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Original Article

Model based on Grey Systems to Assess Water Quality from Mines in Operation and Environmental Liabilities

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Abstract - *Currently, water is essential for human activities, as it is an indispensable source for life and human development. However, one of the main problems that today's society presents is the contamination of water bodies, which reduces water quality. In addition, it generates social conflicts because a body of water contaminated with heavy metals or other wastes can cause critical illnesses. The case study focuses on La Libertad, Peru. There are two open pit mines and several mining environmental liabilities; close to these mines is the Moche River. The methodology used in this paper was the grey clustering method that uses the center-point triangular whitenization weight functions, also known as CTWF, which is based on grey systems. The results showed that there is contamination around the monitoring points around the mining companies and environmental liabilities since these monitoring points present subcategory A3, which is, according to Peruvian legislation, a type of water that needs to be purified with advanced treatment. These results could help to inform the state about the risks presented in the water body so that the governmental entity can proceed to carry out actions to monitor and control effluents from mining environmental liabilities present in the area and mining units.*

Keywords - *Environmental liabilities, Mining operations, Grey systems, Grey clustering, Water quality.*

1. Introduction

Peru is a country that has a large amount of economically extractable natural resources. One of them is copper, which is present to a large extent in the country and generates the largest amount of foreign currency, which is equal to 23% of the total value of exports [1]. However, it should be noted that extracting minerals can cause conditions for the dispersion of contamination in water by chemical pollutants, and high concentrations of heavy metals, among others [2]. Likewise, in Peru, many environmental liabilities affect the quality of life of people and the environment. These complex physicochemical characteristics make their control and rehabilitation difficult and expensive [3].

The grey clustering method is based on Deng's grey systems theory in 1985 [4]. It is generally used when there is poor information on the case study [5] or the behavior of the system is unknown or unclear, such as in a water quality study using monitoring points [6]. This method quantifies qualitative information, classifying the studied objects into grey classes and evaluating the observed objects to determine if they belong to predetermined classes [7].

Our case study focused on the study of the Moche River basin, located in the Quiruvilca district, Santiago de Chuco province, La Libertad department. This place is characterized by the presence of active mines and environmental liabilities. So, monitoring points were established throughout the basin to determine if these environmental liabilities or mines were contaminating it.

For the case, the objective was to analyze the impact of mining and mining environmental liabilities on water quality in the studied location. For this, eleven monitoring points were used: five points to analyze the impact of mines and six points to analyze the impact of environmental liabilities on water.

For the present study, the new contributions are that an evaluation is made for an area with mining and an area with mining environmental liabilities. In addition, a comparison is made between these areas to know who pollutes the Quiruvilca area the most. In this way, containment can be carried out if the results show filtrations both in the environmental liabilities and in the mining area; in the same way, the mining companies and the state can correct the management of the mining effluents be carried out. Therefore, our research marks a difference between the studies carried out in "Grey Clustering Method for Water Quality Assessment to Determine the Impact of Mining Company, Peru" [8] and "Artificial intelligence model based on grey systems to assess water quality from Santa River watershed" [9], since they only evaluate the quality of the water for the impact that may be caused by having mining areas around this body of water.

The structure of this study is divided into the following sections: Section II, which describes and explains the CTWF methodology, Section III, which describes the case study on which this research focuses, Section IV, which details the results obtained and a discussion is made about them and, finally, Section V which shows the conclusions obtained from the study.

2. Methodology

Grey clustering is a methodological approach used in different contexts such as social, science, engineering, and mathematics. In the present paper, the CTWF method is applied to assess the impact on water quality in the Moche river basin under the influence of mining areas and environmental liabilities. This method is usually used when data are uncertain, unquantifiable and incomplete [10]. The CTWF method has 6 steps in Figure 1 [11] [12].

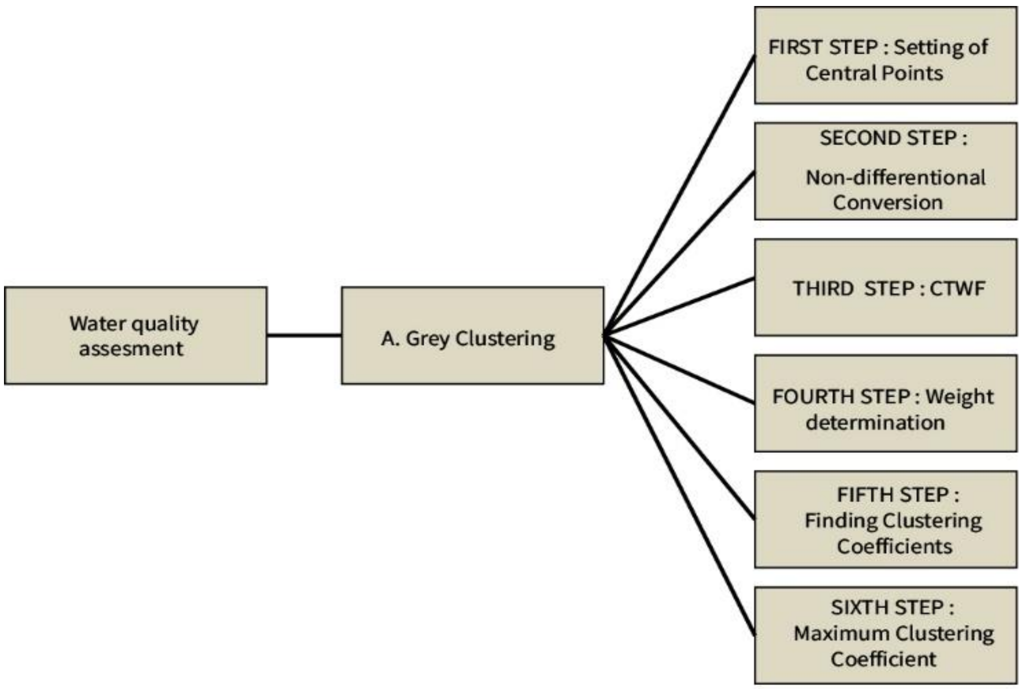

Fig. 1 Methodology scheme

2.1. First Step: Setting of Central Points

To calculate Central Points, the Peruvian standard rule for water quality is necessary as delimitation points. Thus, we will convert these points into three Grey Classes (λ1, λ2 and λ3).

2.2. First Step: Setting of Central Points

Original values must be converted to non-dimensional values. These are applied for standards and monitoring points. This conversion is calculated by Eq. 1.

$$P_{ij} = \frac{Z_{ij}}{\frac{\sum_{j=1}^{n} Z_{iij}}{n}} \qquad (1)$$

Then, these non-dimensional values will make a matrix arrangement: Z = Zij.

Also, each criterion has the following form: Cj

Where: i = 1, 2, 3, ..., m and j = 1, 2, 3, ..., n

2.2. Third Step: Triangular functions (CTWF)

Previous Grey Classes, λ1, λ2 and λ3, are used in Eq. 2-4.

$$f_j{}^1(x_{ij}) = \begin{cases} 0, x \in \left[\lambda_j^2, +\infty >\right. \\ \frac{\lambda_j^2 - x}{\lambda_j^2 - \lambda_j^1}, x \in < \lambda_j^1, \lambda_j^2 > \\ 1, x \in \left[0,\ \lambda_j^1\right] \end{cases} \qquad (2)$$

$$f_j{}^2(x_{ij}) = \begin{cases} 0, x \in \left[0, \lambda_j^1\right] \cup \left[\lambda_j^3, +\infty >\right. \\ \frac{\lambda_j^3 - x}{\lambda_j^3 - \lambda_j^2}, x \in < \lambda_j^2, \lambda_j^3 > \\ \frac{x - \lambda_j^1}{\lambda_j^2 - \lambda_j^1}, x \in < \lambda_j^1, \lambda_j^2 > \end{cases} \qquad (3)$$

$$f_j{}^3(x_{ij}) = \begin{cases} 0, x \in \left[0, \lambda_j^2\right] \\ 1, x \in \left[\lambda_j^3, +\infty >\right. \\ \frac{x - \lambda_j^2}{\lambda_j^3 - \lambda_j^2}, x \in < \lambda_j^2, \lambda_j^3 > \end{cases} \quad (4)$$

Then, these new functions are plotted, madding Fig. 2.

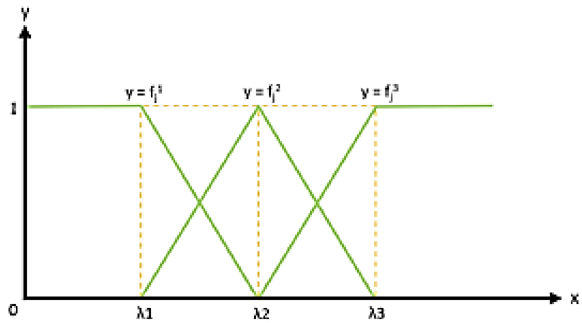

Fig. 2 CTWF Representation

2.3. Fourth Step: Determination of the Weight for each Criterion

To calculate the weight of the grey class parameters, the harmonic mean will be used by Eq. 5.

$$\boldsymbol{n_j^k} = \frac{\frac{1}{\lambda_j^k}}{\sum_{j=1}^{n}\frac{1}{\lambda_j^k}} \quad (5)$$

2.4. Fifth Step: Determination of the Clustering Coefficient

To determine the Clustering Coefficient for each point i, i=1, 2, 3, …, m, Eq. 6 and corresponding grey class k, k = 1, 2, 3 are necessary.

$$\sigma_i^k = \sum_{j=1}^{n} f^k(x_{ij}).n_j \quad (6)$$

Where:
$\boldsymbol{f^k(x_{ij})}$ = The value from CTWF and $\boldsymbol{n_j}$ is the weight for each parameter.

2.5. Sixth Step: Determination of the Max Coefficient

Finally, the maximum coefficient value is the category for each monitoring point. Eq. 7 will be applied.

$$\boldsymbol{max_{1\le k<s}\{\sigma_i^k\} = \{\sigma_i^{k*}\}} \quad (7)$$

3. Case Study

The case study focuses on the district of Quiruvilca, province of Santiago de Chuco, in the department of La Libertad. The location of the area in Peru can be seen in Figure 3 [13]. There are two open-pit mines and several mining environmental passives in this place. On the one hand, close to these mines is the Moche River, which is used both in mining operations and in the town of Quiruvilca. Around this area, monitoring points were established by ANA (National Water Authority of Peru) to obtain information about the impact of mining on water quality.

On the other hand, ANA established other monitoring points around the mining environmental passives located in the city of Salpo and Samne to establish whether the mining environmental passives present in the area affect water quality, as their impact on water is manifested in two aspects: chemical contamination, due to the solubilization of metals or other elements by chemical weathering of the elements present in the MEL, and physical contamination, due to the dragging of fines [14]. The data published by ANA on monitoring points in the described areas were collected in 2020 [15]. With the above, the purpose is to analyze whether the water maintains its quality along the river or suffers contamination from mining processes.

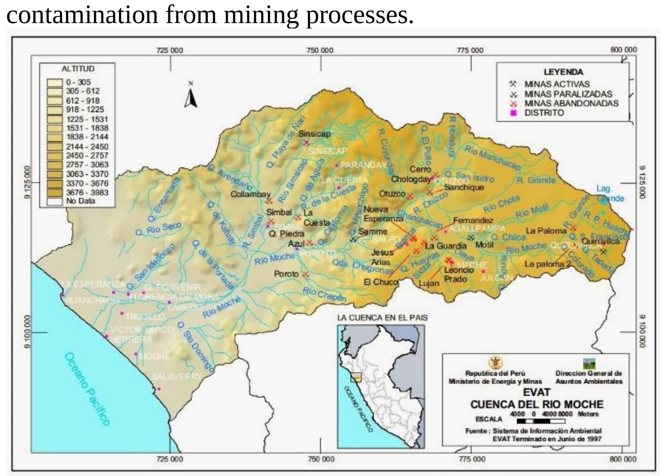

Fig. 3 A case study

3.1. Definition of Objects Study

The report on monitoring surface water quality in the Moche River basin considers thirty-two monitoring points. Nevertheless, for this research, only eleven of these points were selected, of which five correspond to analyzing the impact of mining on water quality. The remaining six are to analyze mining environmental liabilities and their possible impact on water quality. These points are shown in Table 1 and indicated in Fig. 4.

Fig. 4 Monitoring points from the Moche river

Table 1. Selected Monitoring Points

Codes	Points	Coordinates (UTM WGS84)			Altitude (masl)
		Zone	East	North	
G1	LGran1	17M	796305	9121692	4001
G2	LSLor1	17M	796448	9119903	3953
G3	RSCat1	17L	796988	9113156	3805
G4	RMoch1	17M	792998	9114162	3552
G5	RMoch2	17 M	791103	9116114	3552
G6	QADul1	17 M	768205	9116710	2969
G7	RChan1	17 M	765521	9116438	2670
G8	QCush1	17 M	755143	9115627	1381
G9	RMoch12	17M	755350	9115400	1376
G10	RMoch13	17M	754124	9114680	1224
G11	RMoch6	17 L	749580	9114059	820

3.2. Definition of Evaluation Criteria

Since the impact generated by the environmental liabilities and the surrounding mining operations will be assessed, criteria that are chemically related to the mining operations will be used. These selected criteria are shown in Table 2.

Table 2. Notation of Criterions

Criterion	Units	Notation
pH	1 al 14	C1
Al	mg/L	C2
As	mg/L	C3
Cd	mg/L	C4
Cu	mg/L	C5
Fe	mg/L	C6
Mn	mg/L	C7
Pb	mg/L	C8
Zn	mg/L	C9

3.3. Definition of Grey Classes

The analysis was carried out based on the criteria present in the Peruvian water quality standards ECA [16] for subcategory A of category 1, as this subcategory is based on surface water that will be used to produce water for human consumption. Within the subcategory, there are three conditions: A1, A2 and A3. The first indicates that the water quality is good, as only disinfection is needed to make it potable. On the other hand, the second one only needs a conventional treatment, and, for the third one, advanced treatment is necessary, as pollutants seriously affect the water quality [16]. For this reason, each condition A1, A2 and A3 will correspond to a $\lambda1$, $\lambda2$ and $\lambda3$ after dimensioning the values. The selected parameters of the ECA subcategory A are shown in Table 3. However, the Peruvian National Water Authority (ANA) classifies the Moche river in category 3 [16], which means its water is destinated for vegetable irrigation and livestock drink (D.S. N° 004-2017-MINAM, 2017). For this reason, the values of category 3 were taken for certain parameters that only had a single value.

Table 3. Original Criterions for Grey Classes

Parameters	Quality Index Condition		
	Water might be purified by disinfection	Water might be purified by conventional treatment	Water might be purified by advanced treatment
pH	6.5 - 8.5	5.5 - 9.0	5.5 - 9.0
Al (mg/L)	0.9	5	5
As (mg/L)	0.01	0.01	0.15
Cd (mg/L)	0.003	0.005	0.01
Cu (mg/L)	2	2	2
Fe (mg/L)	0.3	1	5
Mn (mg/L)	0.4	0.4	0.5
Pb (mg/L)	0.01	0.05	0.05
Zn (mg/L)	3	5	5

3.4. Calculations by using CTWF Method

3.4.1. First step: Setting of Central Points

First, adjustments must be made to the criteria in Table 3, as there are values that, in the different conditions A1, A2 and A3, are the same. Therefore, it is necessary to make adjustments, so each parameter has a different value. For pH, because it is in a range, the maximum value was selected due to the alkalinity of the Moche river. Likewise, the average between extreme conditions was applied for the case of Al, As, Mn and Zn since the two classes had the same value. Finally, in the case of copper, which has three equal values, the minimum value was obtained from the category 3 ECA [16] for vegetable irrigation. The A2 was calculated with the average of both categories. This adjustment is shown in Table 4.

Table 4. Modified Criterions for Grey Classes

Parameters	Quality Index Condition		
	Water might be purified by disinfection	Water might be purified by conventional treatment	Water might be purified by advanced treatment
pH	8.5	8.75	9
Al (mg/L)	0.9	2.95	5
As (mg/L)	0.01	0.08	0.15
Cd (mg/L)	0.003	0.005	0.01
Cu (mg/L)	0.2	1.1	2
Fe (mg/L)	0.3	1	5
Mn (mg/L)	0.4	0.45	0.5
Pb (mg/L)	0.01	0.03	0.05
Zn (mg/L)	3	4	5

3.4.2. Second step: Non-dimensional Conversion

The values in Table 4 must then be converted to non-dimensional values. It is done by dividing each of the three grey classes with the average of these (Eq. 1). This non-dimensional value for each parameter is shown in Table 5. At this point, the λ1, λ2 and λ3 values for each parameter (As, Cd and more) are shown. In the same way, the same procedure is performed for the monitoring points.

Then, the values of λ1, λ2 and λ3 that correspond to each parameter C1, C2, C3, C4, C5, C6, C7, C8 and C9 must be substituted in Eq. 2-4 to have the equations that will be used to evaluate the data obtained at the monitoring points.

Table 5. Non – Dimensional Standard Values

Codes	Quality Index Condition		
	λ1	λ2	λ3
C1	0.971	1	1.029
C2	0.305	1	1.695
C3	0.125	1	1.875
C4	0.5	0.833	1.667
C5	0.182	1	1.818
C6	0.143	0.476	2.381
C7	0.889	1	1.111
C8	0.333	1	1.667
C9	0.75	1	1.25

Table 6. Non – Dimensional Monitoring Points Values

Codes	Quality Index Condition					
	C1	C2	C3	C4	C5	C6
G1	0.811	0.007	0.019	0.017	0.002	0.055
G2	0.789	0.027	0.086	0.128	0.015	0.097
G3	0.753	0.054	0.023	0.31	0.033	0.06
G4	0.263	12.031	64.225	55.133	19.555	180.81
G5	0.286	6.146	28.263	28.01	9.582	88.19
G6	0.263	9.858	0.025	251.333	9.373	5.700
G7	0.918	0.040	0.043	0.075	0.004	0.114
G8	0.979	0.043	0.280	0.050	0.005	0.123
G9	0.251	2.316	4.771	9.743	3.192	17.671
G10	0.255	4.725	11.563	10.657	3.402	37.119
G11	0.249	5.780	10.805	9.475	3.029	35.681

3.4.3. Third step: Triangular functions (CTWF)

After replacing each λ with its respective parameter C in the functions, the monitoring point values obtained in Table 6 are evaluated in these functions (Eq. 2-4). For example, results for G1 and G2 are shown in Table 7.

Table 7. Parameters Evaluated at All Monitoring Points

Codes	Eqs.	C1	C2	C3	C4	C5	C6
G1	f1 (x)	1.000	1.000	1.000	1.000	1.000	1.000
	f2 (X)	0.000	0.000	0.000	0.000	0.000	0.000
	f3 (x)	0.000	0.000	0.000	0.000	0.000	0.000
G2	f1 (x)	1.000	1.000	1.000	1.000	1.000	1.000
	f2 (X)	0.000	0.000	0.000	0.000	0.000	0.000
	f3 (x)	0.000	0.000	0.000	0.000	0.000	0.000

3.4.4. Fourth step: Determination of the Weight for each Criterion

It is necessary to calculate the clustering weights. As mentioned in the methodology, the harmonic mean method (Eq. 5) was used to find the clustering weights. This procedure is important because the clustering coefficient will be found with these weights values. The results are shown in Table 8.

Table 8. Clustering Weights

Weight	λ1	λ2	λ3
C1	0.032	0.097	0.163
C2	0.102	0.097	0.099
C3	0.248	0.097	0.089
C4	0.062	0.117	0.101
C5	0.17	0.097	0.092
C6	0.217	0.204	0.07
C7	0.035	0.097	0.151
C8	0.093	0.097	0.101
C9	0.041	0.097	0.134

3.4.5. Fifth step: Determination of the Clustering Coefficient

After the clustering weights are obtained, the clustering coefficient is calculated using the equation (Eq. 6). This result is shown in Table 9.

Table 9. Clustering Coefficient

Codes	λ1	λ2	λ3
G1	1.000	0.000	0.000
G2	1.000	0.000	0.000
G3	0.983	0.046	0.000
G4	0.032	0.000	0.837
G5	0.032	0.000	0.837
G6	0.280	0.000	0.748
G7	1.000	0.000	0.000
G8	0.947	0.044	0.000
G9	0.032	0.000	0.837
G10	0.032	0.000	0.837
G11	0.032	0.000	0.837

3.4.6. Sixth step: Determination of the Max Coefficient

The highest value of the clustering coefficient is chosen for each parameter C. Having selected this maximum value, the grey class to which it belongs is determined (Eq. 7). This value is shown in Table 10.

Table 10. Value of max. Clustering coefficient

Points	Codes	Max-Coef	Subcategory
LGran1	G1	1.000	λ 1
LSLor1	G2	1.000	λ 1
RSCat1	G3	0.983	λ 1
RMoch1	G4	0.837	λ 3
RMoch2	G5	0.837	λ 3
QADul1	G6	0.748	λ 1
RChan1	G7	1.000	λ 1
QCush1	G8	0.947	λ 1
RMoch12	G9	0.837	λ 3
RMoch13	G10	0.837	λ 3
RMoch6	G11	0.837	λ 3

4. Results and Discussion

4.1. About the Case Study

After the methodology has been developed, the monitoring points will be classified according to Peruvian Legislation in the ECA – Category 1A, "Surface water that will be used for the production of water for human consumption". Table 11 shows the results obtained for the points near the active mining area. On the other hand, Table 12 shows those close to the environmental liabilities.

Table 11. Results According to the Data Obtained From Active Mining Areas

Points	Codes	Subcategory
LGran1	GI	A1
LSLor1	G2	A1
RSCat1	G3	A1
RMoch1	G4	A3
RMoch2	G5	A3

Table 11 shows the results obtained for the points near the active mining area. This table found that LGran1, LSLor1 and RSCat1 belong to subcategory A1, the first two of which have the best quality. It is consistent with the fact that these sampling points belong to an area upstream of the mine effluent. On the other hand, RMoch1 and RMoch2 are in subcategories A3, indicating that they have the worst quality, such as water that can be disinfected with advanced treatment. It may indicate that the mine effluent discharged does not have a good wastewater management system.

Table 12. Results According to the Data Obtained from the Areas Surrounding the Environmental Liabilities

Points	Codes	Subcategory
QADul1	G6	A3
RChan1	G7	A1
QCush1	G8	A1
RMoch12	G9	A3
RMoch13	G10	A3
RMoch6	G11	A3

Table 12 shows the mining environmental liabilities. In this table, it was found that RChan1 and QCush1 belong to subcategory A1, while QADul1, RMoch12, RMoch13 and RMoch6 belong to category A3. In the case of QCush1, water quality was expected to be in subcategory A3 since this monitoring point is in the zone of influence of the passives. Nevertheless, good water quality was obtained because the mining environmental liabilities in the Salpo area do not filter any pollutants into the Moche river. According to MINEM, the type of soil in the Samne district is a premontane desert scrub [17][18], and the river water will be captured, and quickly it will seep into the subsoil, causing it to leak and evacuate to the Moche River; In other words, there is constant infiltration and contamination of the mining environmental liability into the Moche River. Likewise, about RChan1, this monitoring point is located after the liability zones, so it has a positive value, in other words, in Subcategory A1.

4.2. About the Methodology

The Grey clustering methodology considers the uncertainty in its analysis [11], which means that the data with which this methodology is used will be processed effectively and, with this, the error in the results will be reduced. Likewise, it should be mentioned that the whitening functions present in the Grey clustering methodology are easily adaptable when you want to change with other types of legislation or standard, which allows obtaining a result that, according to the legislation, can be positive or negative. However, a factor that should always be considered is that highly variable characteristics will change the study environment, making it a dynamic evolutionary process [19]. This factor is very important due to the difficulty in analyzing these environmental changes and, consequently, will affect decision-making.

5. Conclusion

From the results obtained, it is concluded that the environmental liabilities have a strong negative impact on the Moche River since four of the six monitoring points evaluated for this zone were in subcategory A3. Similarly, for the active mining zone, two monitoring points were obtained with poor quality, indicating that the effluent discharges of the mining companies in the area are not properly managed. Therefore, the results obtained can be of great help to the national environmental control authorities in taking decisions for the management and regularization of water resources.

Regarding the applied methodology, the grey clustering method was used, which helped to classify the monitoring points evaluated based on the information provided by the National Water Authority (ANA) and the parameters established in Peruvian legislation. Likewise, this methodology gives us a mathematical advantage since it allows us to apply triangular functions and use the harmonic mean to establish the weights of the selected parameters in evaluating the body of water.

Finally, it should be highlighted that the application of the methodology is very versatile since it is adapted based on the legislation evaluated. It makes it possible for future research to carry out a more detailed study with comparisons between water quality categories by type of legislation according to each country.

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