Expressing the Results of the Surface Water Quality Monitoring in Lagoons of the El Padrino Mining Project in Linguistic Categories Using the Grey Clustering Methodology of the Fuzzy Logic System

Alexi Delgado¹, Katherine Barreto¹, Victor Dávila¹, Kevin Rivera¹, Enrique Lee Huamaní²

¹Mining Engineering Section, Pontificia Universidad Católica del Perú, Lima, Perú

² Image Processing Research Laboratory, Universidad de Ciencias y Humanidades, Lima, Perú

Abstract: Mining activities are perceived by the population as an activity that degrades the water quality in the area in which it takes place; likewise, the communication of the results of the monitoring campaigns is unclear as it is not expressed in corresponding linguistic categories for the transmission and understanding of the information. The grey clustering methodology is a discipline within the fuzzy logic system that allows linguistic expression based on numerical variables, allowing the results to be stated appropriately for human communication. El Padrino mining project is located in Áncash. It is in the evaluation process, as part of the baseline study that has carried out the monitoring of surface water quality in the lagoons of the study area. The values obtained for the classification coefficients express the water quality of the lagoons as excellent, acceptable, and slightly polluted. The position of the evaluation points expresses natural processes of contamination in the lagoons Milpo and s/n2. The information obtained will be useful for the communication of the monitoring campaigns' results to the inhabitants of the study area. Due to the research focus, it will be of interest both for the development of future research on environmental engineering and linguistics.

Keywords: Fuzzy logic, grey clustering, linguistics, surface water quality.

使用模糊逻辑系统的灰色聚类方法来表达埃尔帕德里诺采矿项目泻湖中语言类别的地 表水水质监测结果

摘要:居民将采矿活动视为一种活动,使活动发生地区的水质下降;同样,不清楚监测活动 结果的传达方式,因为没有以相应的语言类别来表达信息的传递和理解。灰色聚类方法是模糊逻 辑系统中的一门学科,它允许基于数值变量的语言表达,从而使结果能够适当地表达出来,以进 行人为交流。 埃尔帕德里诺 采矿项目位于安卡什。在基线研究的过程中,正是在评估过程中, 对研究区域的泻湖中的地表水水质进行了监测。从分类系数获得的值将泻湖的水质表示为极好, 可以接受且受到轻微污染。评价点的位置表示了泻湖米尔波 和 s/n2 中污染的自然过程。所获得 的信息将有助于将监测活动的结果传达给研究区域的居民。由于研究的重点,它对未来环境工程 和语言学研究的发展都将引起兴趣。

关键词:模糊逻辑,灰色聚类,语言学,地表水水质。

1. Introduction

The baseline is part of the Environmental Impact assessment necessary for the approval of the projects in

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About the authors: Alexi Delgado, Katherine Barreto, Victor Dávila, Kevin Rivera, Mining Engineering Section, Pontificia Universidad Católica del Perú, Lima, Perú; Enrique Lee Huamaní, Image Processing Research Laboratory, Universidad de Ciencias y Humanidades, Lima, Perú Peru. Referring to mining projects, water is an important component due to the associated conflict. In particular, surface water like streams, rivers, lakes, wetlands, estuaries, lagoons, and coasts supports human life and industrial production. They are more susceptible to contamination by it. Water pollution in the area of mining projects is due, in part, to the introduction of heavy metals into the aquatic system as a result of the weathering of soils and rocks, as well as the elimination of liquid effluents, land runoff, and leachates that transport chemicals related to mining activity, as well as atmospheric deposition.

Monitoring activities are a means to understand and subsequently improve aquatic habitats. The analysis of quality data helps quantify environmental changes and serves to develop better management practices for decision-making.

However, the results of the monitoring activities cannot be adequately expressed and transmitted to the population in the study area. They are not represented by appropriate linguistic expressions but rather in independently measured parameter values that do not allow the transmission of the processes: natural conditions or initial conditions related to water bodies.

The El Padrino Mining Project is located on the surface land of the Aquia Rural Community, in the Aquia District, Bolognesi Province, Ancash department. The Pachapaqui Town Center is the closest to the Project area (6.20 km) and is an Annex of the Rural Community of Aquia, and approximately 72 km (in a straight line) to the southeast is the city of Huaraz. It is located mainly on the Andes Mountains western flank in the sierra sector, basically formed by a strip of hills, mountains, and snow-capped mountains covered with moraine deposits, at an average altitude that varies between 4000 to 4800 meters above sea level. The operations will be carried out on the surface lands of the Aquia Rural Community, in the Aquia District, Bolognesi Province, Ancash department [3].

The methodology selected for evaluating the surface water monitoring data for the lagoons in the El Padrino mining project area is due to the advantages of applying fuzzy logic methods. One of the techniques within this approach for solving problems where one starts from a referential position is the grey clustering method, where the elements are grouped in a comprehensive clusterization coefficient vector [4]. Clustering in coefficient vectors is appropriate for quantitative evaluation problems under a set of parameters of different meanings and dimensions over traditional Aristotelian logic methodologies [5].

The research objective is to determine the surface water quality of the set of lagoons in the studied area of the El Padrino mining project and express the results as a linguistic expression. The surface water quality is assessed by comparing analytically determined monitoring data based on physicochemical parameters with threshold values allowed in legislation packages or pollution index internationally established [6]. Understanding and integrating users' opinions in the design and communication to them allows addressing important challenges during the environmental assessment of mining projects. Transmitting the information in adequate terms allows obtaining the community's support to avoid the rejection and development of socio-environmental conflicts [7].

In this paper, Section II develops the state-of-the-art review related to the application of the grey clustering method in the evaluation of water quality. Section III details the methodological procedure for the application of the grey clustering method. The case study and related calculations are developed in Section IV. The results and their discussion are presented in Section V, and the conclusions are developed in Section VI.

2. Literature Overview

As stated in [8], the grey clustering method was used because of the difficulty of assessing estuaries for nitrogen pollution when there is little monitoring information and the access to it is complicated. They proposed a reliable tool for decision-making. For this, the following indices were used: Grey Nitrogen Management Priority Index, which assesses the need for a nitrogen pollution management system, and Grey Land Use Pollution Index, which evaluates the anthropic pressure in the estuaries of the Gulf of Mexico that are considered threatened by anthropogenic nitrogen pollution. The use of the methodology proved to generate an efficient tool for decision making with limited resources, and the method can be used in the field of other pollutants.

The grey clustering method was applied to evaluate water quality with the information generated in 2008 on the monitoring campaigns of the water quality of the Fenchuan River [9]. The results obtained served as a reference for water use management and the environmental protection of the water body based on the seriously polluted degree determined for the river based on the Standards of surface water quality GB3838-2002.

Because of the deficiency of the classical method for water quality evaluation, the method of grey grouping relationships was proposed for the evaluation of the Suzhou River [10]. The traditional evaluation was compared to the grey clustering method, giving a more objective result due to a clustering ratio coefficient. This method proved to be more objective by applying the relationship between the data on the categorization provided by the Standard surface water quality GH2B1-2002.

The grey clustering method was applied in 20 sections of the Suzhou River [11]. The model application was determined by the deficiency of the traditional methods for evaluating the environment quality under the conditions of presenting a low amount of information. The standards used for the evaluation corresponded to the Standards of surface water quality GH2B1-2002. The method application proved to be feasible and simple due to an algorithm of high processing capacity.

The fuzzy synthetic assessment methods were compared to the grey clustering method in thirteen sections of the city of the Three Gorges reservoir area. Both methods proved to be more reliable than the traditional method [12]. They had a more practical and powerful application since it made possible to generate proposals for the management of contamination in the reservoir area.

Mathematical tests were carried out in 2007 to determine the influence of equal weights in applying the weighting of the functions determined in the grey clustering process as water quality criteria, referring to the GB3838-88 legislation [13]. The grey clustering methods were compared to the assignment of weights with the traditional grey clustering method. A strong influence on the consideration of equal weights in neighboring classes was determined, which results in different categorizations for the selected monitoring information.

3. Research Methodology

The methodology used to determine water quality and the degree of contamination of the lagoons in the study area of the El Padrino mining project is called Grey Clustering Analysis, which is found within the fuzzy logic system. This discipline is based on a logical system of artificial intelligence in which the variables are words instead of numbers, closer to human intuition and reasoning. Within this discipline, expressions are used that are neither totally true nor completely false [14].

The grey clustering analysis methodology was developed in conjunction with the applied Prati index, which is based on determining the quality of surface water based on the effect of contamination rather than quantifying the pollution factor [15].

Both were developed together to process the monitoring data for determining the initial quality of the set of lagoons in the study area that is part of the lands of the rural community of Aquia. The linguistic determination of the water quality status in the lagoons allows an anticipated, fluent, and understandable communication with the community.

2.1. Grey Clustering Analysis Methodology

The methodology is carried out according to a group of criteria, a group of classes, and a set of objects. Once defined, the steps of the method are as follows [16]. **Step 1:** Determining the center points

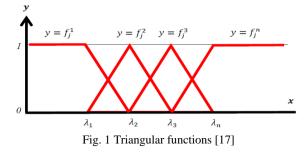
Define center points $\lambda 1$, $\lambda 2$, and λs of each of the grey-classes.

Step 2: Non-dimension data

Given that in the evaluation of water quality, the indices have a different meaning, it is not possible to proceed with the calculation directly to solve this problem; the values of the objects are divided by the average of the central data of each grey class that corresponds to the value medium standard.

Step 3: Determine the Triangular Functions and Values

Set the triangular functions according to the greyclasses. In this way, the correspondence rules are obtained. It is shown in Figure 1.



The correspondence rule for triangular functions is presented in Equations 1-3.

$$f_j^1(x_{ij}) = \begin{bmatrix} 1, x \in [0, \lambda_1] \\ \frac{\lambda_2 - x}{\lambda_2 - \lambda_1}, x \in \langle \lambda_1, \lambda_2 \rangle \\ 0, x \notin [\lambda_2, \infty] \end{bmatrix}$$
(1)

$$f_{j}^{c(c\neq k,1)}(x_{ij}) = \begin{bmatrix} \frac{x-\lambda_{2}}{\lambda_{2}-\lambda_{2}}, x \in [\lambda_{2},\lambda_{3}] \\ \frac{\lambda_{n}-x}{\lambda_{2}-\lambda_{2}}, x \in \langle\lambda_{3},\lambda_{n}\rangle \\ 0, x \notin [\lambda_{2},\lambda_{n}] \end{bmatrix}$$
(2)

$$f_j^k(x_{ij}) = \begin{bmatrix} \frac{x - \lambda_{k-1}}{\lambda_k - \lambda_{k-1}}, x \in [\lambda_{k-1}, \lambda_k] \\ 1, x \in \langle \lambda_k, \infty \rangle \\ 0, x \notin [0, \lambda_{k-1}] \end{bmatrix}$$
(3)

Step 4: Determining the Criteria Weights

This step is added to the revised methodology as it provides an objective criterion for the clusterization vector weighting. It is calculated according to the harmonic mean of the central data of the grey classes by Equation 4 [18].

$$n_j^k = \frac{\frac{1}{\lambda_j^k}}{\sum_{j=1}^s \frac{1}{\lambda_j^k}} \tag{4}$$

Step 5: Determine the Classification Coefficient

Determination of the clusterization vector σ_i^k for objects i, i=1, 2, ..., m, in the grey classes k, k=1, 2, ..., s, is defined by Equation 5.

$$o_i^k = \sum_{j=1}^n f_j^k \left(x_{ij} \right) . n_j \tag{5}$$

Step 6: Results using Max. Clustering coefficient $\max_{(1 \le k \le s)} \{\sigma_i^k\} = \sigma_i^k$, then the value representing the object's membership in the associated grey class is chosen.

4. Case Study

This mining project is located on the lands of the rural community of Aquia in the department of Áncash.

The study area was delimited during the surface water monitoring campaigns during the environmental impact study preparation.

The methodology was applied to ten surface water monitoring points located in the lagoons of the El Padrino mining project study area, shown in Figure 2.

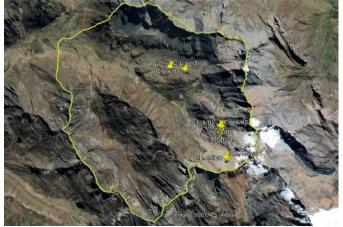


Fig. 2 Monitoring points in waters in the study area of the El Padrino mining project

4.1. Definition of the Study Objects

The monitoring points were established during the preparation of the baseline of El Padrino EIA. These are part of a surface water monitoring campaign, and the lagoons were taken into account due to their importance for the rural community of Aquia.

Table 1 shows the description and geo references of all the study objects selected for the grey-clustering method evaluation.

Table 1 Surface water	monitoring	points in the	he El Padrino	o project

		stuc	ly area		
Code	Station	Description	Coordina WC a	Altitude (msnm)	
			East	North	
P1	I.L. Sh-Sh	Income lagoon ShicraShicra	277,372	8'896,829	4650
P2	S.L. Sh- Sh	Outcome lagoon ShicraShicra	277,290	8'896,905	4637
Р3	C.L Sh-Sh	Center lagoon ShicraShicra	277,378	8'896,902	4648
P4	I.L. s/n2	Income lagoon s/n2	277,450	8'896,285	4838
P5	S.L s/n2	Outcome lagoon s/n2	277,486	8'896,243	4855
P6	C.L s/n2	Center lagoon s/n2	276,654	8'898,640	4440
P7	S.L. Milpo	Outcome lagoon Milpo	277,447	8'897,090	4672
P8	C.L. Milpo	Center lagoon Milpo	277,364	8'897,113	4664
Р9	C.L s/n1	Center lagoon s/n1	277,410	8'897,095	4669
P10	C.L s/n3	Center lagoon s/n3	276,295	8'898,760	4358

4.2. Definition of Evaluation Criteria

For the quality evaluation, five parameters were taken on the Prati scale considering the interest that exists in the presence of heavy metals associated with mining, the pH variations that could result from mining activity, and biological parameters of contamination.

Table 2 presents the evaluation criteria to be used and their coding to develop the grey clustering methodology.

Table 2 Parameters for	the evaluation to	grey clustering methods

Parameters	Coding
Hydrogen potential (pH)	C1
Dissolved ammonia (<i>NH</i> ₂)	C2
Manganese (Mn)	C3
Iron (Fe)	C4
De Biochemical Oxygen Demand (DBO ₅)	C5

4.3. Definition of Grey Classes

The classes have been selected from the Prati index that already presents an approach in the form of intervals called Excellent, Acceptable, Slightly Contaminated, Contaminated, and Heavily Contaminated. The selection of these five classes is based on a comprehensive evaluation effect as a whole of the water body. The classes, criteria, and intervals are set out in the Prati index according to Table 3.

	Table 3	Intervals	proposed	in the	Prati	index
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			Level		
Criteria	Excellent	Acceptable	Slightly polluted	Polluted	Heavily Polluted
C1 (pH units)	6.5-8.0	8.0-8.4	8.4-9.0	9-10.1	>10.1
C2 (ppm)	0-0.1	0.1-0.3	0.3-0.9	0.9-2.7	с
C3 (ppm)	0-0.05	0.05-0.17	0.17-0.5	0.5-1	>1.0
C4 (ppm)	0-20	20-40	40-100	100-278	>278
C5 (ppm)	0.0-1.5	1.5-3.0	3.0-6.0	6.0-12.0	>12.0

4.4. Estimate Using Grey Clustering

Step 1: Determining the center points

The central points for the grey classes of the Prati scale were calculated as the arithmetic means of the intervals; likewise, the central value of the Heavily Contaminated class was calculated as an extrapolation between the two previous values so that the arithmetic mean of the Central value of the Severely Contaminated and Lightly Contaminated classes will result in the central value of the Contaminated class [19].

Table 4 presents the value of the central points according to the grey-clustering methodology.

Table 4 Central points the intervals of the Prati index									
Objects	λ,	λ_2	λ	λ_4	λ,				
C1 (pH units)	7.25	8.2	8.7	9.55	10.4				
C2 (ppm)	0.05	0.2	0.6	1.8	3.0				

C3 (ppm)	0.025	0.11	0.335	0.75	1.165
C4 (ppm)	10	30	70	189	308
C5 (ppm)	0.75	2.25	4.5	189	13.5

Step 2: Non-dimension data

Due to the degree of disparity between the magnitude and the significance between the parameters, the monitoring data is dimensioned to provide constant values for the grey clustering method calculation.

The monitoring data generated for the baseline study is as follows, according to the information presented by SRK Consulting, which can be seen in Table 5.

Table 5	Surface	water	monitoring	g data	in	lagoons	of the	El Padrino
			project s	tudy a	are	a		

Objects	C1	C2	C3	C4	C5
P1	8.7	0.055	0.002	3	2.6
P2	8.7	0.08	0.00005	3	2.6
Р3	8.6	0.05	0.00005	3	2.6
P4	8.4	0.6	0.0011	10	2.6
P5	8.8	0.5	0.0014	12	2.6
P6	7.9	0.23	0.006	4	2.6
P7	8.2	0.017	0.00005	3	2.6
P8	8.1	0.0007	0.00005	3	2.6
Р9	8.3	0.15	0.0011	3	2.6
P10	8.2	0.4	0.004	3	2.6

The normalization of the data obtained in the monitoring campaigns is required; the said normalized data are presented in Table 6.

Table 6 Standardized data from the information obtained from the monitoring points

Objects	P1	P2	P3	P4	Р5	P6	P7	P8	P9	P10
C1	0,986	0,986	0,975	0,952	0,998	0,896	0,930	0,918	0,941	0,930
C2 (ppm)	0,049	0,071	0,044	0,531	0,442	0,204	0,015	0,001	0,133	0,354
C3 (ppm)	0,004	0,000	0,000	0,002	0,003	0,013	0,000	0,000	0,002	0,008

C4 (ppm)	0,025	0,025	0,025	0,082	0,099	0,033	0,025	0,025	0,025	0,025
C5 (ppm)	0,433	0,433	0,433	0,433	0,433	0,433	0,433	0,433	0,433	0,433

Table 7 shows the normalization process of the central points carried out according to the grey-clustering procedure.

	Table 7 N	ormalized da	ta from the H	Prati scale	
	λ,	λ_2	λ _a	λ_4	λ,
C1	0.82	0.93	0.99	1.08	1.18
C2	0.04	0.18	0.53	1.59	2.65
C3	0.05	0.23	0.70	1.57	2.44
C4	0.08	0.25	0.58	1.59	2.54
C5	0.13	0.38	0.58	1.50	2.25

Step 3: Determine the Triangular Functions and Values

Functions for C1

The triangular functions corresponding to the first criterion are generated using equations (1)(2)(3). Equations 6-10 are used to determine the first criterion.

$$f(x) = \begin{bmatrix} 1 & x \in [0, 0.082] \\ \frac{0.93 - x}{0.11} & x \in (0.82, 0.93) \\ 0 & x \in [0.93, +\infty) \end{bmatrix}$$
(6)

$$f(x)2 = \begin{bmatrix} \frac{x-0.82}{0.11} & x \in (0.82, 0.93] \\ \frac{0.9-x}{0.06} & x \in (0.93, 0.99) \\ 0 & x \in [0, 0.82] \cup [0.99, +\infty) \end{bmatrix}$$
(7)

$$f(x)3 = \begin{bmatrix} \frac{x-0.93}{0.06} & x \in (0.93, 0.99] \\ \frac{1.08-x}{0.09} & x \in (0.99, 1.08) \\ 0 & x \in [0, 0.93] \cup [1.08, +\infty) \end{bmatrix}$$
(8)

$$f(x)4 = \begin{bmatrix} \frac{x-0.99}{0.09} & x \in (0.99, 1.08] \\ \frac{1.18-x}{0.1} & x \in (1.08, 1.18) \\ 0 & x \in [0, 0.99] \cup [1.18, +\infty) \end{bmatrix}$$
(9)

$$f(x)5 = \begin{bmatrix} x - 1.08 & x \in (1.08, 1.18) \\ 0.1 & x \in [1.18, +\infty) \\ 0 & x \in [0, 1.08] \end{bmatrix}$$
(10)

Table 8 is generated using equations (6) - (10) and replacing the oversized values of the monitoring data presented in Table 6. The value of the functions is added according to equation (5), resulting in each of the clustering vector values for the monitoring points.

Tabl	le 8 Ca	alculati	on of v	veighti	ng fu	nctions
P1	C1	C2	C3	C4	C5	Result

$f_j^1(x)$	0,00	0,94	1,00	1,00	0.00	0.42
$f_J^2(\mathbf{x})$	0,00	0,06	0,00	0,00	0.85	0.15
$f_J^3(\mathbf{x})$	1,00	0,00	0,00	0,00	0.15	0.33
$f_J^4(x)$	0,00	0,00	0,00	0,00	0.00	0.00
$f_J^5(x)$	0,00	0,00	0,00	0,00	0.00	0.00
P2	C1	C2	C3	C4	C5	Result
$f_j^1(x)$	0,00	0,78	1,00	1,00	0.00	0.45
$f_j^2(\mathbf{x})$	0,00	0,22	0,00	0,00	0.85	0.22
$f_j^3(\mathbf{x})$	1,00	0,00	0,00	0,00	0.15	0.33
$f_j^4(x)$	0,00	0,00	0,00	0,00	0.00	0.00
$f_J^5(x)$	0,00	0,00	0,00	0,00	0.00	0.00
P3	C1	C2	C3	C4	C5	Result
$f_j^1(x)$	0,00	0,97	1,00	1,00	0.00	0.46
$f_j^2(\mathbf{x})$	0,25	0,03	0,00	0,00	0.85	0.23
$f_j^3(\mathbf{x})$	0,75	0,00	0,00	0,00	0.15	0.25
$f_j^4(x)$	0,00	0,00	0,00	0,00	0.00	0.00
$f_J^{\rm s}(x)$	0,00	0,00	0,00	0,00	0.00	0.00
P4	C1	C2	C3	C4	C5	Result
		C2 0,00		C4 0,99		Result
	0,00					0.46
$f_j^1(x)$	0,00 0,63	0,00	1,00	0,99	0.00 0.85	0.46 0.36
$\frac{f_j^1(x)}{f_j^2(x)}$	0,00 0,63 0,37	0,00 0,00	1,00 0,00	0,99 0,01	0.00 0.85	0.46 0.36
$f_{j}^{1}(\mathbf{x})$ $f_{j}^{2}(\mathbf{x})$ $f_{j}^{3}(\mathbf{x})$	0,00 0,63 0,37 0,00	0,00 0,00 1,00	1,00 0,00 0,00	0,99 0,01 0,00	0.00 0.85 0.15	0.46 0.36 0.38
$ f_j^1(\mathbf{x}) $ $ f_j^2(\mathbf{x}) $ $ f_j^3(\mathbf{x}) $ $ f_j^4(\mathbf{x}) $	0,00 0,63 0,37 0,00	0,00 0,00 1,00 0,00	1,00 0,00 0,00 0,00	0,99 0,01 0,00 0,00	0.00 0.85 0.15 0.00	0.46 0.36 0.38 0.00 0.00
$ f_{j}^{1}(x) f_{j}^{2}(x) f_{j}^{3}(x) f_{j}^{4}(x) f_{j}^{5}(x) $	0,00 0,63 0,37 0,00 0,00 C1	0,00 0,00 1,00 0,00 0,00	1,00 0,00 0,00 0,00 0,00	0,99 0,01 0,00 0,00 0,00	0.00 0.85 0.15 0.00 0.00	0.46 0.36 0.38 0.00 0.00
$\frac{f_j^1(x)}{f_j^2(x)}$ $\frac{f_j^3(x)}{f_j^4(x)}$ $\frac{f_j^5(x)}{P5}$	0,00 0,63 0,37 0,00 0,00 C1 0,00	0,00 0,00 1,00 0,00 0,00 C2	1,00 0,00 0,00 0,00 0,00 C3	0,99 0,01 0,00 0,00 0,00 C4	0.00 0.85 0.15 0.00 0.00 C5	0.46 0.36 0.38 0.00 0.00 Result
$ \frac{f_{j}^{1}(x)}{f_{j}^{2}(x)} \\ \frac{f_{j}^{3}(x)}{f_{j}^{4}(x)} \\ \frac{f_{j}^{5}(x)}{P5} \\ \frac{F_{j}^{1}(x)}{F_{j}^{1}(x)} $	0,00 0,63 0,37 0,00 0,00 C1 0,00 0,00	0,00 0,00 1,00 0,00 0,00 C2 0,00	1,00 0,00 0,00 0,00 0,00 C3 1,00	0,99 0,01 0,00 0,00 0,00 C4 0,89	0.00 0.85 0.15 0.00 0.00 C5 0.00	0.46 0.36 0.38 0.00 0.00 Result 0.37
$ \frac{\overline{f_{j}^{1}(x)}}{f_{j}^{2}(x)} + \frac{f_{j}^{3}(x)}{f_{j}^{4}(x)} + \frac{f_{j}^{5}(x)}{P5} + \frac{F_{j}^{5}(x)}{f_{j}^{1}(x)} + \frac{F_{j}^{5}(x)}{F_{j}^{2}(x)} + \frac{F_{j}^{2}(x)}{F_{j}^{2}(x)} + $	0,00 0,63 0,37 0,00 0,00 0,00 0,00 0,91	0,00 0,00 1,00 0,00 0,00 C2 0,00 0,25	1,00 0,00 0,00 0,00 C3 1,00	0,99 0,01 0,00 0,00 0,00 C4 0,89 0,11	0.00 0.85 0.15 0.00 0.00 C5 0.00 0.85	0.46 0.36 0.38 0.00 0.00 Result 0.37 0.23
$ {f_{j}^{1}(x)} \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ f_{j}^{4}(x) \\ f_{j}^{5}(x) \\ {P5} \\ {f_{j}^{1}(x)} \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ {P5} \\ $	0,00 0,63 0,37 0,00 0,00 0,00 0,00 0,91 0,09	0,00 0,00 1,00 0,00 0,00 C2 0,00 0,25 0,75	1,00 0,00 0,00 0,00 0,00 1,00 0,00	0,99 0,01 0,00 0,00 0,00 C4 0,89 0,11 0,00	0.00 0.85 0.15 0.00 0.00 C5 0.00 0.85 0.15	0.46 0.36 0.00 0.00 Result 0.37 0.23 0.48
$ {f_{j}^{1}(x)} \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ f_{j}^{4}(x) \\ {f_{j}^{5}(x)} \\ {f_{j}^{5}(x)} \\ {f_{j}^{1}(x)} \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ f_{j}^{4}(x) $	0,00 0,63 0,37 0,00 0,00 0,00 0,00 0,91 0,09	0,00 0,00 1,00 0,00 0,00 0,25 0,75 0,00	1,00 0,00 0,00 0,00 C3 1,00 0,00 0,00	0,99 0,01 0,00 0,00 0,00 C4 0,89 0,11 0,00	0.00 0.85 0.15 0.00 0.00 C5 0.00 0.85 0.15 0.00	0.46 0.38 0.00 0.00 Result 0.23 0.48 0.02
$ {f_{j}^{1}(x)} \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ f_{j}^{4}(x) \\ {f_{j}^{5}(x)} \\ {f_{j}^{5}(x)} \\ {f_{j}^{1}(x)} \\ f_{j}^{2}(x) \\ f_{j}^{3}(x) \\ f_{j}^{4}(x) \\ f_{j}^{5}(x) $	0,00 0,63 0,37 0,00 0,00 0,00 0,91 0,09 0,00 C 1	0,00 0,00 1,00 0,00 0,00 0,25 0,75 0,00 0,00	1,00 0,00 0,00 0,00 C3 1,00 0,00 0,00	0,99 0,01 0,00 0,00 0,00 0,89 0,11 0,00 0,00	0.00 0.85 0.15 0.00 C5 0.00 0.85 0.15 0.00	0.46 0.38 0.00 0.00 Result 0.37 0.23 0.48 0.02 0.00
$\frac{\overline{f_{j}^{1}(x)}}{f_{j}^{2}(x)} + \frac{\overline{f_{j}^{3}(x)}}{f_{j}^{4}(x)} + \frac{\overline{f_{j}^{5}(x)}}{\overline{f_{j}^{5}(x)}} + \frac{\overline{f_{j}^{5}(x)}}{\overline{f_{j}^{1}(x)}} + \frac{\overline{f_{j}^{3}(x)}}{f_{j}^{4}(x)} + \frac{\overline{f_{j}^{5}(x)}}{\overline{f_{j}^{5}(x)}} + \frac$	0,00 0,63 0,00 0,00 C1 0,00 0,00 0,91 0,09 0,00 C1 0,31	0,00 0,00 1,00 0,00 0,00 0,25 0,75 0,00 0,00 0,00 C2	1,00 0,00 0,00 0,00 C3 1,00 0,00 0,00 0,00 C3	0,99 0,01 0,00 0,00 C4 0,89 0,11 0,00 0,00 0,00 C4	0.00 0.85 0.15 0.00 C5 0.00 0.85 0.15 0.00 0.00 C5	0.46 0.38 0.00 0.00 Result 0.37 0.23 0.48 0.02 0.00 Result
$ \frac{\overline{f_{j}^{1}(x)}}{f_{j}^{2}(x)} + \frac{\overline{f_{j}^{3}(x)}}{f_{j}^{4}(x)} + \frac{\overline{f_{j}^{3}(x)}}{F_{j}^{5}(x)} + \frac{\overline{f_{j}^{3}(x)}}{f_{j}^{3}(x)} + \frac{\overline{f_{j}^{3}(x)}}{f_{j}^{4}(x)} + \frac{\overline{f_{j}^{3}(x)}}{F_{j}^{5}(x)} + \frac{\overline{P6}}{\overline{f_{j}^{1}(x)}} $	0,00 0,63 0,00 0,00 C1 0,00 0,00 0,91 0,09 0,00 C1 0,31 0,69	0,00 0,00 1,00 0,00 C2 0,00 0,25 0,75 0,00 0,00 C2 0,00	1,00 0,00 0,00 0,00 C3 1,00 0,00 0,00 0,00 C3 1,00	0,99 0,01 0,00 0,00 C4 0,89 0,11 0,00 0,00 0,00 C4 1,00	0.00 0.85 0.15 0.00 C5 0.00 0.85 0.15 0.00 0.00 C5	0.46 0.36 0.00 0.00 Result 0.23 0.48 0.02 0.00 Result 0.41

$f_{J}^{4}(x) 0,00$	0,00	0,00	0,00	0.00	0.00
f_j⁵(x) 0,00	0,00	0,00	0,00	0.00	0.00
P7 C1	C2	C3	C4	C5	Result
$f_{j}^{1}(x) 0,00$) 1,00	1,00	1,00	0.00	0.46
$f_{J}^{2}(x)$ 1,00	0,00	0,00	0,00	0.85	0.52
$f_{J}^{3}(x) 0,00$	0,00	0,00	0,00	0.15	0.02
$f_{J}^{4}(x) 0,00$	0,00	0,00	0,00	0.00	0.00
f_j⁵(x) 0,00	0,00	0,00	0,00	0.00	0.00
P8 C1	C2	C3	C4	C5	Result
$f_{J}^{1}(x) 0,11$	1,00	1,00	1,00	0.00	0.46
$f_{J}^{2}(x) 0.89$	9 0,00	0,00	0,00	0.85	0.45
$f_{J}^{3}(x) 0,00$	0,00	0,00	0,00	0.15	0.03
$f_{J}^{4}(x) 0,00$	0,00	0,00	0,00	0.00	0.00
$f_{J}^{5}(x) 0,00$	0,00	0,00	0,00	0.00	0.00
$\frac{f_{f}^{5}(x) \ 0,00}{P9 \ C1}$		0,00 C3	0,00 C4	0.00 C5	0.00 Result
·	C2				Result
P9 C1	C2) 0,34	C3	C4	C5	Result
$\frac{\mathbf{P9} \mathbf{C1}}{\mathbf{f}_{j}^{1}(\mathbf{x}) \ 0,00}$	C2 0 0,34 2 0,66	C3 1,00	C4 1,00	C5 0.00 0.85	Result 0.42 0.50
$\begin{array}{c c} \hline P9 & C1 \\ \hline f_{j}^{1}(x) & 0,00 \\ \hline f_{j}^{2}(x) & 0,82 \end{array}$	C2 0 0,34 2 0,66 3 0,00	C3 1,00 0,00 0,00	C4 1,00 0,00	C5 0.00 0.85	Result 0.42 0.50 0.08
$\begin{array}{c c} \hline \mathbf{P9} & \mathbf{C1} \\ \hline f_{f}^{1}(\mathbf{x}) & 0,00 \\ f_{f}^{2}(\mathbf{x}) & 0,82 \\ f_{f}^{3}(\mathbf{x}) & 0,18 \\ \hline \end{array}$	C2 0 0,34 2 0,66 3 0,00 0 0,00	C3 1,00 0,00 0,00	C4 1,00 0,00 0,00	C5 0.00 0.85 0.15	Result 0.42 0.50 0.08
$\begin{array}{c c} \hline \mathbf{P9} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,00 \\ f_{j}^{2}(\mathbf{x}) & 0,82 \\ f_{j}^{3}(\mathbf{x}) & 0,18 \\ f_{j}^{4}(\mathbf{x}) & 0,00 \end{array}$	C2 0 0,34 2 0,66 3 0,00 0 0,00 0 0,00	C3 1,00 0,00 0,00 0,00	C4 1,00 0,00 0,00 0,00	C5 0.00 0.85 0.15 0.00	Result 0.42 0.50 0.08 0.00
$\begin{array}{c c} \hline \mathbf{P9} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,000 \\ f_{j}^{2}(\mathbf{x}) & 0,822 \\ f_{j}^{3}(\mathbf{x}) & 0,182 \\ f_{j}^{4}(\mathbf{x}) & 0,000 \\ f_{j}^{5}(\mathbf{x}) & 0,000 \\ \hline \end{array}$	C2) 0,34 2 0,66 3 0,00) 0,00) 0,00) 0,00) 0,00	C3 1,00 0,00 0,00 0,00 0,00	C4 1,00 0,00 0,00 0,00 0,00	C5 0.00 0.85 0.15 0.00 0.00	Result 0.42 0.50 0.08 0.00 0.00
$\begin{array}{c c} \hline \mathbf{P9} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,000 \\ f_{j}^{2}(\mathbf{x}) & 0,822 \\ f_{j}^{3}(\mathbf{x}) & 0,182 \\ f_{j}^{4}(\mathbf{x}) & 0,000 \\ \hline f_{j}^{5}(\mathbf{x}) & 0,000 \\ \hline \mathbf{P10} & \mathbf{C1} \\ \hline \end{array}$	C2) 0,34 2 0,66 3 0,00) 0,00) 0,00) 0,00) 0,00) 0,00	C3 1,00 0,00 0,00 0,00 0,00 C3	C4 1,00 0,00 0,00 0,00 0,00 C4	C5 0.00 0.85 0.15 0.00 0.00 C5 0.00	Result 0.42 0.50 0.08 0.00 0.00 Result 0.42
$\begin{array}{c c} \hline \mathbf{P9} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,000 \\ f_{j}^{2}(\mathbf{x}) & 0,82 \\ f_{j}^{3}(\mathbf{x}) & 0,18 \\ f_{j}^{4}(\mathbf{x}) & 0,000 \\ \hline f_{j}^{5}(\mathbf{x}) & 0,000 \\ \hline \mathbf{P10} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,000 \\ \hline \end{array}$	C2) 0,34 2 0,66 3 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00	C3 1,00 0,00 0,00 0,00 0,00 C3 1,00	C4 1,00 0,00 0,00 0,00 0,00 C4 1,00	C5 0.00 0.85 0.15 0.00 0.00 C5 0.00 0.85	Result 0.42 0.50 0.08 0.00 0.00 0.00 0.00 0.42
$\begin{array}{c c} \hline \mathbf{P9} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,00 \\ f_{j}^{2}(\mathbf{x}) & 0,82 \\ f_{j}^{3}(\mathbf{x}) & 0,18 \\ f_{j}^{4}(\mathbf{x}) & 0,00 \\ \hline f_{j}^{5}(\mathbf{x}) & 0,00 \\ \hline \mathbf{P10} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,00 \\ f_{j}^{2}(\mathbf{x}) & 1,00 \\ \hline \end{array}$	C2) 0,34 2 0,66 3 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,50) 0,50	C3 1,00 0,00 0,00 0,00 C3 1,00 0,00	C4 1,00 0,00 0,00 0,00 0,00 C4 1,00 0,00	C5 0.00 0.85 0.15 0.00 0.00 C5 0.00 0.85	Result 0.42 0.50 0.08 0.00 0.00 0.00 0.00 0.42
$\begin{array}{c c} \hline \mathbf{P9} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,00 \\ f_{j}^{2}(\mathbf{x}) & 0,82 \\ f_{j}^{3}(\mathbf{x}) & 0,18 \\ f_{j}^{4}(\mathbf{x}) & 0,00 \\ \hline f_{j}^{5}(\mathbf{x}) & 0,00 \\ \hline \mathbf{P10} & \mathbf{C1} \\ \hline f_{j}^{1}(\mathbf{x}) & 0,00 \\ \hline f_{j}^{2}(\mathbf{x}) & 1,00 \\ f_{j}^{3}(\mathbf{x}) & 0,00 \\ \hline \end{array}$	C2) 0,34 2 0,66 3 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,00) 0,50) 0,50) 0,00	C3 1,00 0,00 0,00 0,00 C3 1,00 0,00	C4 1,00 0,00 0,00 0,00 C4 1,00 0,00	C5 0.00 0.85 0.15 0.00 0.00 C5 0.00 0.85 0.15	Result 0.42 0.50 0.08 0.00 0.00 0.00 0.00 0.00 0.01 0.02 0.42 0.42 0.42 0.00 0.00 0.00 0.42 0.42 0.42 0.45 0.15

Step 4: Estimate the Criteria Weights

The weights of the criteria have been carried out according to equation (4), and the values shown in Table 9 are assigned according to the calculation.

Table 9 Weight	of the criteria	according to the	grey classes

	e > mengine o		according to		40000
	λ,	λ_2	λ	λ_4	λ,
C1	0,10	0,30	0,69	1,32	1,71
C2	1,79	1,59	1,27	0,90	0,76

C3	1,51	1,22	0,96	0,91	0,83	
C4	0,96	1,14	1,17	0,92	0,80	
C5	0,63	0,75	0,90	0,95	0,90	
						-

Step 5: Estimate the Classification Coefficient

According to the calculations presented in the previous step, clustering vectors are obtained for each monitoring point whose values are presented in Table 10. The highlighted values correspond to the highest value of the clustering coefficient in each vector corresponding to each monitoring point.

Table 10 V	Neight c	lustering	vector of	monitoring	points
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	λ,	λ2	۸a	λ,	λ
P1	0.42	0.15	0.33	0.00	0.00
P2	0.45	0.22	0.33	0.00	0.00
P3	0.46	0.23	0.25	0.00	0.00
P4	0.46	0.36	0.38	0.00	0.00
P5	0.37	0.23	0.48	0.02	0.00
P6	0.41	0.55	0.04	0.00	0.00
P7	0.46	0.52	0.02	0.00	0.00
P8	0.46	0.45	0.03	0.00	0.00
P9	0.42	0.50	0.08	0.00	0.00
P10	0.40	0.45	0.15	0.00	0.00

Step 6: Results using Max. Clustering coefficient Next, Table 11 presents the maximum clustering coefficient that indicates each object belonging to the established intervals.

Table 11 Weight clustering vector of the monitoring point

	λ ₁
P1	0.42
P2	0.45
P3	0.46
P4	0.46
Р5	0.37

P6	0.41
P7	0.46
P8	0.46
Р9	0.42
P10	0.40

5. Results and Discussion

5.1. Concerning the Case Study

The results obtained are presented in Table 12 for the different monitoring points according to the Prati index and the clustering coefficient.

Table 12 Results table of the grey clustering method

			<u> </u>
Point	Name	Coefficient	Level
P1	I.L. Sh-Sh	0.42	Excellent
P2	S.L. Sh-Sh	0.45	Excellent
P3	C.L Sh-Sh	0.46	Excellent
P4	I.L. s/n2	0.46	Excellent
Р5	S.L s/n2	0.48	Slightly polluted
P6	C.L s/n2	0.55	Acceptable
P7	S.L. Milpo	0.52	Acceptable
P8	C.L. Milpo	0.46	Excellent
P9	C.L s/n1	0.50	Acceptable
P10	C.L s/n3	0.45	Acceptable

The lagoon s/n2 goes through a contamination process from the entrance to its exit from the system; a similar process occurs in the Milpo lagoon. The communication of these points is pertinent because they show that there are natural or anthropogenic processes that originate this condition prior to the mining project operation.

The processed results are easier to interpret and communicate, unlike the data presented by SRK Consulting. The change due to natural processes in the gaps translated into a linguistic expression is not evident.

The results obtained from the water quality study carried out on the Fenchuan River in China, applying the Grey Clustering methodology, determined that the said water body was contaminated to different degrees. Its quality decreased from the main upper channel to downstream caused by the inadequate development of agricultural activity [9]. Although the results obtained in the Milpo lagoon show similar behavior concerning pollution levels, it cannot be directly attributed to the development of an anthropogenic activity or influence. In this particular case, a decrease in the water quality of the lagoon is evidenced naturally. Therefore, an unfavorable change in the water quality of a body is related to anthropogenic activities and purely natural processes.

5.2. Concerning the Methodology

Unlike a direct application of the Prati index that would provide us with a qualification of the status for each parameter, the application of grey clustering allows the translation into a comprehensive classification of each of the monitoring points, now being fully categorized, as well as representing more simply the state of water quality, which allows obtaining results whose approximation to reality is greater.

Weighting functions are a key part of the proper development of this method. An error in the definition of the functions would completely change the results of the investigation. However, the correct development of the method allows obtaining direct results of quick and easy interpretation.

Likewise, the method has a varied field of application. Such as the quality of surface and groundwater to the prediction of air quality, among others.

6. Conclusions

The surface water quality in the lagoons of El Padrino mining project presents a quality categorized between contaminated, acceptable and slightly excellent depending on the monitoring point, in addition to presenting the development of natural contamination processes evidenced in the changes of category in the entrance and exit of the lagoons being an important precedent in the baseline of the environmental impact study. Likewise, with the categorization obtained, it is now easier to communicate the status of the quality of water bodies to the community than to present the monitoring data used as an input, making it difficult to understand the quality status.

The methodology enables to reach a category that is much easier to communicate, unlike the initial monitoring data. Categorization in a linguistic term allows for easier communication supported by the use of a fuzzy logic method.

From this work, the evaluation of water quality evolution in the project study area can be developed in the future. Once its operations have been approved, it will be possible to process the results of future monitoring campaigns and obtain tools with which the population can interpret the evolution processes of the water quality of the lagoons in the project area. Likewise, the presented methodology can be applied to other projects in general, considering the evaluation of the parameters contained in the Prati index.

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