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Delgado-Villanueva, KA.; Romero Gil, I. (2016). Environmental conflict analysis using an integrated grey clustering and entropy-weight method: A case study of a mining project in Peru. *Environmental Modelling & Software*. 77:108-121. doi:10.1016/j.envsoft.2015.12.011



The final publication is available at

<http://doi.org/10.1016/j.envsoft.2015.12.011>

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Additional Information

Environmental conflict analysis using an integrated grey clustering and entropy-weight method: A case study of a mining project in Peru

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ABSTRACT

Environmental conflict analysis (henceforth ECA) has become a key factor for the viability of projects and welfare of affected populations. In this study, we propose an approach for ECA using an integrated grey clustering and entropy-weight method (The IGCEW method). The case study considered a mining project in northern Peru. Three stakeholder groups and seven criteria were identified. The data were gathered by conducting field interviews. The results revealed that for the groups urban population, rural population and specialists, the project would have a positive, negative and normal social impact, respectively. We also noted that the criteria most likely to generate environmental conflicts in order of importance were: access to drinking water, poverty, GDP per capita and employment. These results could help regional and central governments to seek appropriate measures to prevent environmental conflicts. The proposed method showed practical results and a potential for application to other types of projects.

Keywords:

Grey clustering method

Entropy-weight method

Environmental conflict

Social impact

Mining project

1. Introduction

Environmental conflicts often accompany the planning and implementation of projects and programs, as evidenced by studies of conflicts related to water management (Bolin et al., 2008, Saqalli et al., 2010), energy (Fontaine, 2010, Karjalainen and Järviöski, 2010), exploitation of natural resources (Correia, 2007, Warnaars, 2012, Madani et al., 2014) or ecological tourism (Yang et al., 2013). Therefore, organizations and governments require techniques enabling them to assess social impact and then, given this information, to propose measures for preventing environmental conflicts (Barrow, 2010, Prenzel and Vanclay, 2014). Organizations have obligation as part of their corporate social responsibility to evaluate their social impact to prevent possible conflicts within the affected communities (Kemper et al., 2013). Furthermore, governments are obligated to improve population welfare to achieve sustainable development of countries; therefore, they must measure social impact of their programs and state policies to prevent possible conflicts (Franks and Vanclay, 2013). In addition, stakeholders are a dimension of integrated assessment (Hamilton et al., 2015), and environmental conflicts are generated between stakeholder groups within communities, due to the differences in the assessment of industrial projects (Arun, 2008, Luyet et al., 2012). For this reason, social impact assessment must first be performed for each stakeholder group and then the gap between the groups must be determined in order to predict and prevent possible environmental conflicts.

Thus far, ECA has been mostly carried out using qualitative methods such as those described by Prenzel and Vanclay (2014, based on game theory), who address environmental conflict from an infrastructure development project, or by Griewald and Rauschmayer (2014, based on a capability perspective), who consider environmental conflict in a protected nature area. In addition, there are also quantitative methods for ECA, found, for example, in the study by Al-Mutairi et al. (2008, based on fuzzy logic) of environmental conflict over aquifer contamination caused by a chemical company. In this article, we apply a method for ECA combining the grey clustering method and the entropy-weight method (The IGCEW method), as an extension to the qualitative and quantitative methods.

The grey clustering method enables quantification of qualitative information and classification of observed objects into definable classes, as well as verification of

whether the observed objects belong to predetermined classes – as shown by the studies of Zhang et al. (2013), who analysed a water rights allocation system, or by Zhang et al. (2014), who classified innovation strategic alliances. It can be argued that the grey clustering method is likely to benefit the first stage of ECA in that it helps assess social impact by quantifying the qualitative information obtained from stakeholder groups involved in a given environmental conflict.

In turn, the entropy-weight method is used to calculate objective weights of criteria. If there is a large difference between the objects for a criterion determined, this criterion can be regarded as an important factor for the analysis of alternatives, as shown by the study of Wang and Lee (2009), who resolved a software selection problem, or by Kou et al. (2011), who assessed a case of environmental pollution. In our view, the entropy-weight method would benefit the final stage of ECA, as it allows researchers to determine the criteria for which there is divergence between the stakeholder groups involved in a conflict. The combination of both methods would be beneficial for ECA because it integrates social impact assessment and divergent criteria identification. To illustrate the method we propose, a case study was conducted assessing the exploitation plans of a poly-metallic mine in northern Peru. Three stakeholder groups were identified and a set of seven criteria for ECA were established in the mining project.

The specific objectives of this article are to:

1. Apply the IGCEW method for ECA to the concrete context of the exploitation plans of the poly-metallic mine in Peru.
2. Explore if the IGCEW method exhibits potential for other ECA contexts.

In section 2 the literature review is described. Section 3 provides the details of the IGCEW method for ECA. In Section 4 the case study is described, followed by the results and discussion in Section 5. Conclusions are provided in Section 6.

2. Literature review

Environmental conflicts are characterized by the interaction between (1) ecological and (2) social complexity (Wittmer et al., 2006).

- (1) One central feature of environmental conflicts is the complexity of the ecological system which is the natural base of the conflicts. Even if its understanding is accompanied by a high degree of scientific sophistication, there remains substantial uncertainty and ignorance. Therefore, the process leading to the resolution of environmental conflicts should take into account scientific and idiosyncratic knowledge and should cope with unavoidable uncertainty and ignorance. Certain forms of multi-criteria decision aid could satisfy this demand. (Wittmer et al., 2006).
- (2) Another central feature of environmental conflicts is social complexity. Some stakeholders are also actors who may impede the implementation of a decision, or, put positively, their agreement is necessary for a successful implementation of the decision. Social complexity calls for stakeholder participation. Decision structuring tools offer the possibility to make participatory decision processes more transparent (Wittmer et al., 2006).

The resolution of environmental conflicts should concentrate on both aspects, social and ecological complexity. Wittmer et al (2006) suggest approaching both aspects by an intensive integration of stakeholders and multi-criteria analysis. However, environmental conflict is a social issue and has high level of uncertainty. In addition, in classical multi-criteria analysis methods, the importance degrees of criteria and the performance scores of alternatives are assumed to be known precisely. Moreover, the practical constraints of the real world hinder the use of crisp values. The problems faced in practice occur in such an environment that the goals, constraints and consequences of alternatives are not precise. Furthermore, the ambiguities, uncertainties and vagueness inherent in decision makers' evaluations necessitate the use of methods to model uncertainty in decision problems (Baykasoglu and Gölcük, 2015). There are many methods used to model uncertainty in decision problems. Probabilistic approaches (Augustsson, et al., 2011), fuzzy logic (Zadeh, 1965), and grey systems (Liu and Lin, 2010) are some examples of the options used to model uncertainty.

The grey systems theory is a methodology for studying uncertainty problems (Deng, 1982), in which there are limited information and small samples (Liu and Lin, 2010). In order to explore the differences, we compare grey systems with other main approaches, below.

Comparison between grey systems and probabilistic approaches

A comparison study between grey systems and probabilistic approaches was performed in 1994 by (1) Jiangping Qiu and (2) Xisheng Hua respectively, who established a theoretically delicate statistical regression model and relatively coarse grey model based on the deformation and leakage data of a certain large scale hydraulic dam. Their work shows that their grey model provided a better fit than the statistical regression model. When comparing the errors between the predictions of the two models with the actual observations, it is found that the prediction accuracy of the grey model is generally better than that of the regression model, for more details see Table 1 (Liu and Lin, 2010).

Table 1
Comparison between the prediction errors of a statistical model and a grey model.

N°	Type	Average error	
		Statistical model	Grey model
1	Horizontal displacement	0.862	0.809
	Vertical displacement	1.024	1.029
	Water level of pressure measurement hole	6.297	3.842
2	Horizontal displacement	0.446	0.232
	Vertical displacement	0.465	0.449
	Water level of pressure measurement hole	0.204	0.023

As shown in Table 1, we believe that a model based on grey system could be more accurate than a statistical model. In addition, considering that environmental conflict is a social issue and a very inconstant and subjective topic, which requires a permanent analysis, and that one of the criteria for evaluating methods for ECA is the cost (Wittmer et al., 2006), in this aspect an approach based in grey systems would have a lower cost with respect to a statistical approach, due to the fact that sample size influences the cost of field research.

Comparison between grey systems and fuzzy logic approaches

Fuzzy mathematics emphasizes the investigation of problems with cognitive uncertainty, where the research objects possess the characteristic of clear intention and unclear extension. For example, the instance, “young man” is a fuzzy concept, because everybody understands the idea of “young man”. However, if you are going to determine the exact range within which everybody is young and outside which everybody is not young, then you will find yourself in difficulty. This is because the concept of young man does not have a clear extension. For this kind of problem of cognitive uncertainty with clear intention and unclear extension, the situation is dealt with in fuzzy mathematics by making use of experience and the so-called membership function (Liu and Lin, 2010).

The focus of grey systems theory is on the uncertainty problems of small samples and limited information which are difficult to handle for probability and fuzzy mathematics. One of its characteristics is construct models with small amounts of data. What is clearly different of fuzzy mathematics is that grey systems theory emphasizes the investigation of such objects which process clear extension and unclear intention. A summary of the differences between these approaches is shown in Table 2 (Liu and Lin, 2010).

Table 2
Comparison between grey systems and fuzzy math methods.

Object	Grey systems	Fuzzy math
Research objects	Poor information	Cognitive uncertainty
Basic sets	Grey hazy sets	Fuzzy sets
Methods	Information coverage	Mapping
Procedures	Sequence operator	Cut set
Data requirement	Any distribution	Known membership
Emphasis	Clear extension	Clear intention.
Objective	Laws of reality	Cognitive expression
Characteristics	Small sample	Experience

Based on what is described above, we strongly believe that the grey clustering method based on grey systems could be more convenient than an approach based on fuzzy logic, to analyse an environmental conflict, due to the fact that we have clear extension and unclear intention of ECA criteria. For example, in a historic range of five years, we know the minimum and maximum value of a social variable under analysis. In addition, an affected population within a determined project is clear about when things were good or bad: before or after project implementation.

In turn, ECA should be performed considering stakeholder participation (Wittmer et al., 2006), that is, identifying and analysing divergences between stakeholder groups into the influence areas of a determined project. In addition, social impact assessment and environmental conflict prevention should be integrated (Franks and Vanclay, 2013), in order to properly manage possible environmental conflicts during project development. Stakeholders' analysis is a social topic and has a lot of uncertainty which could be dealt with by applying Shannon entropy theory. Shannon entropy is a quantitative measurement of uncertainty (Kou et al., 2011), which could help us to discern the divergence between stakeholder groups. We strongly believe the entropy-weight method, based on Shannon entropy theory, integrated with the grey clustering method, could contribute to ECA, as it integrates social impact assessment and environmental conflict prevention, in a similar way and under the same philosophy as grey systems. However, so far there has been more research on fuzzy logic or on statistics models than on grey systems or Shannon entropy, which could change to the extent that research based on grey systems or Shannon entropy proposes a further development of the theory and establishment of innovative methods in the different fields of knowledge. Based on what has been discussed above, we summarize the differences between the IGCEW method, proposed in this article, and other principal approaches in Table 3.

Table 3
Comparison between the IGCEW method and other main approaches.

Aspect	The IGCEW method	Approaches based on fuzzy logic	Approaches based on statistics
Epistemological paradigm	Integrate qualitative and quantitative paradigms.	Integrate qualitative and quantitative paradigms.	Prioritize quantitative paradigm.
Uncertainty	Focus on the uncertainty problems of small samples and limited information.	Investigation of problems with cognitive uncertainty.	Stochastic uncertainty.
Data requirement	Any distribution.	Known membership.	Typical distribution.
Emphasis of research object	Clear extension and unclear intention.	Clear intention and unclear extension.	Revealing the historical statistical laws.
Objective of research problem	Laws of reality.	Cognitive expression.	Historical statistical laws.
Costs during application	Low, due to the fact that a small sample is used.	Medium, due to the fact that experience is used.	High, due to the fact that a large sample is used.

The main advantages of the IGCEW method may be summarized as follows:

- (1) The grey clustering method and the entropy-weight method are combined for the first time in ECA literature.
- (2) The IGCEW method is more appropriate than other classical approaches based on multi-criteria analysis, as it considers uncertainty within its analysis.
- (3) The IGCEW method integrates social impact assessment and environmental conflict prevention, performing an analysis of stakeholder groups.
- (4) The IGCEW method is more effective and has a lower cost than other statistical approaches during its application.
- (5) The IGCEW method is more convenient than other approaches based on fuzzy logic, as it analyses environmental conflict considering clear extension of criteria for ECA.

3. Method

This section provides a summary of the grey clustering method and of the entropy-weight method, followed by details of the IGCEW method for ECA.

3.1 Grey clustering method based on CTWF

The grey clustering method is based on grey system theory, originally developed by (Deng, 1985). The grey system is a theory which focuses on the study of problems involving small samples and limited information (Liu and Lin, 2010). In the real world

there are many problems of this type, determining a broad range of applicability of the theory of grey systems, for example:

- Evaluation of web sites (Bindu et al., 2010),
- Transport management (Leng et al., 2012),
- Water management (Zhang et al., 2013),
- Safety management (Li et al., 2015, Wei et al., 2015).

The grey clustering method was developed for classifying observation indices or observation objects into definable classes using grey incidence matrices or grey whitenization weight functions. The grey clustering method using whitenization weight functions is mainly applied to test whether the objects of observation belong to predetermined classes, so that they can be treated accordingly (Liu and Lin, 2010). In this article, we use the grey clustering method based on center-point triangular whitenization weight functions (CTWF) because stakeholder groups can be treated as observation objects for ECA. In addition, since respondents tend to be more certain about the center-point of a grey class as compared with other points within the class, conclusions based on such cognitive certainty are more scientific and reliable (Liu and Lin, 2010). This fact is important for collecting information from stakeholder groups and for assessing objectively the social impact they may be affected by.

The grey clustering method based on CTWF is developed according to the following definition.

Definition 1. Assume that there are a set of m objects, a set of n criteria and a set of s different grey classes, according to the sample value x_{ij} ($i=1, 2, \dots, m; j=1, 2, \dots, n$) of the i th ($i=1, 2, \dots, m$) object, for the criterion j ($j=1, 2, \dots, n$). The steps for grey clustering based on CTWF can be expressed as follows (Liu and Lin, 2010, Zhang et al., 2014):

Step 1: The individual ranges of the criteria are divided into s grey classes, and then center-points $\lambda_1, \lambda_2, \dots, \lambda_s$ of grey classes $1, 2, \dots, s$ are determined.

Step 2: The grey classes are expanded in two directions, adding the grey classes 0 and $(s+1)$ with their center-points λ_0 and λ_{s+1} respectively. Therefore, the new sequence of center-points is established $\lambda_0, \lambda_1, \lambda_2, \dots, \lambda_s, \lambda_{s+1}$ (see Fig. 1). The CTWF for the k th grey

class, $k=1, 2, \dots, s$, of the j th criterion, $j=1, 2, \dots, n$, for an observed value x_{ij} is defined by Eq. (1).

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

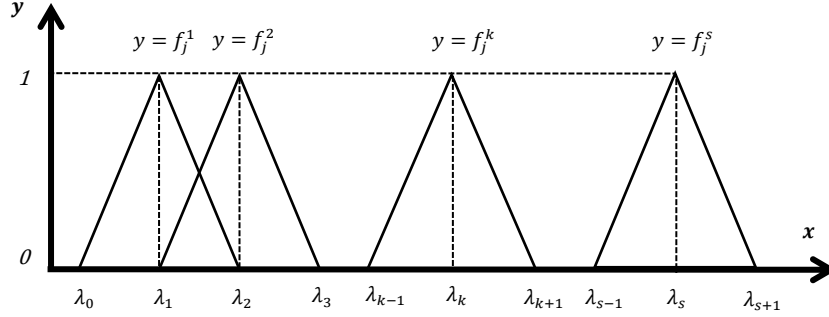


Fig. 1. Center-point triangular whitenization weight functions (CTWF).

Step 3: The comprehensive clustering coefficient σ_i^k , for object i , $i=1, 2, \dots, m$, with respect to the grey class k , $k=1, \dots, s$ is calculated by Eq. (2).

$$\sigma_i^k = \sum_{j=1}^n f_j^k(x_{ij}) \cdot \eta_j \quad (2)$$

where $f_j^k(x_{ij})$ is the CTWF of the k th grey class of the j th criterion, and η_j is the weight of criterion j .

Step 4: If $\max_{1 \leq k \leq s} \{\sigma_i^k\} = \sigma_i^{k^*}$, we decide that object i belongs to grey class k^* . When there are several objects in grey class k^* , these objects can be ordered according to the magnitudes of their comprehensive clustering coefficients.

3.2 Entropy-weight method

The entropy-weight method is based on Shannon entropy, originally developed by Shannon (Shannon and Weaver, 1947). Shannon entropy is a concept which is proposed as a measure of uncertainty in information, formulated in terms of probability theory. Since the concept of entropy is well suited to measuring the relative intensities of contrast criteria in order to represent the average intrinsic information transmitted for

decision-making (Zeleny, 1996), it is an appropriate and convenient choice for our purpose. Subsequent research on Shannon entropy has contributed to the resolution of a range of problems in areas such as:

- Clinical neurophysiology (Cao and Slobounov, 2011),
- Transport systems (Chen et al., 2014),
- Environmental time series data (Srivastav and Simonovic, 2014),
- Fault detection (Heidari Bafroui and Ohadi, 2014).

Shannon developed measure H which satisfies the following properties for all p_i within an estimated joint probability distribution P (Shemshadi et al., 2011, Zitnick and Kanade, 2004):

1. H is a continuous positive function;
2. If all p_i are equal, $p_i=1/n$, then H should be a monotonic increasing function of n ; and,
3. For all, $n \geq 2, H(p_1, p_2, \dots, p_n) = h(p_1 + p_2, p_3, \dots, p_n) + (p_1 + p_2)H(\frac{p_1}{p_1+p_2}, \frac{p_2}{p_1+p_2})$

Shannon showed that the only function which satisfies these properties is:

$$H_{Shannon} = - \sum_i^n p_i \log(p_i) \quad (3)$$

where: $0 \leq p_i \leq 1; \sum_{j=1}^n p_j = 1$

For a certain criterion, if there is a large difference between the alternatives, the criterion will give decision makers a large amount of information and the criterion can be regarded as an important factor (Kou et al., 2011). It can thus be argued that the entropy-weight method can be applied in ECA to determine those criteria for which there is divergence between the compared stakeholder groups.

The entropy-weight method is developed according to the following definition.

Definition 2. Assume that there are m objects for evaluation and each has n evaluation criteria, which form decision matrix $Z = \{z_{ij}; i = 1, 2, \dots, m; j = 1, 2, \dots, n\}$. Then, the steps of the entropy-weight method can be expressed as follows (Fagbote et al., 2014, Ji et al., 2015; Wang and Lee, 2009, Xie and Yang, 2011):

Step 1: The decision matrix $Z = \{z_{ij}; i = 1, 2, \dots, m; j = 1, 2, \dots, n\}$ is normalized for each criterion C_j ($j=1, 2, \dots, n$). The normalized values P_{ij} are calculated by Eq. (4).

$$P_{ij} = \frac{z_{ij}}{\sum_{i=1}^m z_{ij}} \quad (4)$$

Step 2: The entropy H_j of each criterion C_j is calculated by Eq. (5).

$$H_j = -k \sum_{i=1}^m P_{ij} \ln(P_{ij}) \quad (5)$$

k is a constant, let $k = (\ln(m))^{-1}$.

Step 3: The degree of divergence div_j of the intrinsic information in each criterion C_j is calculated by Eq. (6).

$$div_j = 1 - H_j \quad (6)$$

Step 4: The entropy weight w_j of each criterion C_j is calculated by Eq. (7).

$$w_j = \frac{div_j}{\sum_{j=1}^n div_j} \quad (7)$$

3.3 Integration of the grey clustering and entropy-weight methods

The IGCEW method for ECA combines the grey clustering method based on CTWF and the entropy-weight method, as illustrated in Fig. 2.

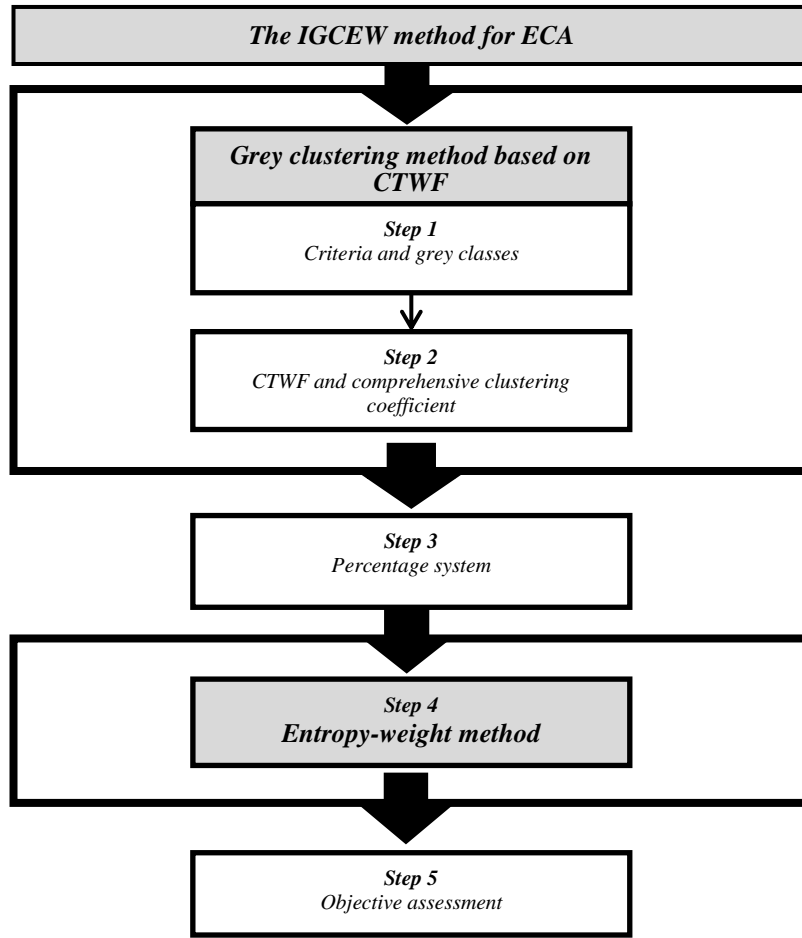


Fig. 2. Schema of the IGCEW method for ECA

The IGCEW method for ECA can be described using the following sets:

1. A set of m objects or stakeholder groups called $G = \{G_1, G_2, \dots, G_m\}$
2. A set of n criteria called $C = \{C_1, C_2, \dots, C_n\}$
3. A set of s grey classes called $V = \{V_1, V_2, \dots, V_s\}$
4. A set of evaluation values called $X = \{x_{ij}, i = 1, 2, \dots, m; j = 1, 2, \dots, n\}$ of $G_i (i = 1, 2, \dots, m)$ with respect to criterion $C_j (j = 1, 2, \dots, n)$.

The steps are described below:

Step 1: Criteria and grey classes. A set of n criteria and a set of s grey classes for ECA are established based on the characteristics of the project under scrutiny.

Step 2: CTWF and comprehensive clustering coefficient. The values of CTWF for each stakeholder group are calculated using Eq. (1). Then, the comprehensive clustering coefficient σ_i^k for object $i, i=1, 2, \dots, m$, with respect to the grey class $k, k=1, \dots, s$, is calculated using Eq. (2).

Step 3: Percentage system. The social impact assessment of each stakeholder group is presented as a percentage system (Chang and Qisen, 2009), defined by values $\alpha_1, \alpha_2, \alpha_3, \dots,$ and α_s , where $\alpha_s=100, \alpha_1=100/s, \alpha_2=\alpha_1+\alpha_1, \alpha_3=\alpha_1+\alpha_2, \dots,$ and $\alpha_{s-1}=\alpha_1+\alpha_{s-2}$; s is the number of grey classes established. The results are given by Eq. (8).

$$z_j^i = \sum_{k=1}^s f_j^k(x_{ij}) \cdot \alpha_k \quad (8)$$

where $f_j^k(x_{ij})$ is the CTWF of the k th grey class of the j th criterion and α_k is the percentage value of each grey class. The results are represented by a matrix determined by Eq. (9).

$$Z = \{z_{ij}, i = 1, 2, \dots, m; j = 1, 2, \dots, n\} \quad (9)$$

Step 4: Entropy-weight method. First, matrix $Z = \{z_{ij}, i = 1, 2, \dots, m; j = 1, 2, \dots, n\}$ is normalized for each criterion $C_j (j=1, 2, \dots, n)$. The normalized values P_{ij} are calculated using Eq. (4). Then, H_j, div_j and w_j are calculated using Eqs. (5), (6) and (7).

Step 5: Objective assessment. The final stage of the ECA is the calculation of objective assessment (Shemshadi et al., 2011) regarding each stakeholder group $i, i=1, 2, \dots, m$, for each criterion $C_j (j=1, 2, \dots, n)$. The objective assessment value is defined by Eq. (10).

$$Q_{ij} = w_j z_{ij} \quad (10)$$

where w_j is the entropy weight of each criterion C_j and z_{ij} is the result of the social impact assessment for each stakeholder group $i, i=1, 2, \dots, m$. The results are represented by a matrix determined by Eq. (11).

$$Q_{ij} = \begin{bmatrix} w_1 z_{11} & w_2 z_{12} & \dots & w_n z_{1n} \\ w_1 z_{21} & w_2 z_{22} & \dots & w_n z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 z_{m1} & w_2 z_{m2} & \dots & w_n z_{mn} \end{bmatrix} \quad (11)$$

The first three steps of the IGCEW method for ECA correspond to social impact assessment, developed in accordance with the grey clustering method based on CTWF and represented by a percentage system. Then, entropy-weight and objective assessment

are applied, which identify the criteria for which there is the greatest divergence between the stakeholder groups.

In order to illustrate and validate the IGCEW method for ECA we conducted a case study described below.

4. Case study

In order to test the IGCEW method, we performed an ECA of the expansion plans of a poly-metallic mine in northern Peru, in the department of Cajamarca (Fig. 3). Our study measured the social impact of this project on the zone of influence and, based on the results, determined the criteria likely to generate environmental conflicts between the identified stakeholder groups.



Fig. 3. Cajamarca, Peru (Wikimedia Commons, 2014).

4.1 Stakeholder Groups

Our field work identified three different stakeholder groups ($k=3$), and the composition of these groups was determined on the basis of the similarities found during the overall assessment of the expansion plans of the mine. The sample size in each group was established by the principle of saturation of discourse, which stipulates that information gathering should end when respondents no longer contribute new observations (Corbetta, 2007). The stakeholder groups were defined as follows:

G₁: Urban population

This group was composed of citizens from the urban areas near the exploitation site. They expressed a generally favourable opinion towards the mining project, and tended to stress the importance of private investment for the resolution of social problems. This group was made up of one hundred and fifteen interviewees.

G₂: Rural population

This group was composed of citizens from the rural areas near the exploitation site, consisting of people undertaking productive activities related to agriculture and livestock. The group of rural population had a generally adverse opinion of the mining project and was made up of one hundred and five interviewees.

G₃: Specialists

This group was composed of professionals from different fields who were familiar with the area of influence and the characteristics of the environmental and social impacts of the mining project, and who manifested a generally neutral assessment of the mining project. This group was made up of thirty-five interviewees.

4.2 Calculations

The calculations for the case study, based on the steps detailed above, proceeded as follows.

Step 1: Criteria and grey classes

The ECA criteria in the studied case were established by taking into account the economic and social situation of the area of influence and the characteristics of the evaluated mining project, as well as consultations with experts. Initially, during the exploratory study, certain criteria were submitted by stakeholders, such as unexpected

death of livestock, lack of health facilities, subsidies for traditional celebrations in the area, and road construction. But these criteria were discarded in the analysis as they were not directly related to the project or were already covered by other previously defined criteria. Seven criteria ($n=7$) were identified as shown in Table 4.

Table 4
ECA criteria identified in the case study.

Criterion	Code	Description
GDP per capita	C ₁	The GDP per capita as soles per month (annual average) in the department of Cajamarca.
Employment rate	C ₂	The employment rate per year in the department of Cajamarca.
Poverty rate	C ₃	The poverty rate per year in the region.
Number of inhabitants per doctor (GP)	C ₄	The number of inhabitants per doctor (GP) per year in the department of Cajamarca.
Enrolment rate in primary education	C ₅	The enrolment rate per year in primary education in the region.
Number of reported crimes	C ₆	The number of reported crimes per year in the department of Cajamarca.
Access to drinking water rate	C ₇	The access to drinking water rate per year in the department of Cajamarca.

Five grey classes (Very Negative, Negative, Normal, Positive and Very Positive) were established for the mining project on the basis of historical information about the 2009-2013 social indicators provided by the Peru government (INEI, 2014) and a qualitative analysis of the consultations with experts – in order to satisfy the need to reflect the social impact of the specific region as accurately as possible (Liu and Lin, 2010). It was decided that the criteria had the same weight ($\eta_j = 0.143$), inasmuch as they were all social criteria (Corbetta, 2007). The grey classes established for each of the seven criteria are shown in Table 5.

Table 5
Grey classes for each criterion determined in the case study.

Code	Grey classes				
	Very Negative (V_1)	Negative (V_2)	Normal (V_3)	Positive (V_4)	Very Positive (V_5)
C_1	$611 \leq x_1^1 \leq 690$	$690 \leq x_1^2 \leq 768$	$768 \leq x_1^3 \leq 847$	$847 \leq x_1^4 \leq 926$	$926 \leq x_1^5 \leq 1004$
C_2	$61.8 \leq x_2^1 \leq 66.2$	$66.2 \leq x_2^2 \leq 70.7$	$70.7 \leq x_2^3 \leq 75.1$	$75.1 \leq x_2^4 \leq 79.6$	$79.6 \leq x_2^5 \leq 84.0$
C_3	$45.4 \leq x_3^1 \leq 52.5$	$38.3 \leq x_3^2 \leq 45.4$	$31.2 \leq x_3^3 \leq 38.3$	$24.1 \leq x_3^4 \leq 31.2$	$17.0 \leq x_3^5 \leq 24.1$
C_4	$2651 \leq x_4^1 \leq 3026$	$2276 \leq x_4^2 \leq 2651$	$1901 \leq x_4^3 \leq 2276$	$1526 \leq x_4^4 \leq 1901$	$1151 \leq x_4^5 \leq 1526$
C_5	$93.0 \leq x_5^1 \leq 93.9$	$93.9 \leq x_5^2 \leq 94.8$	$94.8 \leq x_5^3 \leq 95.7$	$95.7 \leq x_5^4 \leq 96.6$	$96.6 \leq x_5^5 \leq 97.5$
C_6	$7651 \leq x_6^1 \leq 9075$	$6226 \leq x_6^2 \leq 7651$	$4802 \leq x_6^3 \leq 6226$	$3377 \leq x_6^4 \leq 4802$	$1953 \leq x_6^5 \leq 3377$
C_7	$55.1 \leq x_7^1 \leq 61.8$	$61.8 \leq x_7^2 \leq 68.5$	$68.5 \leq x_7^3 \leq 75.2$	$75.2 \leq x_7^4 \leq 81.9$	$81.9 \leq x_7^5 \leq 88.6$

Step 2: CTWF and the comprehensive clustering coefficient

The data obtained from the stakeholder groups were evaluated using CTWF. The grey classes were extended in two directions by adding classes V_0 and V_6 (“extra negative” and “extra positive”, respectively), and their center-points λ_0 and λ_6 were determined. Therefore, there was a new sequence of center-points, $\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ and λ_6 , as shown in Table 6 and Fig. 4.

Table 6
Center-points of the extended grey classes obtained in the case study.

Criteria	Center-points of the extended grey classes						
	Extra Negative impact (λ_0)	Very Negative impact (λ_1)	Negative impact (λ_2)	Normal impact (λ_3)	Positive impact (λ_4)	Very Positive impact (λ_5)	Extra Positive impact (λ_6)
C_1	572	651	729	808	886	965	1044
C_2	59.6	64.0	68.5	72.9	77.4	81.8	86.3
C_3	56.0	48.9	41.8	34.7	27.6	20.5	13.4
C_4	3213	2838	2463	2088	1713	1338	963
C_5	92.5	93.4	94.3	95.2	96.1	97.0	97.9
C_6	9788	8363	6939	5514	4090	2665	1241
C_7	51.7	58.4	65.1	71.8	78.5	85.2	91.9

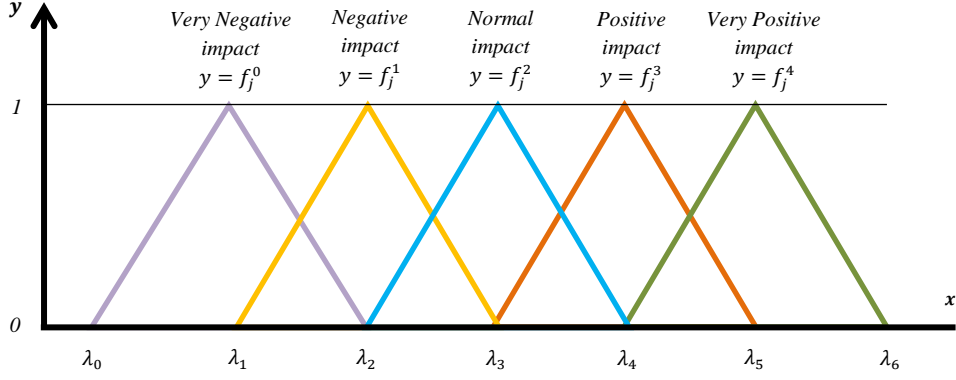


Fig. 4. CTWF in the case study.

To illustrate, for the first criterion C_1 ($j=1$), shown in the first row of Table 2 and Table 3, we first had the grey classes $V_1 = [611; 690]$, $V_2 = [690; 768]$, $V_3 = [768; 847]$, $V_4 = [847; 926]$, and $V_5 = [926; 1004]$, with their center-points being $\lambda_1=651$, $\lambda_2=729$, $\lambda_3=808$, $\lambda_4=886$ and $\lambda_5=965$. The grey classes were then expanded in two directions by adding the grey classes $V_0 = [533; 611]$ and $V_6 = [1004; 1083]$, with their center-points being $\lambda_0=572$ and $\lambda_6=1044$. Thus, we obtained a new sequence of center-points: $\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ and λ_6 . The values were substituted into Eq. (1), and the CTWF of the five grey classes were then obtained. The results for the first criterion C_j ($j=1$) are shown in Eqs. (12), (13), (14), (15) and (16):

$$f_1^1(x) = \begin{cases} 0, & x \notin [572, 729] \\ \frac{x - 572}{79}, & x \in [572, 651] \\ \frac{729 - x}{78}, & x \in [651, 729] \end{cases} \quad (12)$$

$$f_1^2(x) = \begin{cases} 0, & x \notin [651, 808] \\ \frac{x - 651}{78}, & x \in [651, 729] \\ \frac{808 - x}{79}, & x \in [729, 808] \end{cases} \quad (13)$$

$$f_1^3(x) = \begin{cases} 0, & x \notin [729, 886] \\ \frac{x - 729}{79}, & x \in [729, 808] \\ \frac{886 - x}{78}, & x \in [808, 886] \end{cases} \quad (14)$$

$$f_1^4(x) = \begin{cases} 0, & x \notin [808, 965] \\ \frac{x - 808}{78}, & x \in [808, 886] \\ \frac{965 - x}{79}, & x \in [886, 965] \end{cases} \quad (15)$$

$$f_1^5(x) = \begin{cases} 0, & x \notin [886, 1044] \\ \frac{x - 886}{79}, & x \in [886, 965] \\ \frac{1044 - x}{79}, & x \in [965, 1044] \end{cases} \quad (16)$$

The data was collated by means of a field study carried out in the area of influence of the mining project. The information from the stakeholder groups was gathered via direct interviews using a structured questionnaire based on the evaluation criteria and the grey classes established. The questions used in the questionnaire are presented in Table 7.

Table 7
Questions used in the questionnaire.

Question	Grey classes				
	Very Negative (V1)	Negative (V2)	Normal (V3)	Positive (V4)	Very Positive (V5)
1 What effect would the project have on the economic income per person?	Decrease noticeably	Decrease	No effect	Increase	Increase noticeably
2 What effect would the project have on the employment rate?	Decrease noticeably	Decrease	No effect	Increase	Increase noticeably
3 What effect would the project have on the poverty rate?	Increase noticeably	Increase	No effect	Decrease	Decrease noticeably
4 What effect would the project have on the number of inhabitants per doctor (GP)?	Increase noticeably	Increase	No effect	Decrease	Decrease noticeably
5 What effect would the project have on the enrolment rate in primary education?	Decrease noticeably	Decrease	No effect	Increase	Increase noticeably
6 What effect would the project have on the number of reported crimes?	Increase noticeably	Increase	No effect	Decrease	Decrease noticeably
7 What effect would the project have on the access to drinking water?	Decrease noticeably	Decrease	No effect	Increase	Increase noticeably

Table 8 shows the overall results of the evaluation of the three stakeholder groups ($m = 3$) with respect to each criterion. The data were aggregated using arithmetic means (Aznar and Guijarro, 2012).

Table 8
Aggregated values for each criterion for groups G_1 , G_2 and G_3 .

Group	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇
G₁	929	80.3	23	1777	95.9	4578	83
G₂	689	67.6	45	2324	94.7	6369	60
G₃	902	78.2	29	1788	95.2	5799	69

By way of illustration, for group G_1 the values of CTWF were calculated using Eqs. (12), (13), (14), (15) and (16). Subsequently, the comprehensive clustering coefficient (σ_i^k) was calculated for each stakeholder group using Eq. (2). The values of CTWF and σ_i^k obtained for group G_1 ($m=1$) are shown in Table 9.

Table 9
Values of CTWF and σ_i^k for group G_1 .

$f_j^k(x)$	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	σ_i^k
$f_j^1(x)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$f_j^2(x)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$f_j^3(x)$	0.00	0.00	0.00	0.17	0.23	0.34	0.00	0.11
$f_j^4(x)$	0.46	0.34	0.31	0.83	0.77	0.66	0.29	0.52
$f_j^5(x)$	0.54	0.66	0.69	0.00	0.00	0.00	0.71	0.37

Identical procedure was applied to the other groups in the case study.

Step 3: Percentage system

The social impact assessment for the case study was presented as a percentage system, defined by values α_1 , α_2 , α_3 , α_4 , and α_5 , where $\alpha_5=100$, $\alpha_1=100/5=20$, $\alpha_2=\alpha_1+\alpha_1=40$, $\alpha_3=\alpha_1+\alpha_2=60$ and $\alpha_4=\alpha_1+\alpha_3=80$, according to the grey classes established ($s=5$). The results are given in Table 10. To illustrate, the values of social impact assessment for group G_1 were calculated using Eq. (8), as shown in Table 11.

Table 10

The percentage system established in the case study.

Social impact class	Interval	α_k
Very negative	[20, 30]	20
Negative	[30, 50]	40
Normal	[50, 70]	60
Positive	[70, 90]	80
Very positive	[90, 100]	100

Table 11Social impact assessment for group G_1 .

Impact class	α_k	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Total
Very negative	20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Negative	40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Normal	60	0.00	0.00	0.00	10.29	13.71	20.57	0.00	6.37
Positive	80	36.57	27.43	25.14	66.29	61.71	52.57	22.86	41.80
Very positive	100	54.29	65.71	68.57	0.00	0.00	0.00	71.43	37.14
		90.86	93.14	93.71	76.57	75.43	73.14	94.29	85.31
		Very positive	Very positive	Very positive	Positive	Positive	Positive	Very positive	Positive

The values of social impact assessment for groups G_2 and G_3 were obtained using the same procedure as for group G_1 . A complete summary of all the results is shown in Table 12.

Table 12Social impact assessment for groups G_1 , G_2 and G_3 .

Group	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Total	Impact class
G_1	90.86	93.14	93.71	76.57	75.43	73.14	94.29	85.31	Positive impact
G_2	29.71	36.00	29.71	47.43	48.00	48.00	25.71	37.80	Negative impact
G_3	84.00	84.00	76.00	76.00	60.00	56.00	52.00	69.71	Normal impact

Step 4: Entropy-weight method

We next proceeded to apply the entropy-weight method part. First, the criteria values shown in Table 12 were normalized using Eq. (4), the normalized values are given in Table 13. Then, H_j , div_j and w_j were calculated using Eqs. (5), (6) and (7). The results are given in Table 14.

Table 13Normalized values of social impact assessment for groups G_1 , G_2 and G_3 .

Group	C_1	C_2	C_3	C_4	C_5	C_6	C_7
G_1	0.44	0.44	0.47	0.38	0.41	0.41	0.55
G_2	0.15	0.17	0.15	0.24	0.26	0.27	0.15
G_3	0.41	0.39	0.38	0.38	0.33	0.32	0.30

Table 14Values of H_j , div_j and w_j for each criterion in the case study.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
H_j	0.92	0.94	0.92	0.98	0.98	0.99	0.89
div_j	0.08	0.06	0.08	0.02	0.02	0.01	0.11
w_j	0.21	0.16	0.21	0.05	0.04	0.04	0.29

Step 5: Objective assessment

The ECA was completed by calculating objective assessment for each stakeholder group i , $i=1, 2, 3$, for each criterion C_j ($j=1, 2, 3, 4, 5, 6, 7$), using Eq. (10). The results are shown in Table 15.

Table 15

Objective assessment scores for each group in the case study.

Group	C_1	C_2	C_3	C_4	C_5	C_6	C_7
G_1	19.43	14.98	20.05	3.91	2.94	2.63	26.90
G_2	6.36	5.79	6.36	2.42	1.87	1.72	7.34
G_3	17.97	13.51	16.26	3.88	2.34	2.01	14.84

5. Results and Discussion

The results and discussion are presented below in accordance with the two main objectives of this article.

5.1 The case study

The detailed calculations for the case study produced three important findings, which we discuss below.

First, the IGCEW method helped to identify major tensions among the stakeholder groups. Fig. 5 (based on Table 12) shows the score of social impact assessment for each stakeholder group: for group G_1 (urban population) the score was 85.31 (positive impact), for group G_2 (rural population) it was 37.80 (negative impact) and for group G_3

(specialists) it was 69.71 (normal impact). These results suggest a strong antagonism between groups G_1 and G_2 , despite the specialists (G_3) expressing the opinion that the mining project would have an acceptable degree of social impact. The results for G_3 indicate that the mining project would not generate dramatic social problems, but the directly affected populations, as represented by groups G_1 and G_2 , presented contradictory views of the project, the difference suggesting potential conflicts between G_1 and G_2 groups. In order to analyse and more fully understand the mechanisms and forces at play, we need to look at the specific criteria of conflict between G_1 and G_2 , which points to our second important finding.

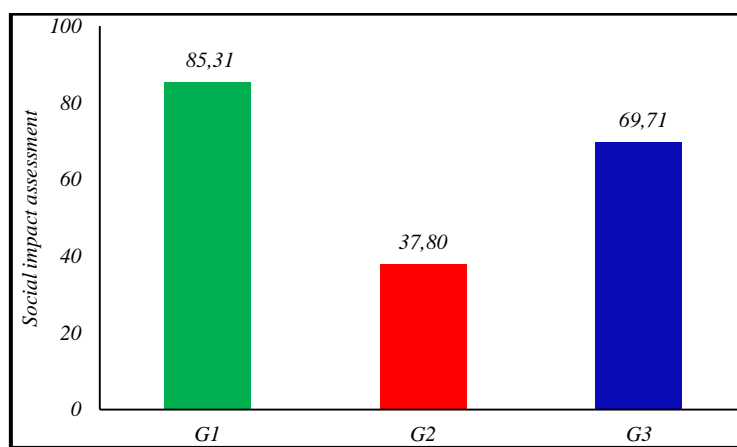


Fig. 5. Total social impact assessment of G_1 , G_2 and G_3 .

The second interesting finding in our case study analysis is that the behaviour of the criteria is considerably different across the affected groups. Fig. 6, derived from Table 12, shows the results of social impact assessment for each criterion. For group G_1 , the criteria C_1 , C_2 , C_3 and C_7 are placed in the range of “very positive impact” (90-100), and the criteria C_4 , C_5 and C_6 occur in the range of “positive impact” (70-90). In addition, for group G_2 , the criteria C_1 , C_3 and C_7 are found in the range of “very negative impact” (20-30), and the criteria C_2 , C_4 , C_5 and C_6 in the range of “negative impact” (30-50). These results pose a need for a closer comparison of all these criteria in order to identify the most controversial ones among them.

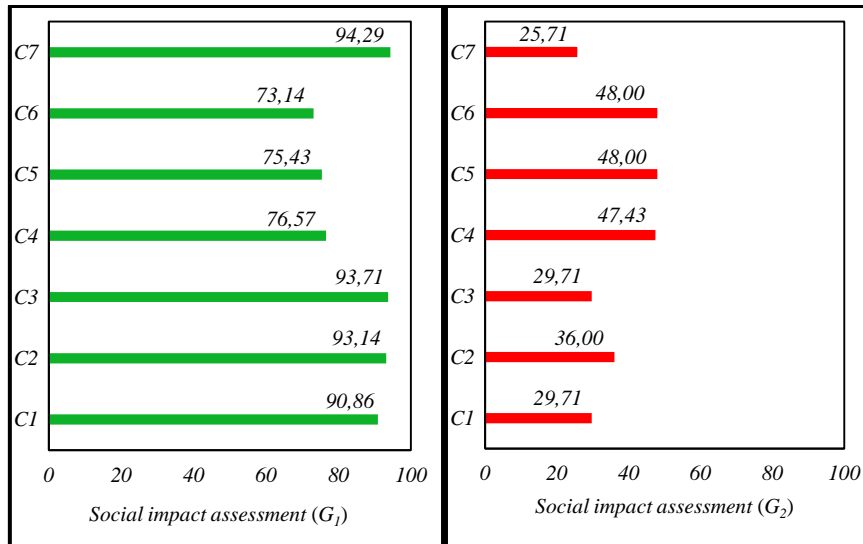


Fig. 6. Social impact assessment for each criterion for groups G_1 and G_2 .

It is at this stage that our third finding and the entropy-weight method proved useful. We were able to identify the most divergent criteria implying the most potential causes of conflict between the affected stakeholder groups. Fig. 7, based on Table 15, shows that the stakeholder groups converge for criteria C_4 (number of inhabitants per doctor (GP)), C_5 (Enrolment rate in primary education) and C_6 (number of reported crimes), while they diverge for criteria C_1 (GDP per capita), C_2 (employment rate), C_3 (poverty rate) and C_7 (access to drinking water rate). The criteria with the greatest divergence are related to access to drinking water, poverty, GDP per capita and employment, in that order. It would thus appear that these four issues should first be taken into account when implementing measures to prevent environmental conflict over the mining project analysed. In addition, Fig. 7 also shows that the criterion with the greatest divergence is related to access to drinking water (C_7). This very issue is especially problematic due to G_2 's strongly expressed belief that the mining company's planned activity would contribute greatly to the contamination of the water sources.

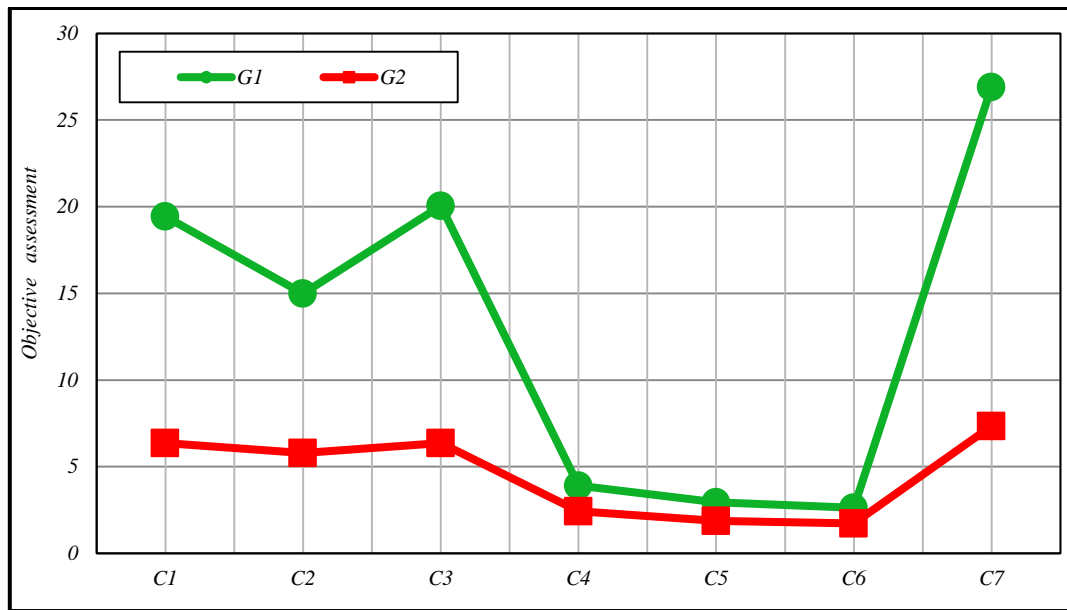


Fig. 7. Objective assessment for each criterion for groups G_1 and G_2 .

5.1.1 Sensitivity Analysis

The IGCEW method is flexible, versatile and adjustable due to the fact that the number of stakeholder groups and number of ECA criteria are determined according to the particularities of the project under scrutiny. In the case studied in this article, we determined seven criteria and three stakeholder groups.

The IGCEW method is sensitive to number and type of stakeholder groups. For example, in our case study, if we were to include the environmental advocacy stakeholder group, see Fig. 8, the mining project would have very negative total impact, as in the opinion of this stakeholder group the mining project is completely non-viable (Sánchez, 2011). If we were to include the government stakeholder group or the company stakeholder group the mining project would have very positive total impact, as in the opinion of these stakeholder groups the mining project is completely viable (Knight Piésold, 2010, MINAN, 2011). In this study, we excluded the environmental advocacy, government and company stakeholder groups, as these stakeholders groups distort the results; in addition, they are not the directly affected population (Wittmer et al., 2006).



Fig. 8. Environmental advocacy stakeholder group (El Comercio, 2015)

5.1.2 Analysis of diverging criteria

The mining project, commonly called Conga, consists of Newmont Mining Corporation (51.35%), *Compañía de Minas Buenaventura* (43.65%), and the World Bank's International Finance Corporation (5%). The planned duration of the mining process is 19 years, including 2 years of construction and 17 years in operation. The standard annual operation consists of the removal of overburden (topsoil and rocks) in order to obtain low-grade metal ores, which are then concentrated using a combination of physical and chemical processes that entail the very intense use of water (Silva-Macher and Farrel, 2014).

In order to establish some measures to prevent environment conflict in the mining project, we analyse the context of the diverging criteria below.

Access to drinking water

Access to drinking water is the most controversial criterion, in terms of the quantity and quality of the water supply to rural and urban areas. The mining project is placed at the headwaters of five important watersheds. In addition, the mining company plans to use four natural lagoons, the lagoon *El Perol* among them, see Fig. 9. These lagoons will be emptied, the first two for mineralogical use and the last two for waste rock dumps (MINAM, 2011). The mining company proposes building four water reservoirs, enough to replace the volumes of the natural lagoons and satisfy the demands of rural and urban areas (Knight Piésold, 2010).



Fig. 9. Lagoon “El Perol”, Cajamarca-Perú (Celendín libre, 2015)

On the one hand, the urban stakeholder group strongly believes that there will be no problems with the quality and quantity of water for urban areas and the economic benefits to the city will be much more advantageous. On the other hand, the rural stakeholder group strongly believes that there will be problems with the quality and quantity of water for rural areas, as the mining company has caused serious environmental damage in previous projects developed in the area (Grufides, 2015), see Fig. 10. In addition, the mining company conducted an environmental impact assessment (EIA) in 2010 (Knight Piésold, 2010), in order to show the viability of the project. However, the rural stakeholder group believes that it is not transparent, as the mining company hired a consulting company to conduct the EIA, even though this is permitted by Peruvian law. This perception was present in all controversial criteria.



Fig. 10. Water conflict on the “Quinua” channel, Cajamarca-Perú (Red verde, 2011)

Poverty

In the department of Cajamarca, about 68% of the population lives in rural areas, hence it is one of the most rural regions of Peru (De Echave and Diez, 2013). In addition, in the Sierra region of Peru, where the department of Cajamarca lies, poverty is 34.7%, higher than the average in the country, which stands at 23.9%. In the Sierra rural area poverty is 52.9% and in the Sierra urban area it is 16.2% (INEI, 2014).

The urban stakeholder group believes that the mining project will reduce the level of poverty, as it will generate direct and indirect economic income for families. While the rural stakeholder group, despite the fact that it has higher rates of poverty, believes the project will make them poorer, as it will destroy their economic base, which is based on agriculture and livestock.

GDP per capita

In the department of Cajamarca, in 1990, agricultural activity, with 42% of total production, was the mainstay of the regional economy, and mining accounted for only 5.9% of total production. In 2010 agricultural activity decreased to 20.1% and mining increased to 20.2%. In addition trade activities, hostelry and manufacturing also increased. This growth mainly benefited urban areas (De Echave and Diez, 2013).

The urban stakeholder group believes that the GDP per capita in the cities will grow, as there will be much more investment in trade activities and other activities in urban areas. The rural stakeholder group does not believe that the GDP per capita in the rural areas will grow, due to the fact that they do not have other economic alternatives to agriculture and livestock, which will be affected by the mining project.

Employment

In recent years mining in Peru has experienced notable growth due to government promoted reforms on investment in mining. However, this economic sector does not generate significant direct employment, as it requires specialized labour. However, the mining industry generates indirect economic movement in other areas such as trade and services, which provides indirect employment (De Echave and Diez, 2013).

The urban stakeholder group strongly believes that the mining project will generate employment in urban areas, as there will be growth in economic sectors such as trade

and services; in addition, the mining company affirms that it will train and hire people from the villages around the project area (Knight Piésold, 2010). However, the rural stakeholders group believes that when the mining project ends, it will leave serious environmental damage, and it will not be possible to use the land for agriculture or livestock, which means job losses in the rural area.

Based on what is analysed above, we believe that in order to prevent environmental conflict the following measures could be implemented:

- Due to the fact that the rural population has lost confidence in the mining company and central government, we propose the implementation of a permanent committee of environmental and social monitoring, in which the rural population is represented.
- We propose a change in legislation, so that EIA is not conducted or contracted by the mining company and that EIA must be contracted by the government and with the agreement of the affected population and the mining company.
- The mining company should study and consider other alternatives, which do not involve the use of natural lagoons, due to the fact that they provide ecological balance in the area and also represent the main causes of conflict over water.
- Taxes collected by the implementation of the project should be invested in social development projects in the area of influence, so that the population is able to perceive the benefits of the project.
- Diversification of economic activities in rural areas in order to create jobs to improve agriculture and livestock and take advantage of opportunities in the context of mining.
- The mining company and the government should explain and demonstrate to the directly affected population, that environmental and social impacts will be mitigated when the mining project is finished.

5.2 The broader potential of the IGCEW method

ECA methods are mainly developed as part of qualitative and quantitative approaches. In order to discuss the potential of the IGCEW method, we compare it below with the qualitative methods and then with the quantitative methods.

First, we believe that the IGCEW method for ECA illustrated in this article could contribute to the improvement of the qualitative methods of ECA. For example, the study developed by Griewald and Rauschmayer (2014) or by Prenzel and Vanclay (2014), both conducted using qualitative methods, could be supplemented by applying the grey clustering method based on CTWF, which quantifies the qualitative information obtained from the stakeholder groups and then by a percentage system establishing a ranked order of social impact assessment for each stakeholder group. This knowledge can allow researchers to study environmental conflicts more accurately, because the procedure provides numerical information easy to analyse and to establish comparisons between the stakeholder groups involved in a given conflict.

Second, the IGCEW method for ECA applied in this article would also contribute to the improvement of the quantitative methods. For example, the study developed by Al-Mutairi et al. (2008), conducted under a quantitative method, could be supplemented by applying the entropy-weight method, which identifies the criteria with the greatest divergence factor between the stakeholder groups, and thus helps to define the causes of environmental conflict more closely, enabling researchers to find more accurate measures of conflict prevention.

6. Conclusions

The application of the IGCEW method for ECA to the mining project in Peru has made it possible to quantify the qualitative information provided by the three stakeholder groups identified, allowing us to establish the values of social impact for each stakeholder group objectively. In addition, the application of the IGCEW method determined the divergent criteria most likely to produce environmental conflicts between the stakeholder groups. The specific results obtained, we believe, could help analysts in the mining company or in the Peruvian government to seek appropriate measures to prevent conflict over the mining project.

We also strongly believe that the IGCEW method for ECA described in this article could be applied as an extension to the qualitative and quantitative methods for ECA, as it provides quantitative information of social impact for each stakeholder group by applying the grey clustering method based on CTWF. In addition, the results from the entropy-weight method can show clearly the criteria most likely leading to environmental conflicts.

The limitations of the IGCEW method may be summarized as follows:

- (1) It presents subjective aspects during information gathering and the establishment of limits of grey classes.
- (2) The grey systems and Shannon entropy approaches are not widely diffused compared to approaches based on fuzzy logic or on statistics models.
- (3) The calculations are a little tedious when processing data. This could be improved by implementing a computer system.
- (4) As it is a new approach it needs to be validated in other contexts to improve its effectiveness.

In future research, the IGCEW method for ECA could be applied to other types of projects, such as water resources management, industrial projects, public construction projects, hydrocarbons exploitation projects, as well as be used to measure the social impact of public policies or governmental programs of conflict prevention.

Acknowledgments

This paper was reviewed by Przemysław Kaszubski, PhD, from the Faculty of English at the Adam Mickiewicz University in Poznan, Poland. The authors would like to thank him for his valuable comments and suggestions.

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