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Analysis of water contamination in the mining zone of Cerro de Pasco, Peru using the grey clustering method

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ABSTRACT

Water quality assessment is a complex topic, since many parameters have to be considered in order to perform a correct evaluation. For this type of studies, the grey clustering method represents a useful tool to determine the quality of water, using artificial intelligence criteria. In this work, fourteen monitoring points on three water bodies in Cerro de Pasco were assessed using the parameters established by MINAM in the Decreto Supremo N°015-2015. The data used from this study was collected from the Water National Authority of Peru. The results showed that 57.1% of the points presented an acceptable water quality that just needs disinfection to be purified; while 21.4% presented an intermediate water quality, which could be purified by conventional treatment and other 21.4% presented a poor water quality that needs a special treatment to be purified for human consumption. These results could be used by local authorities to evaluate, inspect and remediate the damage caused by mining activity. The grey clustering method could be applied to different types of assessments such as water, air or social impact.

Key words : Grey Clustering, Mining Activities, Water Quality.

1. INTRODUCTION

The water quality assessment (WQA) is an important topic of study since water is an indispensable resource for the life of human beings, animals and the environment[1]. Not only society needs large quantities of water to live, but mostly a high quality is required in order to ensure the existence of both animals and humans [2]. However, the quality of water is affected by several activities, including mining industry. The risk associated to these effects needs to be evaluated by effective techniques, such as the grey clustering method, which is used in this work as well asthe results of previous water quality assessments [3]–[5].

The grey clustering method, first developed in the grey systems theory by Deng [6], can be applied to many different working fields. The method can help to classify observations or objects into defined classes by using the grey incidence matrices or grey possibility functions. By applying grey clustering, complex cases are often simplified and categorized due to using a minimum amount of data and eliminating all unnecessary variables, without losing any information [7]. Likewise, the grey clustering method is a possibility to test if objects of observations belong to a predetermined class [8].

Since most of the lead and zinc production (91% and 95%, respectively) in Peru [9] come from the central part of the country, the grey clustering method is applied on three important water bodies located in the mining zone of Cerro de Pasco, in central Peru. These water bodies are Huallaga river, San Juan river and Tingo river. Therefore, the main objective of this study is to analyze the water quality in the mining zone of Cerro de Pasco using the grey clustering method.

The present study is divided into 6 sections. Section 2 is a review of other related researches. Section 3 provides details of the grey clustering method. Then, in section 4, the case study is described, followed by the results and discussion in section 5. Finally, conclusions are provided in section 6.

2. LITERATURE REVIEW

Regarding the grey clustering method, a previous study was developed by Delgado et al. in 2017 [3]. As well as the present research, this method was used to assess the water quality but in Santa River watershed in Ancash, Peru. This region is influenced by mining activity, therefore, the importance of performing a study in order to know the procedures needed to purify the water according Peruvian law. The results obtained in this study consider uncertainty, so even when two or more points measured were in the same class; the method showed which point was purer than the other, thus authorities can focus their attention on the most contaminated points.

As water contamination, especially linked to mining activities, usually generates social conflicts, social impact assessments (SIA) are very important. Like developed by [4] and also by [5], the SIA can be calculated with the grey clustering method. The different affected and involved urban and rural population groups, as well as expert groups were used as stakeholders and the data was obtained from their subjective evaluation. The results obtained from these assessments could help the mining companies or the Peruvian government to take appropriate measurements to prevent and minimize social conflicts over mining projects.

In addition, a study developed by Bianchini et al. [10], was focused on evaluating the water quality in Cerro de Pasco, since previous results showed, among many factors, that 53% of children and 9% of pregnant women had high levels of Pb in their blood, which could be related to the 15.8% of infant mortality caused by congenital malformations. The study was developed measuring 10 points in Tingo River, Huallaga River and San Juan River. The results showed that high concentrations of Al, Mn and Pb were present in the water near the mines, and in consequence, in drinking water within the zone.

Another research considered was Orecchio et al. [11]in which Polycyclic Aromatic Hydrocarbons (PAHs) were analyzed and measured in relation to their toxicity to organisms, animals and, in consequence,to human health. All samples were collected in the same stations of the previous study. The results of the study agreed with the previous heavy metal study, finding higher concentrations of PAHs in the major drain of the mine, near the mine waste duct and near waste deposits. The study determined that PAHs concentration is in part caused by compounds derived from petrol used for the transportation, electricity and energy for the explosions in the mine.

3. METHODOLOGY

In this research, the center-point triangular whitenization weight functions (CTWF) are used with objects of observation as stakeholder groups.

First, the stakeholders and the criteria with respective grey classes need to be defined. The standards needed as criteria for the analysis of water samples can be obtained from the equivalent legislature, in this case for Cerro de Pasco the Peruvian legislature needs to be considered. As this article is investigating the quality of water, the used directive is the “Decreto supremo No 015-2015” of the Ministry of Environment (MINAM by its Spanish acronym) in Peru [12]. A set of m objects, of n criteria, of s grey classes and a set of monitoring values x_{ij} ($i = 1,2,\dots,m$; $j = 1,2,\dots,n$) of the i^{th}($i = 1,2,\dots,m$) object, for the criterion j^{th}($j = 1,2,\dots,n$) are assumed. The different steps for the calculations for grey clustering based on CTWF are expressed as following [7], [13]:

Step 1: The center-point values $\lambda_1,\lambda_2,\dots\lambda_n$ of the corresponding grey classes $1,2,\dots,s$ are determined. All data and standards need to be non-dimensional to be comparable.

Step 2: The center-point values for water quality after Peruvian law application are plotted in a triangular function graph (as shown in Figure 1) to its according $\lambda_1,\lambda_2,\dots\lambda_n$ for each standard parameter. For the k^{th} grey class, $k = 1,2,3$, of the j^{th} parameter, $j = 1,2,\dots,n$ for a monitoring valuex_{ij}, the explicit whitenization weight function shown in (1) is used.

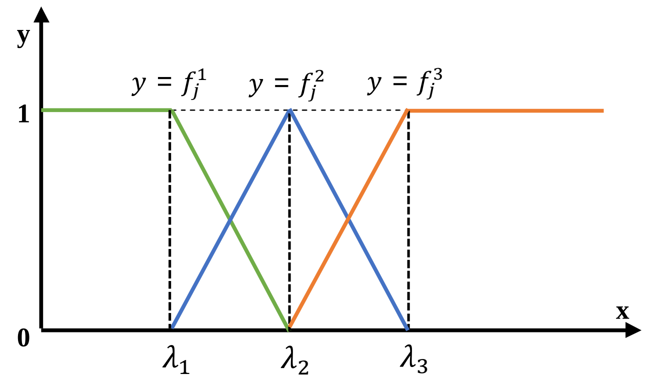

Figure 1: CTWF representation

Where:

$f_j^1 = A_1$: Water might be purified by disinfection.

$f_j^2 = A_2$: Water might be purified by conventional treatment.

$f_j^3 = A_3$: Water might be purified by advanced treatment.

$$f_j^k(xij) = \begin{cases} 0, \; x \notin [\lambda_{k-1},\lambda_{k+1}] \\ \frac{x-\lambda_{k-1}}{\lambda_k-\lambda_{k-1}}, x \notin [\lambda_{k-1},\lambda_k] \\ \frac{\lambda_{k+1}-x}{\lambda_{k+1}-\lambda_k}, x \notin [\lambda_k,\lambda_{k+1}] \end{cases} \quad (1)$$

*Step 3:*To calculate the clustering weight (η_j^k) for each category of the grey classes, (2) is used.

$$\eta_j^k = \frac{1/\lambda_j^k}{\sum_{j=1}^{m} 1/\lambda_j^k} \quad (2)$$

*Step 4:*The comprehensive clustering coefficient σ_i^k for the respective monitoring point $i = 1,2,\dots,m$, with the corresponding grey classes $k = 1,2,3$ is calculated by (3).

$$\sigma_i^k = \sum_{j=1}^{n} f_j^k\left(x_{ij}\right) \cdot \eta_j^k \quad (3)$$

*Step 5:*To identify the grey class of the object of observation, the maximum value of the clustering coefficient needs to be determined. If$\max_{1\le k\le s}\{\sigma_i^k\} = \sigma_i^{k*}$, object i belongs to grey class $k*$.

4. CASE STUDY

The water quality assessment (WQA) was conducted on fourteen monitoring points, in order to get results from the most relevant areas of this context.

4.1 Context Description

The WQA was performed in Pasco department, in central Peru, as shown in Figure 2. Specifically, three bodies of water were selected for this assessment: Huallaga, Tingo and San Juan rivers, where several points within these rivers were analyzed (which are displayed in Table 1). The data used for this study was collected by a research carried out by the Water National Authority (ANA by its Spanish acronym) of Peru in 2014 [14], [15].

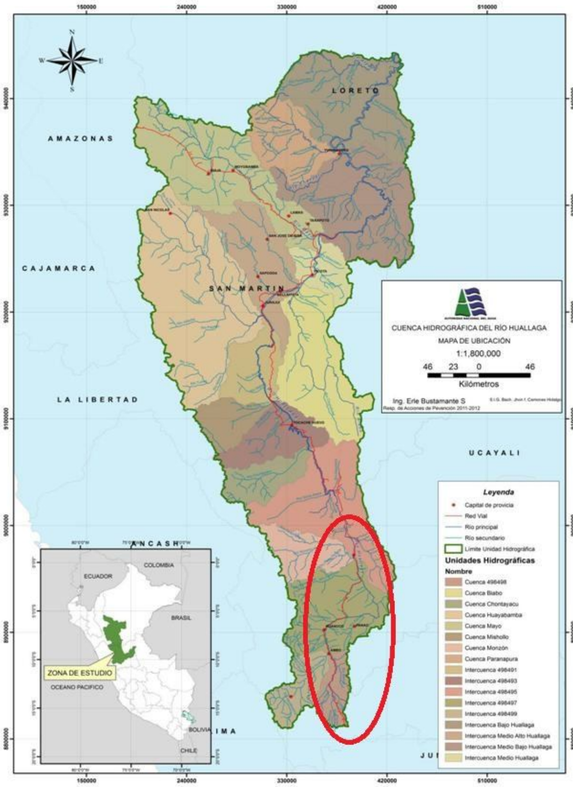

Figure 2: Map of Peru, the red oval corresponds to the area of the study [15]

Table 1: Monitoring points on Huallaga river watershed

N°	Description
1	Huallaga river, 900 m downstream from the intersection of Parimaraca river and Lloclla ravine.
2	Huallaga river, downstream from mining activity.
3	Huallaga river, 100 m upstream before the intersection with Ticlacayan river.
4	Huallaga river, 150 m downstream from the intersection with Ticlacayan river.
5	Huallaga river, upstream before the intersection with Chinchan river.
6	Tingo river, 300 m from Rumillana solid waste dump.
7	Tingo river, before the intersection with Huallaga river.
8	San Juan river, 40 m upstream from Vinchuscancha bridge.
9	San Juan river, 25 m downstream from the bridge to Pacoyan community.
10	San Juan river, 22 m downstream from Los Angeles bridge.
11	San Juan river, 400 m before Brocal's mineral processing plant.
12	San Juan river, 150 m before Andacancha river flows into San Juan river.
13	San Juan river, 22 m downstream the Huayllay highway.
14	San Juan river, 300 m after Blanco river flows into San Juan river

4.2Calculations using the CTWF method

The study calculations, based on the CTWF method, are presented as follow:

*Step 1:*First, non-dimensional standards values based on the Peruvian law DS N° 015-2015-MINAM [12], are shown in Table 2.

Table 2: Non-dimension standard values in the case study

Parameter	SubcategoryA		
	A_1	A_2	A_3
As	0.1250	1.0000	1.8750
Fe	0.1429	0.4762	2.3810
Mn	0.8889	1.0000	1.1111
Pb	0.3333	1.0000	1.6667

Then, the non-dimension data obtained by the Water National Authority [14], [15] are shown in Table 3 for each parameter on every monitoring point.

Table 3: Non-dimension data in the case study

Monitoring Point	As	Fe	Mn	Pb
1	0.0625	0.3181	0.2342	0.7567
2	0.3125	0.2505	1.2271	2.3300
3	0.2125	0.5295	0.6618	2.1867
4	0.1000	0.2971	0.4629	1.2700
5	0.1500	0.1624	0.4938	1.1900
6	0.1875	2.2529	2.0562	3.0967
7	0.0250	0.1976	0.1302	0.3767
8	0.0125	0.0886	0.0276	0.0333
9	0.0250	0.0824	0.0220	0.0167
10	0.1000	0.8429	1.3716	0.9333
11	0.1125	0.8833	0.8860	0.9433
12	0.1250	0.9771	0.9187	1.4367
13	0.0875	0.6743	0.8831	1.1900
14	0.1625	4.4924	1.3296	1.6467

*Step 2:*First, the values presented in the Table 2 were substituted into (1). Equations (4) – (6) shows the results using the parameter "iron" (Fe) in order to appreciate an example of its application.

$$f_1^1(x) = \begin{cases} 1, x \in [0, 0.1429] \\ \frac{0.4762-x}{0.4762-0.1429}, \ x \in [0.1429, 0.4762] \\ 0, \ x \notin [0, 0.4762] \end{cases} \quad (4)$$

$$f_1^2(x) = \begin{cases} 0, x \notin [0.1429, 2.3810] \\ \frac{x-0.1429}{0.4762-0.1429}, \ x \in [0.1429, 0.4762] \\ \frac{2.3810-x}{2.3810-0.4762}, \ x \in [0.4762, 2.3810] \end{cases} \quad (5)$$

$$f_1^3(x) = \begin{cases} 0, \ x \in [0, 0.4762] \\ \frac{x-0,4762}{2.3810-0.4762}, x \in [0.4762, 2.3810] \\ 1, \ x \notin [0, 2.3810] \end{cases} \quad (6)$$

Then, using the data of the parameter “Fe” from Table 3, the CTWF values were calculated with (4) – (6). Table 4 shows the results for three monitoring points.

Table 4: Values of CTWF of first three monitoring points

P_1	As	Fe	Mn	Pb
$f_1^1(x)$	1.0000	0.4743	1.0000	0.3649
$f_1^2(x)$	0.0000	0.5257	0.0000	0.6351
$f_1^3(x)$	0.0000	0.0000	0.0000	0.0000
P_2	**As**	**Fe**	**Mn**	**Pb**
$f_2^1(x)$	0.7857	0.6772	0.0000	0.0000
$f_2^2(x)$	0.2143	0.3228	0.0000	0.0000
$f_2^3(x)$	0.0000	0.0000	1.0000	1.0000
P_3	**As**	**Fe**	**Mn**	**Pb**
$f_3^1(x)$	0.9000	0.0000	1.0000	0.0000
$f_3^2(x)$	0.1000	0.9720	0.0000	0.0000
$f_3^3(x)$	0.0000	0.0280	0.0000	1.0000

Step 3: The clustering weight (η_j^k) for each category was calculated using (2) and the data from Table 2. Such results are shown in Table 5.

Table 5: Clustering weights for each category

Parameter	SubcategoryA		
	A_1	A_2	A_3
As	0.4183	0.1961	0.2174
Fe	0.366	0.4118	0.1712
Mn	0.0588	0.1961	0.3668
Pb	0.1569	0.1961	0.2446

*Step 4:*The comprehensive clustering coefficient (σ_i^k)for the respective monitoring point was calculated using (3). The results are shown in Table 6.

Table 6: Values of clustering coefficient for monitoring points

Monitoring Point	As	Fe	Mn
1	0.7080	0.3410	0.0000
2	0.5765	0.1749	0.6114
3	0.4353	0.4198	0.2494
4	0.6738	0.3071	0.0990
5	0.7732	0.1699	0.0697
6	0.3884	0.0417	0.7711
7	0.9297	0.0803	0.0000
8	1.0000	0.0000	0.0000
9	1.0000	0.0000	0.0000
10	0.4340	0.5090	0.3998
11	0.4905	0.5032	0.0366
12	0.4613	0.4237	0.2052
13	0.4771	0.5091	0.0875
14	0.4004	0.0143	0.7753

*Step 5:*Finally, considering that$\max_{1 \le k \le s}\{\sigma_i^k\} = \sigma_i^{k*}$, object i belongs to grey class $k*$, the grey classes were determined as can be seen in Table 7.

Table 7: Number of max σ_i^k for each category

SubcategoryA	Number of max σ_i^k	Percentage
A_1	8	57.10%
A_2	3	21.40%
A_3	3	21.40%

5. RESULTS AND DISCUSSION

5.1About the Case Study

Firstly, the results show that over half of the points monitored present good water quality since 57.1% of the points are included in category A1. This indicates that just the water disinfection is needed for human consumption, while 21.4% correspond to category A2 and require conventional and special treatment. However, the remaining 21.4% correspond to category A3, which need a special treatment.

Secondly, with regard to the points with category A2, the most significant is point 11, as it indicates that the reason for the water being contaminated is most probably due to the presence of theBrocal S.A. concentrator plant.

Finally, the points with the greatest contamination in water (A3) are closely related with mining activity and waste disposal, which is in good agreement with the conclusions of Bianchini et al. [10] and Orecchio et al. [11], as point 2 is located near to the mining company Atacochaas well as point 6 is near the Rumillana dump.

5.2About the CTWF methodology

Regarding the method used in this analysis, the comparison with other methods shows the advantages of the grey clustering method, since it considers the uncertainty within the analysis [7], [16], [17]. This particularity makes it a more suitable method than other multi-criteria analysis, such as Delphi [18], or analytic hierarchy process (AHP) [19], as Delphi method is time-consuming, laborious and expensive, as experts are required for its development [20]. Likewise, AHP has a high subjective component and needs complementary methods [21]. While, the grey clustering method uses the data obtained applying a mathematical system of simple in principle and calculation [12], so less costs are required.

6. CONCLUSIONS

The grey clustering method based on the CTWF was able to optimally evaluate water samples taken throughout the Huallaga basin with respect to As, Fe, Mn and Pb contamination. 57.1% of the samples taken show good water quality and belong to category A1, while 21.4% are in categories A2 and A3, requiring conventional and special treatment, respectively. The obtained results can help Peruvian authorities to improve water management and mining activities in this watershed.

As the CTWF method considers the uncertainty within the analysis, it is more effective than other multi-criteria methods.The grey clustering method is also more objective with fewer costs. Furthermore, it has a wide application range while needing only a small sample amount.

Finally, the grey clustering method could be simplified by the development of appropriate software. In the future, the method could also be tested for other social, environmental or political problems worldwide.

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