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Applying Grey Systems to Determine if Mining Activity is Main Factor of Water Pollution in Huallaga River in Peru

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Abstract—Peru is a country with a lot of mining activities; however, these activities have a bad reputation due to pollution water. Therefore, the objective of this study is to determine the water quality of the Alto Huallaga watershed, Peru, due to the presence of nearby mining companies and urban populations. To this end, the research question is as follows: Do mining companies pollute the Alto Huallaga River more than urban populations? The research question is answered through the Grey Clustering methodology, which is based on grey systems, using information known from the National Water Authority (ANA). The main purpose of this work is to compare the quality of water that has been influenced by contaminants from mining and non-mining activities. The results obtained in this work show that the environmental management of the mining companies close to the rivered reduces the pollution produced by mining and non-mining activities to levels acceptable by law. On the contrary, it is observed that the absence of mining units has an influence on the increase in urban pollution produced by cities and towns near the watershed, which affects water quality. This research shows that formal mining activity in the watershed has a positive impact on water quality and allows future research to be opened regarding the influence on other environmental factors such as air, soil, biodiversity and even the social environment. Finally, this research is the beginning of a change in perspective on mining in the country.

Keywords-Grey Clustering, Grey systems, Mining Activities, Water Pollution.

I. INTRODUCTION

The water component is affected by various human and industrial activities, leading to a negative impact on bodies of water such as lakes, lagoons, and rivers. In the present work, this impact on the Alto Huallaga watershed will be studied, this basin has a great potential of water resources, forming part of the inter-watershed of the Huallaga River, and provides important environmental services and basic natural resources, essential for human beings, flora, and fauna [1].

In the present work, the Grey Clustering method, which is based on grey systems, was used, since it is the most applicable in the improvement of analytical processes for the evaluation of water quality [2]. In addition, this method is used for the evaluation of water quality parameters in levels [3], it is also possible to create artificial intelligence models based on grey systems [4].

The Alto Huallaga inter-watershed has an area of 12,309.14 km2 and a perimeter of 868.23 km that are delimited by the passage of the Huallaga River from south to north. The river has an initial route from west to east increasing its channel in the city of Huanuco [5]. In this city, the inter-watershed is characterized by having variable ecosystems where the greatest variability of vegetation cover is found [6]. In addition, it has main resources such as water and soil [7].

The main objective of this work is to carry out a comparative study of the quality of water that has been contaminated by mining and non-mining activities. Its development will focus on the analysis of two sections or stretches of the inter-watershed, where one of them is mainly affected by the development of mining projects, such as the discharge of mining effluents on tributaries, while the other section is affected by industrial companies and urban activities carried out by the inhabitants of the city, such as industrial waste and residues or wastes deposited on rivers.

The organization of this research will present the following structure: Section II will show the review literature, section III will present the methodology used in the research, section IV will explain the case study with which the paper was developed, the Results and discussions will be described in section V, and finally the conclusions will be defined in section VI.



II. LITERATURE REVIEW

Wang, Zhang, Li, Lei and Wang emphasized in their study, entitled "Application of Grey Clustering Method Based on Improved Analytic Hierarchy Process in Water Quality Evaluation", the differences in the impacts of the water quality of different criteria or variables obtained from the water samples. The method proposed in this article is that of Grey Clustering, which allows evaluating the quality of the water surface through water quality parameters. These parameters are analyzed according to their degree of contamination that impacts the water body. Monitoring points were selected in four sections of the Qingshui River (China) for their evaluation and application of the Grey Clustering method, giving as results, after a comparison and analysis, that this method is more reliable and reasonable with respect to providing an adequate basis in the evaluation of water quality and the management of the environment in relation to the water component [2].

In the article entitled "Artificial Intelligence model based on Grey systems to assess water quality from Santa River Watershed", 21 points of the river watershed were analyzed and classified within the categories presented by Peruvian regulations. Following the grey clustering methodology, they perform the non-dimension, continuing with the calculation of the clustering weight of each parameter and finally the clustering coefficient values. With the application of the method, the research determined different degrees of contamination: 47.6% of good water quality, and 19.1% of poor water quality. These results were presented thanks to the Grey Clustering method[8].

In the article "Water Quality Assessment using the Grey Clustering Analysis on a river of Taxco, Mexico", the Grey Clustering method is again analyzed to parameterize the water quality levels. A water quality study is carried out near mining units to classify the points within the allowed parameters. The geology that surrounds this area presents an important mineralization with which mining projects are presented for the extraction of economic minerals. Because of this, mining tailings are also generated that affect the river of Taxco. According to the results, the Grey clustering method gives a better precision of the degree of contamination of the river, presenting greater contamination near the mining units [3]

In the research work entitled "Water Quality in Areas Surrounding Mining: Las Bambas, Peru", contamination in the rivers Ferrobamba and Chalhuachuacho is analyzed through 6 monitoring points per river. This is related to Las Bambas mining project, a copper project considered one of the most important in the country. With the analysis of 12 monitoring points, the results are presented by applying the Grey Clustering method to categorize the contamination level of each point. The research allowed local authorities to learn more about the levels of contamination related to mining projects, although the Ferrobamba River had an A1 water categorization[9].

The article entitled "Evaluation of Water Quality in the Lower Huallaga River Watershed using the Grey Clustering Analysis Method", which was used as a reference to develop this paper, worked with the Grey Clustering Method, and the information provided by the National Water Authority (ANA) to analyze some monitoring points in the Huallaga River Watershed. By this method, they determined the river was in the "Uncontaminated" category of the Prati Index. Finally, the method helped to get more reliable results, so it can be applied in studies of water, air and soil quality, landscape, and biodiversity analysis [10].

III. METHODOLOGY

The research objects of grey systems theory consist of such uncertain systems that they are known only partially with small samples and poor information. The theory focuses on the generation and excavation of the partially known information to materialize the accurate description and understanding of the material world. Grey cluster evaluation includes such contents as grey variable weight clustering, grey fixed weight clustering, cluster evaluation based on end-point or center-point triangular whitenization weight functions (CTWF) [11]. Fig. 1 shows the flowchart of the methodology.



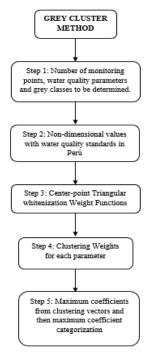


Fig. 1. CTWF method flowchart

In this section, CTWF method will be explained, this method has six steps:

Step 1: To start, a quantity of "m" monitoring points, an amount of grey classes "k" and a set of monitoring values will be determined. Also, a fixed number of "n" water quality parameters which will be coded as C_j and each one grey class as λ_k (k=1,2,3). The monitoring values will be represented by the following notation "x_ij" (i=1, 2..., m; j=1, 2..., n).

Step 2: In this step, all data used for the research will be transformed in non-dimensional values. Water Quality Standard of the Peruvian law [12] will be used to get these values.

Step 3: CTWF of the criteria will be calculated according to Peruvian law, this research will use three functions that are shown in Fig. 2.

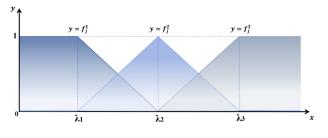


Fig. 2. CTWF according to the Peruvian Law

Where:

 $y = f_j^1 = A_1$ = Water could be purified by disinfection. $y = f_j^2 = A_2$ = Water could be purified by conventional treatment.

 $y = f_j^3 = A_3 =$ Water could be purified by special treatment.

$$f_j^1(x_{ij}) = \begin{cases} 1, & x \in [0; \lambda_j^1] \\ \frac{\lambda_j^2 - x}{\lambda_j^2 - \lambda_j^2}, & x \in \langle \lambda_j^1; \lambda_j^2 \rangle \\ 0, & x \in [\lambda_j^2; +\infty) \end{cases}$$
(1)

$$f_j^2(x_{ij}) = \begin{cases} \frac{x - \lambda_j^1}{\lambda_j^2 - \lambda_j^1}, & x \in \{\lambda_j^1; \lambda_j^2\} \\ \frac{\lambda_j^3 - x}{\lambda_j^3 - \lambda_j^2}, & x \in \{\lambda_j^2; \lambda_j^3\} \\ 0, & x \in [0; \lambda_j^1] \cup [\lambda_j^3; +\infty \rangle \end{cases}$$
(2)

$$f_j^3(x_{ij}) = \begin{cases} 0, & x \in [0; \lambda_j^2] \\ \frac{\lambda_j^3 - x}{\lambda_j^3 - \lambda_j^2}, & x \in \langle \lambda_j^2; \lambda_j^3 \rangle \\ 1, & x \in [\lambda_j^3; +\infty \rangle \end{cases}$$
(3)

In the previous equations, $f_j^k(x_{ij})$ represents the "k"th CTWF of the " j_{th} " parameter for monitoring point " x_{ij} ".

*Step 4:*Then, the clustering weights for each parameter, according to non-dimensional standard values from Peruvian law, are calculated by the next equation:

$$\eta_j^k = \frac{\frac{1}{\lambda_j^k}}{\sum_{j=1}^m \frac{1}{\lambda_j^k}} \tag{4}$$



Step 5: After that, the clustering vector, shown in equation 5, is determined by the sum of products of the parameters with their respective clustering weights. Finally, the grey class of monitoring point will be determined by the maximum coefficient from clustering vector. The equation 6 will determine to which grey class the studied sample belongs:

$$\sigma_i^k = \sum_{j=1}^n f_j^k(x_{ij}).\eta_j$$
(5)
$$max\{\sigma_i^k\} = \sigma_i^{k^*}, \kappa = 1,2,3$$
(6)

It can be asserted that $\sigma_i^{k^*}$ belongs to k the class λ_k .

IV. CASE STUDY

The research and analysis of surface water quality was carried out in two sections of the Alto Huallaga River watershed, which is located in the central part of Peru through the departments of Cerro de Pasco and Huanuco with an approximate area of 12,309.14 km2 [13], represented in Fig. 3 and Fig. 4.



Fig. 3. Peru in South America



Fig. 4. Huallaga River Watershed in Peru

A. Definition of Study Objects

Information is collected from a total of 25 monitoring points of the Alto Huallaga watershed carried out by the National Water Authority (ANA) during November and December 2018 [14].

The monitoring points were chosen because they were located on the trajectory of the Alto Huallaga Watershed; furthermore, these points represent the direct effects due to mining and non-mining activity. The first set of monitoring points, named Section 1 (P1, ..., P13), identifies the section where there is presence of metal contamination, due to the existence of mining companies that have permits to discharge waste on the watershed, while the second set of points, named Section 2 (P14, ..., P25), indicates the presence of contamination by communities, towns, and non-mining industries. This will be detailed in Table 1 and the points will be shown in Fig. 5.

 TABLE I.

 MONITORING POINTS OF WATERSHED [14]

	Sectio	n 1	Section 2				
Poin t	Code	Name	Point	Code	Name		
P1	RLloc1	Lloclla River	P14	RHual6	Huallaga River		
P2	RLloc2	Lloclla River	P15	RHuer2	Huertas River		
P3	RLloc3	Lloclla River	P16	RHual7	Huallaga River		
P4	RLloc4	Lloclla River	P17	RHual8	Huallaga River		
P5	RHual1	Huallaga River	P18	RHual9	Huallaga River		
P6	RHual2	Huallaga River	P19	RHuan2	Huancachupa River		
P7	RHual42	Huallaga River	P20	RHual10	Huallaga River		
P8	RHual43	Huallaga River	P21	RHigu2	Higueras River		
P9	RHual3	Huallaga River	P22	RHual11	Huallaga River		
P10	RTicl1	Ticlacayan River	P23	RHual12	Huallaga River		
P11	RHual4	Huallaga River	P24	RHual13	Huallaga River		
P12	RHual5	Huallaga River	P25	RHual14	Huallaga River		
P13	RChin2	Chinchan River					



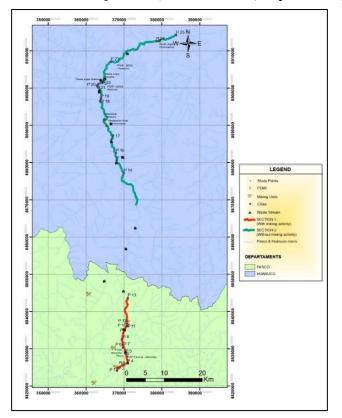


Fig. 5. Monitoring points in two sections of the Alto Huallaga River watershed

B. Definition of Assesment Criteria and Grey Classes

The evaluation criteria defined in this research are delimited by the parameters related to urban metals and pollutants impacting water quality. The importance of these parameters choosing is based on their representativeness of the samples taken at the monitoring points. Support how many levels will be chosen, and how it will be divided, citing the sources and present them in the Table II. In some cases, the parameters values chosen were not found in the Peruvian regulations. Due to this, international regulations had to be used to complement the quality standard. These parameters were taken by American Countries Water Quality Standard [15].

a	N T 4 4	T T •/			
Criterion	Notation	Units	A1	A2	A3
pH	C1	0 - 14	7.500	7.250	7.000
Al	C2	mg/L	0.900	2.950	5.000
As	C3	mg/L	0.010	0.080	0.150
В	C4	mg/L	2.400	3.700	5.000
Be	C5	mg/L	0.012	0.040	0.100
Cd	C6	mg/L	0.003	0.005	0.010
Total Cr	C7	mg/L	0.010	0.050	0.100
Cu	C8	mg/L	0.010	1.000	2.000
Fe	C9	mg/L	0.300	1.000	5.000
Hg	C10	mg/L	0.001	0.002	0.002
Mn	C11	mg/L	0.400	0.450	0.500
Mo	C12	mg/L	0.010	0.040	0.070
Ni	C13	mg/L	0.020	0.045	0.070
Pb	C14	mg/L	0.010	0.030	0.050
Sb	C15	mg/L	0.015	0.020	0.025
Se	C16	mg/L	0.040	0.045	0.050
U	C17	mg/L	0.020	0.025	0.030
Zn	C18	mg/L	3.000	4.000	5.000
Oils and fats	C19	mg/L	0.500	1.100	1.700
Dissolved oxygen	C20	mg/L	6.000	5.000	4.000
Chemical oxygen demand	C21	mg/L	10.000	20.000	30.000
Biochemical oxygen demand (BDO5)	C22	mg/L	3.000	5.000	10.000
Phosphorus	C23	mg/L	0.100	0.125	0.150
Nitrates	C24	mg/L	10.000	30.000	50.000
Chlorides	C25	mg/L	250.000	300.000	350.000
Sulfates	C26	mg/L	250.000	500.000	750.000
Thermotolerant or fecal coliforms	C27	MPN/L	200.0	20000.0	200000.0
Escherichia coli	C28	MPN/L	0.00	4500.0	9000.0

TABLE II. PERUVIAN QUALITY STANDARD FOR DRINKING WATER [12]

C. Calculations using the CTWF method:

In this part, all the steps of the methodology are developed with the data.



Step 1: In this step, the field points and water quality standard parameters values will be determined and represented in the Table III and Table IV.

TABLE III.
WATER QUALITY STANDARD PARAMETERS VALUES FOR METALS
CONTAMINATION [15]

Criterion	Units	A1	A2	A3
Criterion	Units	λ1	λ2	λ3
C1	0 - 14	7.500	7.250	7.000
C2	mg/L	0.900	2.950	5.000
C3	mg/L	0.010	0.080	0.150
C4	mg/L	2.400	3.700	5.000
C5	mg/L	0.012	0.040	0.100
C6	mg/L	0.003	0.005	0.010
C7	mg/L	0.010	0.050	0.100
C8	mg/L	0.010	1.000	2.000
C9	mg/L	0.300	1.000	5.000
C10	mg/L	0.001	0.002	0.002
C11	mg/L	0.400	0.450	0.500
C12	mg/L	0.010	0.040	0.070
C13	mg/L	0.020	0.045	0.070
C14	mg/L	0.010	0.030	0.050
C15	mg/L	0.015	0.020	0.025
C16	mg/L	0.040	0.045	0.050
C17	mg/L	0.020	0.025	0.030
C18	mg/L	3.000	4.000	5.000

 TABLE IV.

 WATER QUALITY STANDARD PARAMETERS VALUES FOR URBAN

 CONTAMINATION [15]

Criterion	Units	A1	A2	A3
Criterion	emus	λ1	λ2	λ3
C1	0 - 14	7.500	7.250	7.000
C19	mg/L	0.500	1.100	1.700
C20	mg/L	6.000	5.000	4.000
C21	mg/L	10.000	20.000	30.000
C22	mg/L	3.000	5.000	10.000
C23	mg/L	0.100	0.125	0.150
C24	mg/L	10.000	30.000	50.000
C25	mg/L	250.000	300.000	350.000
C26	mg/L	250.000	500.000	750.000
C27	MPN/L	200.0	20000.0	200000.0
C28	MPN/L	0.00	4500.0	9000.0

Step 2: In this step, non-dimensional values from the field points and water quality standard parameters values will be determined. Values from water quality standard parameters will be shown in Tables V and VI. Values from field Points will be shown in Tables VII and VIII.

 TABLE V.

 Non-Dimensional Standard Values for Metal Parameters

Criterion	λ1	λ2	λ3
C1	1.0345	1.0000	0.9655
C2	0.3051	1.0000	1.6949
C3	0.1250	1.0000	1.8750
C4	0.6486	1.0000	1.3514
C5	0.2368	0.7895	1.9737
C6	0.5000	0.8333	1.6667
C7	0.1875	0.9375	1.8750
C8	0.0100	0.9967	1.9934
C9	0.1429	0.4762	2.3810
C10	0.6667	1.0000	1.3333
C11	0.8889	1.0000	1.1111
C12	0.2500	1.0000	1.7500
C13	0.4444	1.0000	1.5556
C14	0.3333	1.0000	1.6667
C15	0.7500	1.0000	1.2500
C16	0.8889	1.0000	1.1111
C17	0.8000	1.0000	1.2000
C18	0.7500	1.0000	1.2500



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TABLE VI Non-Dimensional Standard Values for Urban Parameters								
Criterion	λ1	λ2	λ.3					
C1	1.034	1.000	0.966					
C19	0.455	1.000	1.545					

1.000

1.000

1.200

0.500

C20

C21

C22	0.500	0.833	1.667
C23	0.800	1.000	1.200
C24	0.333	1.000	1.667
C25	0.833	1.000	1.167
C26	0.500	1.000	1.500
C27	0.003	0.272	2.725
C28	0.000	1.000	2.000

TABLE VII NON-DIMENSIONAL STANDARD VALUES FOR METAL CONTAMINATION FIELD DATA

0.800

1.500

Criterion	P1	P2	P3	P12	P13	P14	P15	P22	P23	P24
C1	1.2290	1.1310	1.2014	1.2055	1.1462	1.1724	1.1931	1.1752	1.1559	1.1283
C2	0.0193	0.0139	0.0068	0.0393	0.0251	0.2092	0.1461	0.1339	0.3797	0.2637
C3	0.0723	0.3716	0.2319	0.0984	0.0109	0.0355	0.0739	0.0470	0.0630	0.0535
C4	0.0005	0.0235	0.0103	0.0041	0.0005	0.0038	0.0205	0.0119	0.0397	0.0114
C5	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
C6	0.0017	0.0017	0.1150	0.0017	0.0017	0.0017	0.0017	0.0017	0.0017	0.0017
C7	0.0094	0.0788	0.0600	0.1219	0.0094	0.0356	0.0113	0.0188	0.0338	0.0300
C8	0.0019	0.0029	0.0046	0.0526	0.0030	0.0070	0.0012	0.0031	0.0042	0.0045
C9	0.0399	0.0267	0.0273	0.0904	0.0358	0.3994	0.3237	0.2519	0.4072	0.5705
C10	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200
C11	0.0262	0.0812	0.0935	0.1456	0.0220	0.1045	0.0693	0.0740	0.1214	0.1392
C12	0.0050	0.0828	0.0303	0.0983	0.0095	0.0293	0.0268	0.0230	0.0268	0.0205
C13	0.0111	0.0156	0.0089	0.0489	0.0044	0.0244	0.0222	0.0200	0.0289	0.0378
C14	0.4100	0.2633	0.8467	0.4167	0.0300	0.1200	0.0467	0.0600	0.1067	0.0900
C15	0.0615	0.2800	0.2655	0.2795	0.0320	0.0078	0.0485	0.0545	0.0735	0.0540
C16	0.0089	0.0089	0.0089	0.0311	0.0089	0.0267	0.0289	0.0089	0.0089	0.0489
C17	0.0324	0.0283	0.0274	0.0243	0.0001	0.0157	0.0114	0.1468	0.1696	0.0161
C18	0.0044	0.0071	0.0244	0.0136	0.0045	0.0060	0.0025	0.0032	0.1109	0.0032

TABLE VIII NON-DIMENSIONAL STANDARD VALUES FOR URBAN PARAMETERS

Criterion	P1	P2	P3	P12	P13	P14	P15	P22	P23	P24
C1	1.2289	1.1310	1.2014	1.2069	1.1462	1.1724	1.1931	1.1752	1.1559	1.1283
C19	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	0.9091	1.7273
C20	2.2000	2.8240	3.6480	2.3380	3.2020	3.5560	2.9320	0.9220	0.9220	0.9500
C21	0.1000	0.1000	0.1000	0.2500	0.1000	6.7500	0.1000	0.5000	0.6000	3.5500
C22	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.5000
C23	1.4960	1.1920	1.0480	0.5440	0.3600	1.3040	1.0800	1.7040	0.8400	1.6720
C24	0.0320	0.0849	0.1000	0.0575	0.0126	0.0325	0.0168	0.0340	0.0379	0.0609
C25	0.0022	0.0392	0.0150	0.0166	0.0081	0.0074	0.0355	0.0252	0.0244	0.0225
C26	0.0614	0.2434	0.2136	0.2302	0.0159	0.0677	0.0574	0.0595	0.0575	0.0506
C27	0.0067	0.0023	0.0002	0.0031	0.0037	0.1499	0.1771	38.1471	2.9973	1.2807
C28	0.0378	0.0244	0.0040	0.0289	0.0378	0.7333	1.0889	155.5556	4.8889	15.5556



Step 3: In this step, it will be shown the results of the CTWF functions for P1, P2, P3, P22, P23, and P24 in the Table IX. Those points were evaluated by using metals and urban contamination parameters.

As example, the results from thermotolerant coliforms (C27) are shown in Equations 7-9.

$$f_j^1(x_{ij}) = \begin{cases} 1, & x \in [0; \ 0.0027] \\ \frac{0.2725 - x}{0.2725 - 0.0027}, & x \in \langle 0.0027; \ 0.2725 \rangle \\ 0, & x \in [0.2725; +\infty) \end{cases}$$
(7)

$$f_j^2(x_{ij}) = \begin{cases} \frac{x - 0.027}{0.2725 - 0.0027}, & x \in \langle 0.0027; \ 0.2725] \\ \frac{0.2725 - 0.0027}{0.27248 - x}, & x \in \langle 0.2725; \ 2.7248 \rangle \\ \frac{0.27248 - 0.2725}{0, x \in [0; \ 0.0027] \cup [2.7248; +\infty \rangle} \end{cases}$$
(8)

$$f_j^3(x_{ij}) = \begin{cases} 0, x \in [0; \ 0.2725] \\ \frac{x - 0.2725}{2.7248 - 0.2725}, x \in (0.2725; \ 2.7248) \\ 1, x \in [2.7248; +\infty) \end{cases}$$
(9)

TABLE IXCTWF VALUES FOR P1, P2, P3, P22, P23 and P24

P1	C1	C3	С9	C11	C14	C20	C21	C22	C24	C27	C28
$f_j^1(x)$	1.0000	1.0000	1.0000	1.0000	0.8850	1.0000	1.0000	1.0000	1.0000	0.9854	0.9622
$f_i^2(x)$	0.0000	0.0000	0.0000	0.0000	0.1150	0.0000	0.0000	0.0000	0.0000	0.0146	0.0378
$f_i^3(x)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	C1	C3	C9	C11	C14	C20	C21	C22	C24	C27	C28
$f_j^1(x)$	1.0000	0.7181	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9756
$f_i^2(x)$	0.0000	0.2819	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0244
$f_i^3(x)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P3	C1	C3	С9	C11	C14	C20	C21	C22	C24	C27	C28
$f_j^1(x)$	1.0000	0.8779	1.0000	1.0000	0.2300	1.0000	1.0000	1.0000	1.0000	1.0000	0.9960
$f_i^2(x)$	0.0000	0.1221	0.0000	0.0000	0.7700	0.0000	0.0000	0.0000	0.0000	0.0000	0.0040
$f_i^3(x)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P22	C1	C3	C9	C11	C14	C20	C21	C22	C24	C27	C28
$f_j^1(x)$	1.0000	1.0000	0.6730	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000	0.0000	0.0000
$f_i^2(x)$				0 0000	0.0000	0.7600	0.0000	0.0000	0.0000	0.1667	0.0000
$J_j(\lambda)$	0.0000	0.0000	0.3270	0.0000	0.0000	0.7000	0.0000	0.0000	0.0000	0.1007	0.0000
$\frac{f_j(x)}{f_j^3(x)}$	0.0000 0.0000	0.0000 0.0000	0.3270	0.0000	0.0000	0.7000	0.0000	0.0000	0.0000	0.8333	1.0000
					0.0000			0.0000			
$f_j^3(x)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.2400	0.0000	0.0000	0.0000	0.8333	1.0000
$\begin{array}{c} f_j^3(x) \\ \hline P23 \\ f_j^1(x) \end{array}$	0.0000 C1	0.0000 C3	0.0000 C9	0.0000 C11	0.0000 C14	0.2400 C20	0.0000 C21	0.0000 C22	0.0000 C24	0.8333 C27	1.0000 C28
$\begin{array}{c} f_j^3(x) \\ P23 \end{array}$	0.0000 C1 1.0000	0.0000 C3 1.0000	0.0000 C9 0.2069	0.0000 C11 1.0000	0.0000 C14 1.0000	0.2400 C20 0.0000	0.0000 C21 1.0000	0.0000 C22 1.0000	0.0000 C24 1.0000	0.8333 C27 0.0000	1.0000 C28 0.0000
$\begin{array}{c} \hat{f_{j}^{3}(x)} \\ \hline P23 \\ f_{j}^{1}(x) \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ \hline P24 \end{array}$	0.0000 C1 1.0000 0.0000	0.0000 C3 1.0000 0.0000	0.0000 C9 0.2069 0.7931	0.0000 C11 1.0000 0.0000	0.0000 C14 1.0000 0.0000	0.2400 C20 0.0000 0.6100	0.0000 C21 1.0000 0.0000	0.0000 C22 1.0000 0.0000	0.0000 C24 1.0000 0.0000	0.8333 C27 0.0000 0.0000	1.0000 C28 0.0000 0.0000
$ \begin{array}{r} f_{j}^{3}(x) \\ \hline P23 \\ f_{j}^{1}(x) \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ \end{array} $	0.0000 C1 1.0000 0.0000 0.0000	0.0000 C3 1.0000 0.0000 0.0000	0.0000 C9 0.2069 0.7931 0.0000	0.0000 C11 1.0000 0.0000 0.0000	0.0000 C14 1.0000 0.0000 0.0000	0.2400 C20 0.0000 0.6100 0.3900	0.0000 C21 1.0000 0.0000 0.0000	0.0000 C22 1.0000 0.0000 0.0000	0.0000 C24 1.0000 0.0000 0.0000	0.8333 C27 0.0000 0.0000 1.0000	1.0000 C28 0.0000 0.0000 1.0000
$\begin{array}{c} \hat{f_{j}^{3}(x)} \\ \hline P23 \\ f_{j}^{1}(x) \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ \hline P24 \end{array}$	0.0000 C1 1.0000 0.0000 0.0000 C1	0.0000 C3 1.0000 0.0000 0.0000 C3	0.0000 C9 0.2069 0.7931 0.0000 C9	0.0000 C11 1.0000 0.0000 0.000 C11	0.0000 C14 1.0000 0.0000 0.0000 C14	0.2400 C20 0.0000 0.6100 0.3900 C20	0.0000 C21 1.0000 0.0000 0.0000 C21	0.0000 C22 1.0000 0.0000 0.0000 C22	0.0000 C24 1.0000 0.0000 0.0000 C24	0.8333 C27 0.0000 0.0000 1.0000 C27	1.0000 C28 0.0000 0.0000 1.0000 C28



Step 4: In this step, weights for each parameter will be determined according of their level, using the Harmonic Mean. These are shown in the Table X and Table XI.

TABLE X
WEIGHT FOR EACH PARAMETER ACCORDING TO WATER QUALITY
STANDARD CLASIFICATION FOR METAL CONTAMINATION

Weights	λ1	λ2	λ3
C1	0.0065	0.0509	0.0845
C2	0.0219	0.0509	0.0481
C3	0.0535	0.0509	0.0435
C4	0.0103	0.0509	0.0604
C5	0.0282	0.0645	0.0413
C6	0.0134	0.0611	0.0489
C7	0.0357	0.0543	0.0435
C8	0.6707	0.0511	0.0409
C9	0.0468	0.1069	0.0343
C10	0.0100	0.0509	0.0612
C11	0.0075	0.0509	0.0734
C12	0.0267	0.0509	0.0466
C13	0.0150	0.0509	0.0524
C14	0.0201	0.0509	0.0489
C15	0.0089	0.0509	0.0653
C16	0.0075	0.0509	0.0734
C17	0.0084	0.0509	0.0680
C18	0.0089	0.0509	0.0653

TABLE XI Weight For Each Parameter According to Water Quality Standard Clasification for Urban Contamination

Weights	λ1	λ2	λ3
C1	0.00253	0.07210	0.12908
C19	0.00575	0.07210	0.08064
C20	0.00218	0.07210	0.15579
C21	0.00523	0.07210	0.08309
C22	0.00523	0.08652	0.07478
C23	0.00327	0.07210	0.10386
C24	0.00784	0.07210	0.07478
C25	0.00314	0.07210	0.10683
C26	0.00523	0.07210	0.08309
C27	0.95960	0.26460	0.04574
C28	0.00000	0.07210	0.06232

Step 5: In this step, clustering vector for each sample points will be determined for metals and urban parameters. Also, results using Maximum Clusterization coefficient will be shown by choosing the higher Clustering vector. These are shown in the Table XII and Table XIII.

 TABLE XII

 Clustering Vector For Each Sample Point for Metals

 Parameters

Sample point $\lambda 1$ $\lambda 2$ $\lambda 3$				
P1	0.99769	0.00586	0.00000	
		0.00000		
P2	0.98493	0.01435	0.00000	
P3	0.97803	0.04543	0.00000	
P4	0.91693	0.00060	0.07777	
P5	1.00000	0.00000	0.00000	
P6	0.83987	0.04739	0.06526	
P7	0.86368	0.05449	0.00000	
P8	0.91547	0.00489	0.11188	
P9	0.90440	0.06322	0.02362	
P10	0.93761	0.04682	0.05262	
P11	0.96879	0.01473	0.00000	
P12	0.96853	0.00857	0.00000	
P13	1.00000	0.00000	0.00000	
P14	0.96399	0.08230	0.00000	
P15	0.97462	0.05801	0.00000	
P16	0.95285	0.08605	0.00696	
P17	0.95179	0.08345	0.00858	
P18	0.94605	0.12370	0.00000	
P19	0.97759	0.03645	0.08449	
P20	0.96453	0.08106	0.00000	
P21	0.98712	0.02942	0.00000	
P22	0.98470	0.03497	0.00000	
P23	0.96053	0.09029	0.00000	
P24	0.95321	0.10165	0.00170	
P25	0.92108	0.01071	0.08239	

TABLE XIII Clustering Vector For Each Sample Point for Urban Parameters

Sample point	λ1	λ2	λ3	
P1	0.97788	0.06668	0.10386	
P2	0.99194	0.06473	0.09971	
P3	0.99194	0.11516	0.02493	
P4	0.76742	0.16134	0.00000	
P5	0.98786	0.08665	0.00000	
P6	0.69957	0.19447	0.00000	
P7	0.99521	0.06133	0.00000	
P8	0.99521	0.06037	0.00000	
P9	0.99521	0.06080	0.00000	
P10	0.95159	0.08332	0.00000	
P11	0.98891	0.06550	0.00000	
P12	0.99375	0.06257	0.00000	
P13	0.99181	0.06374	0.00000	
P14	0.46329	0.25728	0.18695	
P15	0.37159	0.34008	0.04708	
P16	0.03016	0.31535	0.19602	
P17	0.03022	0.13002	0.21192	
P18	0.03329	0.16042	0.10043	
P19	0.02817	0.24646	0.31813	
P20	0.03016	0.12641	0.22438	
P21	0.17949	0.35196	0.04708	
P22	0.03016	0.15898	0.24168	
P23	0.03016	0.10406	0.27268	
P24	0.03173	0.13290	0.16881	
P25	0.02397	0.20989	0.38766	



V. RESULTS AND DISCUSSION

A. About the Case Study

It is showed in Table XII the results of the analysis using metals contamination parameters. The monitoring points P5 and P13 have the best water quality, and points P6 and P7 have the lowest water quality. This happens because P5 is near to Palomar Drinking Water Treatment Plant - Palomar (PTAP-Palomar), the mining company water treatment plant, and P13 is in the area furthest from the section with mining influence. For the next section, although is in an area with no mining influence, it presents minimum metals values due to the industry activities and town waste dumps near to the Alto Huallaga watershed. Also, the second section has a tributary river, Tingo River, which has mining activities upstream from some monitoring points. These reasons can explain the presence of metals in a zone without mining activities near to the Alto Huallaga watershed. Everything mentioned above reflects that the metals contamination values are minimal, which means that could be purified by disinfection.

On the other hand, it is showed in Table XIII the results of the analysis using urban contamination parameters. The monitoring points show low water quality in the Section 2. For that reason, it needs a special treatment to be purified, according to Peruvian law [12]. Low water quality is due to the high values of E. coli and thermotolerant coliforms, produced by the town waste dumps along the Alto Huallaga watershed. The monitoring point P25 has the lowest water quality, due to its closeness to a waste dump in Churubamba Town, in Huanuco. The monitoring point P23 is another area which has a poor water quality due to its location at the exit of Huanuco City. On the other hand, P24 has the best water quality because it's in the area furthest from the Huanuco City waste dumps. That means the river has a selfpurification process, but organic pollutants stay near to the riverbed. However, water quality levels in Section 1 keep their good quality. This information regarding the quality of the water is useful to verify the main objective, which is to know if the mining activity is the main contaminator of the Alto Huallaga watershed.

B. About the Methodology

As it is seen, Grey Clustering method, based on the Grey system methodology [16], is the most appropriate in analysis with a great uncertainty, such as river water quality evaluations, in addition to being complemented with other methods for the analysis of water receiving bodies [17].

However, Peruvian water quality standard values had to be modified using other international standards to make the Grey Clustering method works with the Alto Huallaga watershed data. Comparing to other logic methods as the Analytical hierarchy [18] and Delphi [19], these methods do not consider uncertainty in their analysis. On the other hand, Fuzzy Logic [20] can work on high uncertainty issues, but lacks on accuracy, and their results are not always widely accepted.

Finally, Grey Clustering method was useful to compare water quality levels of the Alto Huallaga River using two different parameters. Although other water quality assessment using Grey Clustering method [8], which analysis can determine the monitoring points with highest and lowest water quality, this assessment compares between the metals and urban contamination to analyze the influence of the mining activity in the Alto Huallaga River.

The difference of the present research study in relation to the review literature focuses on the comparison between two grey clustering analysis on the same monitoring points in the Alto Huallaga watershed. Each grey clustering analysis was made using different parameters related with mining and non-mining activities for both sections. In the first section, the prevalence of certain contaminating chemical elements in the river can be noted since the mining units discharge wastewater as a result of their mineral treatment processes. Regarding the second section, the monitoring points indicate the representativeness of urban pollutants; that is, chemical or biological parameters produced by solid waste from cities and towns that are discharged into the river as waste, in addition to the presence of certain nonmining industries that also generate urban pollutants.

VI. CONCLUSIONS

It can be concluded that the mining companies are not the main factor in water pollution near to the Alto Huallaga watershed. Mining companies do not produce metal contamination which affects the water quality, and controls urban contamination in their direct influence. This is due of a good environmental management, which efforts to have an adequate effluent control and invests on water and waste treatment plants. On the other hand, due of the towns waste dumps, high levels of E. Coli and Thermotolerant coliforms have appeared. This means that the urban influence over the river is bigger than from mining activities, and municipality governments have the responsibility to solve it.



According to the methodology. Grey Clustering method is very efficient for evaluating water quality levels. This is due to its ability to work on high uncertainty issues and its high accuracy, comparing to other logic methods. For that reason, this method can be used on rivers which data is not enough to apply other methodologies. However, it is important to have a good water quality standard to make this method work correctly, since there are some parameters limits not evaluated in Peruvian legislation.

Finally, data used for this assessment is from 2018, and until now it has not been updated. It is necessary to maintain a continuous inspection to evaluate the mining companies' good environmental management. Also, research can be done to design an economical waste treatment to prevent further contamination of the Alto Huallaga River

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