065	0.089	0.032	0.117	0.054

Finally, we can determine the whitenization functions from the Table of distribution of grey values classes according to Kelley directives without dimensions as follows:

$$f1 = \begin{cases} 1 & ,x \in [0; 0.053] \\ \dfrac{x-0.053}{0.160-0.053} & ,x \in [0.053; 0.160] \\ 1 & ,x \in [0.160; \infty] \end{cases} \quad (5)$$

$$f2 = \begin{cases} \dfrac{x-0.053}{0.160-0.053} & ,x \in [0.053; 0.160] \\ \dfrac{0.266-x}{0.266-0.160} & ,x \in [0.160; 0.266] \\ 0 & ,x \in [0.266; \infty] \end{cases} \quad (6)$$

$$f3 = \begin{cases} \dfrac{x-0.0160}{0.266-0.0160} & ,x \in [0.160; 0.266] \\ \dfrac{1.596-x}{1.596-0.266} & ,x \in [0.266; 1.596] \\ 0 & ,x \in [1.596; \infty] \end{cases} \quad (7)$$

$$f4 = \begin{cases} \dfrac{x-0.260}{1.596-0.266} & ,x \in [0.266; 1.596] \\ \dfrac{2.926-x}{2.926-1.596} & ,x \in [1.596; 2.926] \\ 0 & ,x \in [0; 0.266] \cup [2.926; \infty] \end{cases} \quad (8)$$

$$f5 = \begin{cases} \dfrac{x-1.596}{2.926-1.596} & ,x \in [1.596; 2.926] \\ 1 & ,x \in [2.926; \infty] \\ 0 & ,x \in [0;\ 1.596] \end{cases} \quad (9)$$

These functions must be determined for each parameter.

Step 5: We will calculate the weights for each criterion using the equation number 4, the table of grey classes without dimensions will give us the next table by inverse[18].

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TABLE XV.
INVERSE VALUES OF DISTRIBUTION OF GREY VALUES CLASSES ACCORDING TO KELLEY DIRECTIVES WITHOUT DIMENSIONS

Inverse					
Parameters	**SNC**	**CL**	**CM**	**CA**	**CMA**
C1	18.800	6.267	3.760	0.627	0.342
C2	18.800	6.267	3.760	0.627	0.342
C3	18.900	5.400	2.520	0.630	0.360
C4	15.200	5.067	2.533	0.633	0.362
C5	36.900	10.543	2.952	0.615	0.343
C6	15.200	5.067	2.533	0.633	0.362
Sum	123.800	38.610	18.059	3.765	2.111

Then, we can calculate the weights by a division between each value and the sum.

TABLE XVI.
WEIGHTS OF EACH CRITERION BY HARMONIC MEAN

Calculation of weights by harmonic mean					
Parameters	**SNC**	**CL**	**CM**	**CA**	**CMA**
C1	0.152	0.162	0.208	0.166	0.162
C2	0.152	0.162	0.208	0.166	0.162
C3	0.153	0.140	0.140	0.167	0.171
C4	0.123	0.131	0.140	0.168	0.171
C5	0.298	0.273	0.163	0.163	0.163
C6	0.123	0.131	0.140	0.168	0.171

Step 6: We will calculate the clustering coefficients. The following tables show the result values of using the table of values of the mean presence of the chosen parameters, by sector without dimensions data in the whitenization functions.

The results of the tables are calculated by multiplying each weight by the value obtained for each point according to the corresponding grey class and parameter.

TABLE XVII.
CLUSTERING COEFFICIENTS FOR SECTOR 1

SECTOR 1							
CRITERION	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**Results**
f1j(x)	1.000	1.000	1.000	0.214	0.559	1.000	0.772
f2j(x)	0.000	0.000	0.000	0.786	0.441	0.000	0.224
f3j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
f4j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
f5j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE XVIII.
CLUSTERING COEFFICIENTS FOR SECTOR 2

SECTOR 2							
CRITERION	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**Results**
f1j(x)	1.000	0.000	1.000	0.000	0.838	0.824	0.655
f2j(x)	0.000	0.000	0.000	0.722	0.162	0.175	0.162
f3j(x)	0.000	0.604	0.000	0.278	0.000	0.000	0.165
f4j(x)	0.000	0.396	0.000	0.000	0.000	0.000	0.066
f5j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE XIX.
CLUSTERING COEFFICIENTS FOR SECTOR 3

SECTOR 3							
CRITERION	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**Results**
f1j(x)	1.000	1.000	1.000	0.489	0.618	1.000	0.823
f2j(x)	0.000	0.000	0.000	0.511	0.382	0.000	0.171
f3j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
f4j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
f5j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE XX.
CLUSTERING COEFFICIENTS FOR SECTOR 4

SECTOR 4							
CRITERION	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**Results**
f1j(x)	1.000	0.000	1.000	0.053	0.000	0.611	0.386
f2j(x)	0.000	0.000	0.000	0.947	0.893	0.389	0.419
f3j(x)	0.000	0.553	0.000	0.000	0.106	0.000	0.132
f4j(x)	0.000	0.447	0.000	0.000	0.000	0.000	0.074
f5j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE XXI.
CLUSTERING COEFFICIENTS FOR SECTOR 5

SECTOR 5							
CRITERION	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**Results**
f1j(x)	1.000	1.000	1.000	0.000	0.603	1.000	0.759
f2j(x)	0.000	0.000	0.000	0.712	0.397	0.000	0.202
f3j(x)	0.000	0.000	0.000	0.287	0.000	0.000	0.040
f4j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
f5j(x)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Step 7:*As a sixth and last step we will use the maximum values obtained of each sector to classify the contamination of the sector by the grey classes.

TABLE XXII.
CONTAMINATION LEVEL BY SECTOR

Sectors	Name of the Sector	Maximum	Contamination level
1	MichiquillayMisceláneo Roca	0.772	**SNC**
2	QuinuayocSogoron	0.655	**SNC**
3	SogoronMisceláneo Roca	0.823	**SNC**
4	Michiquillay	0.419	**CL**
5	Bofedales	0.759	**SNC**

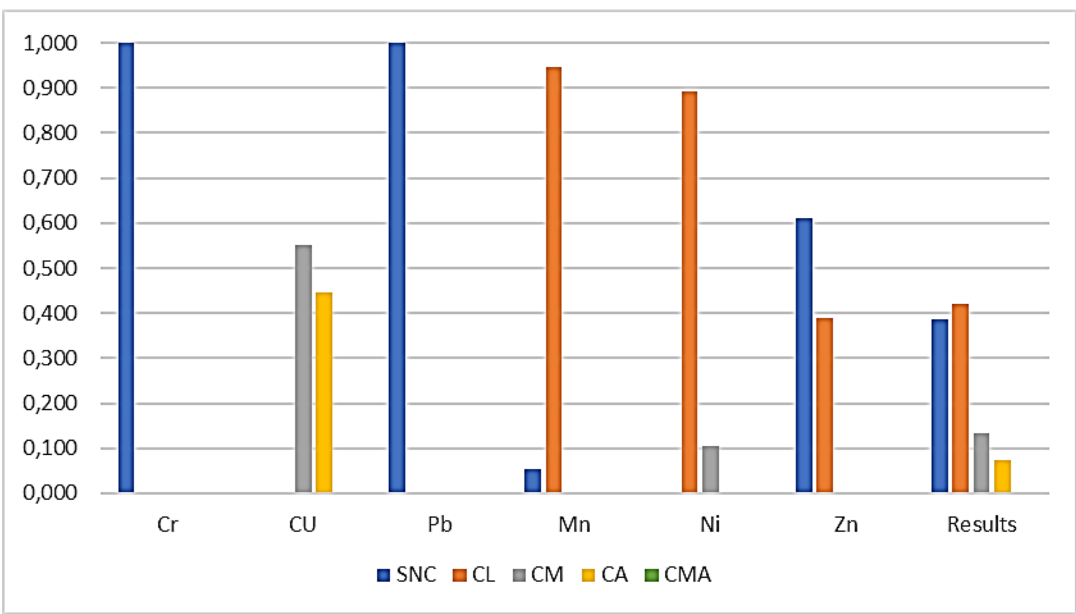
IV. Results And Discussion

A. Study Case

The present study considered 5 sectors for the evaluation of the level of contamination. Likewise, the data obtained from 12 sampling points and 120 samples obtained from them were considered. The location of the 12 sampling points was distributed among the 5 considered sectors. On the other hand, we worked based on the following 6 parameters: Chrome, Copper, Lead, Manganese, Nickel and Zinc. These parameters were considered as criteria due to the use of the Kelley directives and their presence in all the sectors evaluated. In addition, the mean obtained in the presence of the mentioned parameters was considered for the evaluation of each sector.

Then, the results of the evaluation represent the mean level of contamination in each sector, since only one mean value was considered per criterion in each sector and not several values corresponding to various points or sampling zones per sector. Once the previous premise was established, it was obtained that only the sector corresponding to Michiquillay presented a degree of light contamination while the other sectors resulted in soils not contaminated with certainty according to the method used.

Therefore, the reasons why the sector corresponding to Michiquillay resulted in light contamination will be analyzed. The following graph was prepared with the objective of analyzing the factors that concluded in the classification of the sector.



Graph 1: percentage of contribution of each parameter in the classification of soils and results

It can be seen in the graph that the elements that contributed to the classification as slightly contaminated soil (CL) are manganese, nickel and zinc, the latter with a more significant contribution to the classification of non-contaminated. In addition, it is appreciated that copper, although it did not contribute directly to the classification as slightly contaminated soil, its contribution to higher classifications (CM and CA) deprived of contribution to the classification of non-contaminated. Finally, it is observed that, if the raw contribution of each element were added directly, the classification would be uncontaminated soil. The difference lies in the weights by quality criteria, in which the weight for the nickel element is considerably greater than the weight of the other elements and significantly affects the results of the classification factor as slightly contaminated. In any case, the classification between slightly contaminated and non-contaminated soil has very close results.

B. The Grey Clustering method

The Grey Clustering method has a good performance in this case analysis, mainly, because of the quantification needed. The Kelley directives are used for the study. These classify the ground contamination level based in metals concentration level.

The Delphi method generates professionals' opinions which help making decisions about the case study. These professionals will be consulted about possible situations linked to the case study. One method disadvantage is that after two or more questions rounds, their opinion could change.

The AHP method will first define the evaluation criteria and alternatives. According to the Saaty scale, values will be assigned, and a matrix will be developed. This matrix consistency will depend on the consistency ratio and the matrix size.

V. CONCLUSIONS

For this case studied, it was possible to conclude that through Kelley's directives, it was obtained that most of the sectors did not present any contamination in the soil, but in one sector (Sector 4) it was obtained that there was a slight contamination according to table 16 that was obtained from the calculations. These results are consistent with the context of the case study due to the fact that it is a study prior to a mining project.

Regarding the methodology, it was concluded that the Grey Clustering analysis method is very useful since, with the development of the Grey Classes with the parameters and objects of study already defined, a correct classification was made following the respective steps of this method. The classification obtained is very consistent with the case study, indicating that this method is very successful.

With the results obtained in this academic report, comparison studies could be carried out with future mining projects near the site. It would also be interesting to use these results for future analyzes of the same place, but with the mining project already underway and in the exploitation development phase, to determine if these mining activities would be harming or contaminating the soil in the area.

REFERENCES

[1] I. M. Jiskaniet al., “Distinctive Model of Mine Safety for Sustainable Mining in Pakistan,” Min MetallExplor, vol. 37, no. 4, pp. 1023–1037, Aug. 2020, doi: 10.1007/S42461-020-00207-8.

[2] S. Lodhia, MINING AND SUSTAINABLE DEVELOPMENT : current issues. TAYLOR & FRANCIS, 2018. Accessed: Aug. 09, 2022. [Online]. Available: https://www.routledge.com/Mining-and-Sustainable-Development-Current-Issues/Lodhia/p/book/9780367593377

[3] A. Delgado and I. Romero, “Environmental conflict analysis on a hydrocarbon exploration project using the Shannon entropy,” in Proceedings of the 2017 Electronic Congress, E-CON UNI 2017, Jun. 2017, vol. 2018-January, pp. 1–4. doi: 10.1109/ECON.2017.8247309.

[4] C. Zhu and Q. Liu, “Evaluation of water quality using grey clustering,” Proceedings - 2009 2nd International Workshop on Knowledge Discovery and Data Mining, WKKD 2009, pp. 803–805, 2009, doi: 10.1109/WKDD.2009.28.

[5] R. Temino-Boes, R. Romero-Lopez, S. P. Ibarra-Zavaleta, and I. Romero, “Using grey clustering to evaluate nitrogen pollution in estuaries with limited data,” Science of The Total Environment, vol. 722, p. 137964, Jun. 2020, doi: 10.1016/J.SCITOTENV.2020.137964.

[6] I. M. Jiskani, S. Han, A. U. Rehman, N. M. Shahani, M. Tariq, and M. A. Brohi, “An Integrated Entropy Weight and Grey Clustering Method–Based Evaluation to Improve Safety in Mines,” Mining, Metallurgy & Exploration 2021 38:4, vol. 38, no. 4, pp. 1773–1787, Jun. 2021, doi: 10.1007/S42461-021-00444-5.

[7] F. Guan, W. W. Cui, L. F. Li, and J. Wu, “A Comprehensive Evaluation Method of Sensor Selection for PHM Based on Grey Clustering,” Sensors 2020, Vol. 20, Page 1710, vol. 20, no. 6, p. 1710, Mar. 2020, doi: 10.3390/S20061710.

[8] L. Fajardo, L. Ancco, and J. Alvarez, “Determinación de losvalores de nivel de fondo y de referencia para metales y metaloides de lossuelosMichiquillay, MichiquillayMisceláneoo Roca, QuinuayocSogoron, SogoronMisceláneo Roca y bofedalesen las comunidadescampesinas de Michiquillay y La Encañada,” 2019. https://repositorio.oefa.gob.pe/handle/20.500.12788/175 (accessed Aug. 09, 2022).

[9] Liu Kea, Shen Xiaoliub, and Tan Zhongfua, “Enterprise merger of the main way risk profiles. Industrial technology economy,” Systems Engineering Procedia, vol. 3, pp. 55–62, 2001, doi: 10.1016/j.sepro.2011.11.008.

[10] L. Ke, S. Xiaoliu, T. Zhongfu, and G. Wenyan, “Grey Clustering Analysis Method for Overseas Energy Project Investment Risk Decision,” Systems Engineering Procedia, vol. 3, pp. 55–62, Jan. 2012, doi: 10.1016/J.SEPRO.2011.11.008.

[11] S. Liu and Y. Lin, “Grey Systems: Theory and Applications,” vol. 68, pp. xx–379, 2014, Accessed: Aug. 09, 2022. [Online]. Available: http://link.springer.com/book/10.1007/978-3-642-16158-2

[12] A. Delgado, A. Aguirre, E. Palomino, and G. Salazar, “Applying triangular whitenization weight functions to assess water quality of main affluents of Rimac river,” Proceedings of the 2017 Electronic Congress, E-CON UNI 2017, vol. 2018-Janua, pp. 1–4, 2018, doi: 10.1109/ECON.2017.8247308.

[13] A. Delgado, P. Montellanos, and J. Llave, “Air quality level assessment in Lima city using the grey clustering method,” in IEEE ICA-ACCA 2018 - IEEE International Conference on Automation/23rd Congress of the Chilean Association of Automatic Control: Towards an Industry 4.0 - Proceedings, Jan. 2019. doi: 10.1109/ICA-ACCA.2018.8609699.

[14] A. Delgado, A. Espinoza, P. Quispe, P. Valverde, and C. Carbajal, “Water quality in areas surrounding mining: Las Bambas, Peru,” International Journal of Innovative Technology and Exploring Engineering, vol. 8, no. 12, pp. 4427–4432, Oct. 2019, doi: 10.35940/ijitee.L3807.1081219.

[15] Decreto Supremo N° 011-2017-MINAM, “ApruebanEstándares de Calidad Ambiental (ECA) para Suelo | SINIA | Sistema Nacional de Información Ambiental,” 2019. https://sinia.minam.gob.pe/normas/aprueban-estandares-calidad-ambiental-eca-suelo-0 (accessed Aug. 09, 2022).

[16] M. Segovia, “Bioaccesibilidad y biodisponibilidad de elementostrazaensueloscontaminados y plantas,” 2014. https://repositorio.uchile.cl/handle/2250/138279 (accessed Aug. 09, 2022).

[17] A. Delgado and H. Flor, “Selection of the best air purifier system to urban houses using AHP,” in 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies, CHILECON 2017 - Proceedings, 2017, vol. 2017-Janua. doi: 10.1109/DISTRA.2017.8229622.

[18] M. Kim, Y. C. Jang, and S. Lee, “Application of Delphi-AHP methods to select the priorities of WEEE for recycling in a waste management decision-making tool,” J Environ Manage, vol. 128, pp. 941–948, Oct. 2013, doi: 10.1016/J.JENVMAN.2013.06.049.