Journal of Cleaner Production 182 (2018) 57–66

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

An analysis of the environmental information in international companies according to the new GRI standards

Isabel Gallego-Álvarez [a, *, 1], María Belén Lozano [a, 1], Miguel Rodríguez-Rosa [b]

[a] Multidisciplinary Institute for Enterprise (IME), Department of Business Administration, Campus Miguel de Unamuno, Edificio FES, University of Salamanca, 37007, Salamanca, Spain
[b] Department of Statistics, Campus Miguel de Unamuno, Alfonso X el Sabio S/N, University of Salamanca, 37007, Salamanca, Spain

ARTICLE INFO

Article history:
Available online 7 February 2018

Keywords:
Environmental index
Statistical techniques
Consolidated GRI standards
International companies

Abstract

This research builds an index to analyze the type of environmental information reported by international companies and recorded in the Thomson Reuters database. We use the environmental information disclosed by 5414 international companies pertaining to 9 geographical areas. To build the environmental index, we use the statistical techniques categorical principal component analysis and partial triadic analysis, which provide a numerical value for specific environmental issues. We also examine whether companies' environmental information disclosure is adapted to the international standards of the 2016 Global Reporting Initiative (GRI), specifically the GRI 300 sustainability reporting standards on environment issues that take effect on July 1, 2018. In addition, we identify environmental disclosure based on geographical zones and industries. This index allows regulators, governments, and firms to encourage disclosure by identifying the strengths and weaknesses of firms' disclosure practices.

1. Introduction

Environmental issues have become more and more important in recent years, not only in the business world and in society at large but also in academic research. Many firms have been criticized for their negative impact in regard to social and environmental issues, rather than praised for their technological and economic outcomes (Reverte, 2009). As society becomes increasingly focused on these issues, the disclosure of information about environmental concerns has increased notably in the last few years (Patten, 2002). This disclosure is of great relevance because of the current interest in both companies and society in environmental issues. According to Burrit (2002), environmental disclosure includes qualitative and quantitative information that measures, calculates, or estimates the environmental impact of a company's activities. Due to the growing importance attached to environmental concerns and the subsequent need to disclose environmental information to stakeholders, firms have tended to voluntarily disclose more information about their environmental impacts, and, therefore, environmental issues have been included in the companies' accounting information systems (Cormier and Magnan, 2015).

Moneva and Llena (2000) find that numerous relevant agencies worldwide have recommended the inclusion of environmental issues in the annual company report (Institute of Chartered Accountants in England and Wales, 1992; Fédération des Experts Comptables Européenes, 1995). Various stakeholders take into account information regarding a company's relation to the environment in their strategic decision-making (Blacconiere and Patten, 1994; Blacconiere and Northcut, 1997; Richardson and Welker, 2001; Reverte, 2009), These stakeholders focus not only on the magnitude and trends of profits but also on the social and environmental aspects of the companies with which they associate (Gray et al., 1995; Brady and Honey, 2007; Dragomir and Cristina, 2009). Indeed, companies may disclose environmental information to improve their image and show themselves be to a responsible member of society, thus responding to stakeholder expectations (Deegan and Samkin, 2000). Firms therefore use environmental disclosures to protect their reputation and identity by engaging with stakeholders through what the literature refers to as a form of moral discourse (Vanhamme and Grobben, 2009; Reynolds and Yuthas, 2008). In effect, companies attempt to reduce their environmental impact to improve their image and to avoid the negative consequences caused by conflicts with

* Corresponding author.
E-mail addresses: igallego@usal.es (I. Gallego-Álvarez), beloga@usal.es (M.B. Lozano), miguel_rosa90@usal.es (M. Rodríguez-Rosa).
[1] http://ime.usal.es/english.

https://doi.org/10.1016/j.jclepro.2018.01.240
0959-6526/

stakeholders (Monteiro and Aibar-Guzmán, 2010).

This study analyzed environmental information provided by Thomson Reuters Eikon database. Using the environmental information provided by companies to Thomson Reuters Eikon, which is one of the most important databases at the international level, we built an environmental index that reflected the information quality of companies around the world that disclose environmental information.

To build the environmental index, we use the statistical techniques of categorical principal component analysis (CATPCA) and partial triadic analysis (PTA) to analyze the different types and characteristics of environmental information of 5414 international firms. Also, we studied the extent to which this information is relevant to Section 300 of the Global Reporting Initiatives (GRI), which addresses environmental sustainability reporting standards and goes into effect on July 1, 2018 (GRI, 2016). In addition, we use between-groups analysis to determine whether a relation exist between the GRI 300 standards, industries, and geographical regions.

Our environmental index is a linear combination of the values of all the original numeric variables as well as in the original categorical variables, which are transformed into numeric variables, for each company. This index thus provides an overall measure of the relevant environmental sustainability information in a global context, making it very useful for the companies, governments, and society. Companies can use the index as a measuring stick to discern their weak and strong areas in environmental sustainability in relation to their peers, based both on region and sector. Regulators can identify companies' strengths and weaknesses in reporting to reward good practices and encourage increased disclosure, for example, by demanding more information in a given country or a given industry. Our results can also be used by future studies that require environmental information disclosure information.

The remainder of the paper is structured as follows. Section 2 discusses previous works and limitations. Section 3 provides the research methods, sample description, and analysis technique. Section 4 presents the results of the empirical analysis in detail. Finally, Section 5 offers some conclusion and avenues for future research.

2. Previous works and limitations

The number of investigations on environmental issues has notably increased in the last decades (Shi, 2004; Scrieciu, 2007). Earlier studies focus on U.S. companies. For example, Wiseman (1982) examines environmental disclosure by considering an 18-item index that includes aspects related to environmental litigation and pollution abatement activities, among others. Later, studies extended to a global scale. Guthrie and Parker (1990) find that U.S. companies provided more environmental information compared to UK and Australian firms. In addition, Adams and Kuasirikum (2000) find that German companies reported more environmental aspects than UK firms during the same period of time. Other research also compared the environmental disclosure of companies from different countries (Cormier et al., 2005; Liu and Anbumozhi, 2009; Clarkson et al., 2008).

Freedman and Jaggi (2005) study the disclosure of environmental issues (especially greenhouse gas emissions) from 120 large companies in the chemical, oil, energy, motor vehicle, and casualty insurance industries. Using a sample of Chinese firms, Meng et al. (2001) examine 2360 firm-year observations and 10 environmental indicators. They find evidence that information related to ISO environmental system authentication, influence of government environmental protection policy, firms' environmental protection policies, disposal and treatment of generated waste and recycling and environmental-related information -such as environmental education, tree planting, biodiversity conservation, and other environmental projects-promote public welfare. These components are also closely related to the key items of environmental disclosure identified in much of the existing literature (e.g., Brammer and Pavelin, 2006; Cho and Patten, 2007; Fallan and Fallan, 2009).

The way in which prior studies obtain environmental information varies considerably. Gray et al. (2001) use the number of pages or phrases that contain some type of environmental information in the annual report to measure the level of environmental disclosure. Deegan and Gordon (1996) use the number of words related to the environment to measure disclosure. More commonly, the literature employs a disclosure-scoring methodology derived from context analysis to appraise the level of environmental disclosure (Al-Tuwaijri et al., 2004; Freedman and Jaggi, 2005). For example, Meng et al. (2001) rates each item of their index from zero to 3 according to the level of disclosure: Components described in monetary and quantitative terms are rated 3; described specifically, 2; in general terms, 1; and no information, zero (i.e. Al-Tuwaijri et al., 2004; Bewley and Li, 2000; Cho and Patten, 2007; Hughes et al., 2001, Wiseman, 1982; Zeng et al., 2010). Other studies use binary variables to measure environmental disclosure. These variables equal 1 if data are published on the company's website or in its sustainability reports, and zero otherwise (Gallego-Álvarez and Vicente-Villardón, 2012; Dangelico and Pontrandolfo, 2010).

Although numerous prior studies consider environmental disclosure, many have limitations. Some studies do not consider many environmental issues (20 in some cases). Other research is limited due to the method used to obtain environmental information. Most prior literature employs content analysis and through the analysis of absence or presence of environmental information. To a lesser extent, studies use categorical and numerical variables that can identify positive or negative environment aspects; these variables require special treatment using different methodologies based on the presence or absence of certain information. Finally, some prior literature is limited by the number of firms analyzed and/or the geographical scope (i.e., single-country studies; Meng et al., 2001).

Given the limitations of previous studies, we adopt a different technique that better represents the environmental disclosure of a larger number of both companies and countries. As such, in our analysis we aim to be more representative of the real environmental situation, including both positive and negative factors of the firms from across the globe (Boyce et al., 2016).

Specifically, we use the statistical techniques CATPCA (Gifi, 1990) and PTA (L'Hermier des Plantes, 1976). Both techniques allow us to obtain a numerical value for each of the environmental factors for each of our sample firms. The final numeric value is the environmental index score, which is a linear combination of the values of the original numeric variables and the original categorical variables that are transformed into numeric variables. This index allows us to obtain a global measure of relevant environmental information worldwide.

Therefore, we build the proposed index to create a common language for firms and stakeholders that allows for greater transparency and accountability between organizations. This new index allows us to expand the scope for measuring and analyzing environmental disclosure across both industry sector and country or geographical region. The utilization of CATPCA and PTA allows us to deal with both categorical and numeric variables in the publicly available information. The algorithm developed from these methodologies can solve the missing values problem as well as problems related to combining the categorical and numerical variables published by the firms and collected in the databases. Because our index more closely reflects the actual situation of the environmental policies currently being carried out by companies in different countries and geographical areas, we open a new avenue of research on environmental issues.

3. Research methods

3.1. Sample description

We select a sample of companies from different countries and geographical regions of the world, including the United States, Australia, the European Union, China, Hong Kong, and Indonesia, among others. Table 1, Panel A, provide a complete listing of countries and geographical regions. Firms also belong to various activity sectors including energy, materials, telecommunications, software and services, health care equipment, technology hardware and equipment, consumer services, retailing, and food and tobacco, among others. Panel B reports the sample based on sector. In sum, the sample comprises 5414 companies from the Thomson Reuters Eikon database. We use the latest available information, which is data from 2014.

Each of the firms in the Thomas Reuters Eikon database provides environmental information on 128 variables dealing with different environmental aspects such as water use, energy use, policy emissions, renewable energy use, biodiversity, greenhouse gas emissions, and so on. We omit repeated information reported in multiple formats. For example, we generate our variable Toxic Chemicals Reduction from the two original indicators: Toxic Chemicals or Substances Reduction (Does the company report on initiatives to reduce, reuse, substitute or phase out toxic chemicals or substances?) and Toxic Chemicals Reduction Partnership (Has the company joined an agency or a group that aims to reduce the generation of harmful chemicals?). We thus build an index comprising 71 environmental variables. Table 2 provides details on the variables.

Next, we analyzed each environmental variable to consider three issues that affect the construction of our index. First, some variables are categorical and other are numerical variables. Thus, we used CATPCA to transform categorical variables into numerical variables. Section 3 explains the algorithm in detail.

Second, many data are missing and, thus, they should not have any weight in the index. However, the fact that a firm does not report information provides us with a relevant indicator. Thus, we used missing values to show the information that companies do reveal. Also, the CATPCA methodology solves the problem of missing values, which is a frequent problem in such investigations due to lack of data.

Finally, some information is reported positively and other information is reported negatively. For example, to the Policy Energy Efficiency question “Does the company have a policy to improve its energy efficiency?” an affirmative answer favors the environment. However, for the Greenhouse Gas Emissions question, which requests the “Total CO_2 and CO_2 equivalents emission in tonnes,” higher values compute negatively in the index because a greater amount of CO_2 does not favor the environment. Consequently, we assigned the value of 1, 0 and −1 to each variable to take into account the positive or negative direction of the variables and the presence or absence of information for the corresponding item. Thus, a variable with a value of zero for a variable does not the lack of information. Instead, we used the value zero to indicate that the corresponding indicator is not an important issue for that company. Thus, zero reveals the same quality of information than the positive (negative) values of 1 (−1) indicate.

Table 1
Sample descriptive statistics.

Panel A. Number of companies by region		
Region	**Code**	**Number companies**
Latin America	1	174
Europe	2	413
Africa	3	55
Asia	4	547
Oceania	5	77
Middle East	6	190
Russian Federation	7	27
Canada	8	450
USA	9	3481
Panel B. Number of companies by sector		
Sector	**Code**	**Number companies**
Automobiles & Components	1	55
Capital Goods	2	434
Commercial & Professional Services	3	150
Consumer Durables & Apparel	4	166
Consumer Services	5	192
Diversified Financials	6	42
Energy	7	792
Food & Staples Retailing	8	45
Food, Beverage & Tobacco	9	255
Health Care Equipment & Services	10	286
Household & Personal Products	11	82
Materials	12	799
Media	13	135
Pharmaceuticals, Biotechnology & Life Sciences	14	445
Real State	15	14
Retailing	16	173
Semiconductors & Semiconductor Equipment	17	148
Software & Services	18	477
Technology Hardware & Equipment	19	294
Telecommunication Services	20	101
Transportation	21	157
Utilities	22	172

3.2. Analysis technique

3.2.1. CATPCA

Our original variables are categorical, most of which are NULL-TRUE-FALSE, and thus no calculation can be done. One option is to transform the categorical variables into a simple natural scale such as 0~NULL, 1~TRUE, and −1~FALSE and then do the corresponding calculations. But this method is neither correct or convenient because the three numbers (0, 1, −1) lack necessary criteria and thus would be chosen arbitrarily. It would also require us to determine whether the distance between the NULL value and the FALSE value $(0-(-1)=1)$ is equal to the distance between the TRUE value and the NULL value $(1-0=1)$. Alternatively, the CATPCA algorithm allows us to assign objectively calculated values—after rather than before implementing the algorithm—to each one of our three responses, regardless of how they were initially encoded.

The CATPCA method (Gifi, 1990) uses a data set made of n rows corresponding to the individual companies and m columns corresponding to the codified categorical variables, that is, a matrix $H(n \times m)$. At first, we do not assign any values to the codifications of the categories for each variable; that is, if we have k_j different categories for the jth variable, we initialize the categories as just the numbers 1, …, k_j. In our case, most of the variables are NULL-TRUE-FALSE type, so we can initialize, for example, 1~NULL, 2~TRUE, 3~FALSE, or any other combination. At the end of the algorithm these categories have different objectively calculated values (although if we have initialized, for example, 1~FALSE, 2~NULL, 3~TRUE, we will obtain the same result after performing the algorithm).

Let k_j for $j=1, \ldots, m$ be the number of different categories for

Table 2
Environmental indicators.

Indicator	Code	Indicator	Code
Policy Energy Efficiency	V01	Carbon Offsets/Credits	V40
Resource Reduction Policy	V02	Emissions Trading	V43
Policy Water Efficiency	V03	Climate Change Commercial Risks Opportunities	V44
Policy Sustainable Packaging	V04	NOx and SOx Emissions Reduction	V45
Policy Environmental Supply Chain	V05	NOx Emissions	V46
Environment Management Team	V07	SOx Emissions	V47
Environment Management Training	V08	VOC Emissions Reduction	V49
Environmental Materials Sourcing	V09	Particulate Matter Emissions Reduction	V50
Toxic Chemicals Reduction	V10	VOC Emissions	V51
Energy Use	V11	Total Waste	V52
Renewable Energy Use	V12	Waste Recycling Ratio	V53
Renewable Energy Supply	V13	Hazardous Waste	V54
Energy Use Total	V14	Waste Reduction Total	V55
Energy Purchased Direct	V15	e-Waste Reduction	V56
Energy Produced Direct	V16	Discharge into Water System	V57
Indirect Energy Use	V17	Water Discharged	V58
Electricity Purchased	V18	Water Pollutant Emissions	V59
Renewable Energy Purchased	V20	ISO 14000 or EMS	V60
Renewable Energy Produced	V21	EMS Certified Percent	V61
Renewable Energy Use	V22	Environmental Restoration Initiatives	V62
Water Use	V23	Environmental Expenditures	V64
Water Withdrawal Total	V24	Environmental Provisions	V65
Fresh Water Withdrawal Total	V25	Environmental Investments Initiatives	V66
Water Recycled	V26	Environmental Partnerships	V68
Environmental Supply Chain Management	V27	Environmental Products	V69
Environmental Supply Chain Monitoring	V28	Eco-Designs Product	V70
Env Supply Chain Partnership Termination	V29	Noise Reduction	V73
Land Environmental Impact Reduction	V30	Hybrid Vehicles	V74
Environmental Controversies	V31	Equator Principles	V76
Policy Emissions	V32	Environmental Asset under Management	V77
Biodiversity Impact Reduction	V34	Product Environmental Responsible Use	V78
Greenhouse Gas Emissions	V35	Agrochemical Products	V79
CO_2 Equivalents Emission Total	V36	Renewable/Clean Energy Products	V80
CO_2 Equivalents Emission Direct	V37	Water Technologies	V81
CO_2 Equivalents Emission Indirect	V38	Sustainable Building Products	V82
CO_2 Equivalent Indirect Emissions, Scope 3	V39		

each of the variables. We define G_j for $j = 1, \ldots,$ and m as the following matrix with n rows and k_j columns:

$$(G_j)_{ik} = 1 \text{ if } H_{ij} = k$$
$$(G_j)_{ik} = 0 \text{ if } H_{ij} \neq k$$

We define $D_j = G_j^t G_j$; that is, D_j is a diagonal matrix with the number of firms that belong to each of the categories for each of the variables.

The objective of the CATPCA method is to find a new matrix X with the same n rows but p columns with p not higher than m, thus reducing both the dimensionality of the original matrix H and transforming the original categorical variables into numerical variables. This method produces a collection of matrices Y_j for $j = 1, \ldots,$ m with k_j rows and p columns and thus numeric scores for all categories of the original variables. This algorithm allows us to reduce the dimensionality of both the individuals and the categories and assigns a numeric value to all variables, which allows us to run our analysis.

From a mathematical point of view, the objective of the CATPCA method is to minimize the function:

$$f(X,\ Y_j) = \frac{1}{n}\sum_{j=1}^{m} Tr\left[(X - G_jY_j)^t(X - G_jY_j)\right],$$

where X is centered and standardized by columns using an iterative algorithm, in which we assign X^z and Y_j^z to the matrices obtained after the zth iteration.

We run the CATPCA algorithm as follows.

1. We randomly choose a matrix X^0 so that it is centered and standardized by columns.
2. Iteration step, $z = 1, \ldots$:
   a. For $j = 1, \ldots,$ m we compute $Y_j^z = D_j^{-1}G_j^tX^{z-1}$.
   b. We compute $X^* = \sum_{j=1}^{m} G_jY_j^z$, and we center X^* by columns.
   c. If we perform the singular value decomposition for X^* (i.e., $X^* = U\Lambda^{1/2}V^t$), we recalculate X^z as $X^z = \sqrt{n}X^*V\Lambda^{-1/2}V^t$.
   d. We compute $f(X^z, Y_j^z)$.
   e. This step is stopped if the absolute difference between $f(X^{z-1}, Y_j^{z-1})$ and $f(X^z, Y_j^z)$ is lower than the initially established value.
3. The matrices X and Y_j are defined as obtained after the zth iteration, $X = X^z$, $Y_j = Y_j^z$.
4. X and Y_j are rotated so they achieve the principal axes orientation, and each column of X must be reflected if the mean of squared scores with a negative sign is higher than the mean of squared scores with a positive sign. This step is performed because many different solutions can be obtained, but all are the same up to rotations and reflections.
5. We can calculate the percentages of explained variance for each p dimension as

$$VAR_p = \frac{1}{m\sqrt{n}}\left(\Lambda^{\frac{1}{2}}\right)_{pp} \times 100,$$

where $\Lambda^{1/2}$ is the matrix with the singular values obtained in the zth iteration.

6. We use Cronbach's alpha as a measure of the reliability of the results, which is computed as

$$\alpha_p = \frac{m}{m-1}\left(1 - \frac{\sqrt{n}}{\left(\Lambda^{1/2}\right)_{pp}}\right).$$

Consequently, the CATPCA provides numerical values for all categorical variables, assigning them positive, null, or negative values. A category with a null value means that the company to which it is assigned does not place much importance on that environmental indicator. Negative (positive) indicators point to a negative (positive) effect on the company and thus are given more importance by the company.

3.2.2. PTA

The CATPCA algorithm provides a matrix X with the categorical variables, although the transformation into numerical variables reduces dimensionality. Because our original data comprises both categorical and numeric values, after we transform the categorical data, we need to combine it with the original numerical variables before reducing the dimensionality.

To homogenize all variables, we used PTA, which is part of Structuration des Tableaux À Trois Indices de la Statistique (STATIS; L'Hermier des Plantes, 1976). First, we computed a matrix with as many rows as the original matrix H and as many columns as the number of categorical variables. This matrix is similar to the original matrix H (and is also named H). The difference is that we used the numerical transformation of the categorical variables if $p = 1$:

$H_{ij} = (G_j Y_j)_i$ for $i = 1, \ldots, n$ and $j = 1, \ldots, m$.

We then joined all the numerical variables in matrix M, with the same n rows but J columns: the m categorical variables transformed into numerical variables, plus the original numerical variables.

Next, we reduced the dimensionality of the matrix M to a one-dimensional vector (i.e., a matrix with only one column), which is our final index. We evaluated this matrix using PTA, which allowed us to find a one-dimensional vector through a linear combination of all the columns of M by using a vector $\alpha = (\alpha_1, \ldots, \alpha_J)$ with the different weights assigned to each column. The algorithm to find this vector is as follows:

1. M must be centered and standardized by columns.
2. We compute the variances−covariances matrix, Cov, for each pair of columns as

$$Cov_{j_1 j_2} = \frac{1}{n}\sum_{i=1}^{n} M_{ij_1} M_{ij_2}.$$

3. Let $D_J(J \times J)$ be the diagonal matrix with $1/J$ in the diagonal. If we perform the eigendecomposition for Cov D_J (i.e., $Cov\ D_J = V\Lambda V^t$) and recalculate the first column of V as its absolute value, we obtain

   α as $\alpha_j = \frac{V_{j1}}{\sum_{j=1}^{J} V_{j1}}$.
4. Finally, the result obtained from the PTA method is the "average" column called compromise vector, M_c, calculated as $(M_c)_i = \sum_{j=1}^{J} M_{ij}\alpha_j$.

We can draw an interstructure graphic with the similarities between the compromise vector and all the columns (variables) of M. This graphic allows us to interpret how the different weights are obtained: the nearer to the positive horizontal axis a variable is and the longer its vector is, the higher its weight is. In other words, long variables near the positive horizontal axis are more related to the compromise whereas short vectors, or variables near to the vertical axis, are not as important to obtain the compromise. Long vectors near the negative horizontal axis mean that these variables are important for the compromise but in an opposite way; that is, high values in these variables mean low value in the compromise.

After performing the previously described steps of the CATPCA and PTA algorithms, we obtained the index that assigns a numeric value for each row of the original matrix—in our case, 5414 companies all over the world. This index is a linear combination of the values for each company of all the original numeric variables and in the original categorical variables transformed into numeric values.

The final index follows a standard normal distribution: although they are not exactly zero and 1, the mean of the index is −1.118e-15 and the standard deviation is 0.8658, and thus we can approximate the index with a standard normal distribution. These results can help to explain the obtained value for each company. If the value is near zero, the company's environmental rating is, on average, similar manner to other companies. If the value is closer to 1 or −1, the company's environmental rating deviates from the average positively or negatively respectively, not more than 1 standard deviation. This result accounts for 68% of the sample companies. If the value is higher than 2 or lower than −2, the company's environmental policy deviates from the average value more than 2 standard deviations. These companies, which account for roughly 5% of the sample, stand out for their exceptionally higher or lower than the average behavior.

To clarify the meaning of standard normal distribution of the index means, let us use an example. The index value for the 2,379th company, a coal producer, is 3.124. If we use the Z score in any standard normal distribution, we obtain a value of 0.99910. In order words, about 99.91% of the companies in our sample have a lower environmental rating than this company. Because only 0.09% of the companies have a higher average environmental rating, this company distinguishes itself for its extraordinary behavior.

Therefore, in the first step of our analysis we build an index that measures relevant information on the environment for an international sample of companies from the Thomson Reuters Eikon database. The global nature of our sample is important because not only can companies reflect on and compare their behavior to their peers, the public has insight into the environmental ratings not only of individual companies but also across geographic regions and industry sectors. That is, having obtained the index for every company, we can calculate the average index according to industry or location, providing another metric to which companies can compare and evaluate their behavior.

In a second step of our study, we investigate whether the index can follow a different distribution. We repeat the analysis assuming a quadratic relation because the disclosure may possibly have a positive effect on the environment to a certain limit, and thus this effect disappears. The results are similar to the previous findings: the distribution of the variables in the interstructure is practically the same, and each squared variable nearly coincides with the original variable (or with its opposite if the original variable is negative).

3.2.3. Between-groups analysis

Finally, we perform a between-groups analysis to determine whether the GRI 300 standards are related to industry sector or geographical regions. When the companies in the data matrix represented by the rows belong to different defined groups—as in our case, where companies belong to different geographical regions and/or different industries—the between-groups analysis can graphically represent the relations, for example, by means of a principal components analysis (Gabriel, 1971). A table provides the averages of the values of the individual companies from each group. The rows of the initial table are then projected on the plot to find the coordinates of the rows for each company. Thus, we can graphically determine whether companies from a specific geographical region or industry place more or less importance on specific GRI indicators.

4. Results

Table 3 provides the weights for all environmental indicators distributed in four variable groups. We identify each variable as categorical and/or negative prior to the CATPCA step in the algorithm. Negative variables indicate information that is reported negatively; higher values on these variables compute negatively because they do not favor the environment. For example, V31, Environmental Controversies, is defined by the question "Is the company under the spotlight of the media because of a controversy linked to the environmental impact of its operations on natural resources or local communities?" It is both categorical (the only possible answer is yes or no) and negative (an affirmative answer does not favor the environment).

We use the weight of each variable and the total of each group as the coefficients to build the average of all the variables—that is, the proposed index. The greater value a weight has, the more the variable contributes to the definition of the index. Again, we use V31 in the third group as an example: Its weight is 0.0129 out of 1. Therefore, V31 provides 1.29% of the total information of the whole index.

In particular, variables in Group 4 have a greater weight in the index; therefore, Group 4 collects more relevant variables relative to the entirety of the information provided by the sample companies. In other words, positive categorical variables exert a greater influence on the index.

The variables in the other three groups encompass very diverse topics including materials, emissions, compliance, and, to a lesser extent, waste. Group 1, related to water and emissions, has a significant weight in the index. Group 3 includes more general aspects of the environment such as environmental compliance and supplier environmental assessment. Finally, Group 2, which, in general, addresses the topics of energy and effluents and waste, has the lowest weight in the index.

The classifications in our analysis are consistent with the standards of the Global Reporting Initiative (GRI, 2016), specifically, GRI 300, which establishes a set of environmental norms with the aim of creating a common language for all the organizations and stakeholders to allow greater transparency and responsibility. Group 1 is directly related to GRI, which correspond to water and emissions, respectively. Group 2 corresponds to on energy and effluents and waste, respectively. Group 3, which refers to more general aspects of the environment, corresponds to on environmental compliance and supplier environmental assessment, respectively. Group 4, which addresses materials, corresponds to section 301 on materials. These results suggest that international companies are currently disclosing environmental information required by the GRI 300, even though the standards do not take effect until July 1, 2018.

To check our results obtained through the CATPCA and PTA algorithms, we built an interstructure plot. Fig. 1 shows the relations between and the construction of the index. The index is represented by the positive horizontal semi-axis: variables near the positive semi-axis have more weight when we build the index.

In this interstructure plot (Fig. 1), the construction of the index can be interpreted by mean of the length and the angle of the vectors that represent the different variables. Recall that the proposed index is a weighted average of all the variables, so variables contribute more than others to the index's formation. Both axes in Fig. 1 equally reflect these contributions. Although these axes do

Table 3
Variables in each group (c – categorical, n – negative) with their weights for the proposed index.

Variables	n	c	Weight
Group 1: Negative variables			
V24: Water Withdrawal Total	x		0.0058
V25: Fresh Water Withdrawal Total	x		0.0055
V36: CO_2 Equivalents Emission Total	x		0.0054
V18: Electricity Purchased	x		0.0054
V38: CO_2 Equivalents Emission Indirect	x		0.0051
V37: CO_2 Equivalents Emission Direct	x		0.0044
V58: Water Discharged	x		0.0038
V47: SOx Emissions	x		0.0031
V39: CO_2 Equivalent Indirect Emissions, Scope 3	x		0.0023
Total			0.0407
Group 2: Low contribution variables			
V52: Total Waste	x		0.0043
V14: Energy Use Total	x		0.0041
V15: Energy Purchased Direct	x		0.0039
V53: Waste Recycling Ratio			0.0034
V64: Environmental Expenditures	x		0.0033
V16: Energy Produced Direct			0.0030
V51: VOC Emissions	x		0.0027
V12: Renewable Energy Use			0.0026
V26: Water Recycled			0.0023
V54: Hazardous Waste	x		0.0023
V46: NOx Emissions	x		0.0020
V40: Carbon Offsets/Credits	x		0.0019
V17: Indirect Energy Use	x		0.0018
V59: Water Pollutant Emissions	x		0.0017
V21: Renewable Energy Produced			0.0016
V57: Discharge into Water System	x		0.0002
V13: Renewable Energy Supply			0.0001
V35: Greenhouse Gas Emissions	x		0.0000
V11: Energy Use	x		0.0000
V23: Water Use	x		0.0000
Total			0.041
Group 3: Other variables			
V02: Resource Reduction Policy		x	0.0131
V31: Environmental Controversies	x	x	0.0129
V28: Environmental Supply Chain Monitoring		x	0.0110
V61: EMS Certified Percent			0.0079
V20: Renewable Energy Purchased			0.0041
V65: Environmental Provisions			0.0038
Total			0.0529
Group 4: Categoric variables			
V68: Environmental Partnerships		x	0.0244
V27: Environmental Supply Chain Management		x	0.0244
V66: Environmental Investments Initiatives		x	0.0244
V29: Env Supply Chain Partnership Termination		x	0.0244
V10: Toxic Chemicals Reduction		x	0.0244
V22: Renewable Energy Use		x	0.0244
V55: Waste Reduction Total		x	0.0244
V44: Climate Change Commercial Risks Opportunities		x	0.0244
V34: Biodiversity Impact Reduction		x	0.0244
V62: Environmental Restoration Initiatives		x	0.0244
V78: Product Environmental Responsible Use		x	0.0244
V30: Land Environmental Impact Reduction		x	0.0244
V70: Eco-Designs Product		x	0.0244
V43: Emissions Trading		x	0.0244
V73: Noise Reduction		x	0.0244
V69: Environmental Products		x	0.0244
V45: NOx and SOx Emissions Reduction		x	0.0244
V74: Hybrid Vehicles		x	0.0244
V56: e-Waste Reduction		x	0.0244
V76: Equator Principles		x	0.0244
V77: Environmental Asset Under Management		x	0.0244
V79: Agrochemical Products		x	0.0244
V82: Sustainable Building Products		x	0.0244
V49: VOC Emissions Reduction		x	0.0244
V50: Particulate Matter Emissions Reduction		x	0.0244
V81: Water Technologies		x	0.0244
V80: Renewable/Clean Energy Products		x	0.0244
V04: Policy Sustainable Packaging		x	0.0243
V60: ISO 14000 or EMS		x	0.0242
V32: Policy Emissions		x	0.024
V09: Environmental Materials Sourcing		x	0.0226

Table 3 (*continued*)

Variables	n	c	Weight
V08: Environment Management Training		x	0.0226
V07: Environment Management Team		x	0.0226
V03: Policy Water Efficiency		x	0.0224
V05: Policy Environmental Supply Chain		x	0.0224
V01: Policy Energy Efficiency		x	0.0223
Total			0.8655

not have a unit of measurement, the horizontal axis represents the index built by these means. Thus, the closer a variable is to the horizontal axis, and the longer it is, the more weight it has in the calculation of the index.

Group 4 has the highest weights used to build the index, accounting for 86.55% of the total index weight. This group's variables are very close to the positive horizontal semi-axis and have long vectors. Group 3 accounts for 5.29% of the index's total weight. This group has a lower weight because either the vectors are short or they are not near the positive horizontal semi-axis. For similar reasons, Group 1 account for 4.07% of the total weight of the index. However, all Group 1's variables are in the second quadrant, that is, in the negative horizontal semiplane (i.e., the variables have a negative value). Thus, the variables with a high value translated into a low value on the index, and vice versa. Group 2 contributes 4.1%, to the total index weight. These variables are very near the origin; that is, they have a low contribution in the interstructure, and thus they add little to the index build.

To check the robustness of the group classifications, we perform a discriminant analysis. This analysis allows us to determine whether we define the groups correctly from a statistical point of view. Table 4 shows that 69 out of the 71 variables are classified in the same groups as our original group definitions. Specifically, all 9 variables in Group 1, 6 variables in Group 2, and 36 variables in Group 4 remain in their respective groups according to the discriminant analysis. However, the discriminant analysis shows that only 18 of the 20 variables in Group 2 belong to that group. Thus, our analysis finds that 97.2% of the originally grouped variables are correctly classified. These findings provide statistical validity to our results obtained from the previous analyses.

Table 4
Results of the classification.

Original group	Predicted membership group				Total
	1	2	3	4	
1	**9**	0	0	0	9
2	2	**18**	0	0	20
3	0	0	**6**	0	6
4	0	0	0	**36**	36

Next, we perform a between-groups analysis for the same matrix using the 5414 companies by row and the 71 environmental indicators by column. However, because we want to examine the relation between geographical regions and industry sectors and GRI indicators, we must first evaluate the average of the values in the initial indicators for each company according to the GRI 300 standards. Table 5 shows the relation between specific GRI 300 sections and the variables. Thus, we apply the between-groups analysis to a matrix made of 5414 rows (the companies) and 8 columns (the GRI 300 indicators), where, at the same time, the rows belong to 22 industries and 9 countries or geographical regions.

We will explain the meaning of Fig. 2, i.e. for the geographical regions, the meaning for Fig. 3 is analogous.

As in this moment our matrix is made of 9 rows (the geographical regions) and 8 columns (the GRI indicators), if we

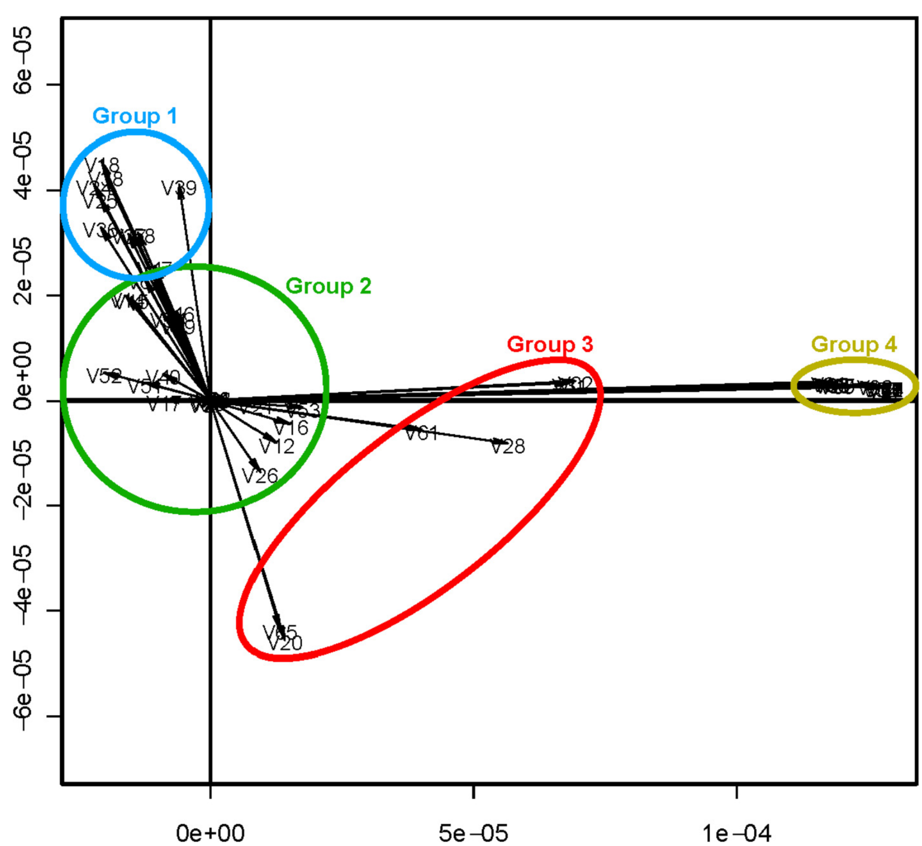

Fig. 1. Plot with the interstructure for the variables.

Table 5
Environmental indicators for each series GRI standard.

GRI indicators	Code	Environmental indicators
Materials	X301	V02, V04, V09, V40, V62, V69, V70, V73, V74, V78, V79, V80, V82
Energy	X302	V01, V11, V12, V13, V14, V15, V16, V17, V18, V20, V21, V22
Water	X303	V03, V23, V24, V25, V26, V57, V58, V59, V81
Biodiversity	X304	V34
Emissions	X305	V10, V32, V35, V36, V37, V38, V39, V43, V45, V46, V47, V49, V50, V51
Effluents and waste	X306	V52, V53, V54, V55, V56
Environmental compliance	X307	V07, V08, V30, V31, V44, V60, V61, V64, V66, V76, V77
Supplier environmental assessment	X308	V05, V27, V28, V29, V65, V68

wanted to graphically represent the first matrix we would need a space with 8 dimensions and draw a point for each of the rows, or conversely, a space with 9 dimensions on which to draw 8 points. Here is where the reduction of the dimensionality appears. We have two point collections: one with 9 points in the space with 8 dimensions and the other with 8 vectors (we use vectors in order to differentiate them from the points) in the space of 9 dimensions; so we orthogonally project them at the same time into a subspace of 2 dimensions, i.e. a plane, in such a way that the lossofthe information is as low as possible, that is, the difference between the original collections and the projected ones will be minimized. This process is somewhat similar to the one used to find a linear regression line (just the calculations, not the meaning), but two-dimensional. This plane is Fig. 2, so its x and y axes are the first two orthogonal directions with minimal loss of information.

Figs. 2 and 3 illustrate the relation between the GRI and country or geographical area (industry) based on the between-group analysis. Similar to Fig. 1, the axes do not have units of measurement; they are simply a way to graphically represent the relations between the geographical areas (Fig. 2) or the industries (Fig. 3) and the GRI indicators based on quadrants or the length and angle of the vectors. However, the axis does provide the explained variance as a percentage. Because our data encompasses more than two rows and columns, when we reduce the information in a two-dimensional plot, we lose some information; the exact amount of the information captured or retained by each axis is provided as a percentage.

The explained variance for the horizontal axis is very high in both figures. Because 95.049% and 94.74% of the results are plotted in the right or left half-planes for Figs. 2 and 3, respectively, we do not discuss the upper or lower half-planes. For both region and sector, companies plotted in the right half-plane pay more attention, that is, have higher values, to the indicators in the right half-plane, but they have low values in the indicators in the left-plane.

The 'Codes' column in Table 1 represents the meaning of the numbers in Figs. 2 and 3: in Fig. 2, on the left, the codes for the 9 geographical regions are placed according to the explanation above related to the reduction in the dimensionality, whereas in Fig. 3, again on the left, the codes for the 22 industries are placed.

The 'Codes' column in Table 5 represents the meaning of the labels in Figs. 2 and 3 as well: on the right, the codes for the 8 GRI indicators are placed by mean of vectors according to the same explanation of the reduction of the dimensionality.

Fig. 2 shows that Oceania and the Russian Federation (codes 5 and 7) are plotted in the right half-plane; they have high values in all GRI indicators except in water (X303), in which they have low values. The opposite holds for other geographical regions. These results are in line with the finding of previous studies that in Australia (Oceania) companies place more importance on certain environmental topics such as energy and materials. Thus, in Australia different sources of energy are considered very important. Australian Academy of Science (2009), which highlights alternative energy sources such wind turbines, solar thermal, and solar photovoltaic, among others, supports this finding. This report also describes several government initiatives such as an economic stimulus package to improve insulation in housing, increase the use of renewable energies by 20% by 2020, interest-free green loans, renewable energy development funds, and programs for generating renewable energies in remote areas. The Australian government also offers discounts for installing solar panels and provides for feed-in tariffs to help boost the use of renewable energies and energy savings. In New Zealand, where the wine-growing sector is important, the materials aspect is especially important in the case of spray containers, packaging materials, plastics, cartons, papers, and wine bottles (Gabzdylova et al., 2009).

Emissions are particularly important in Russia as the country is

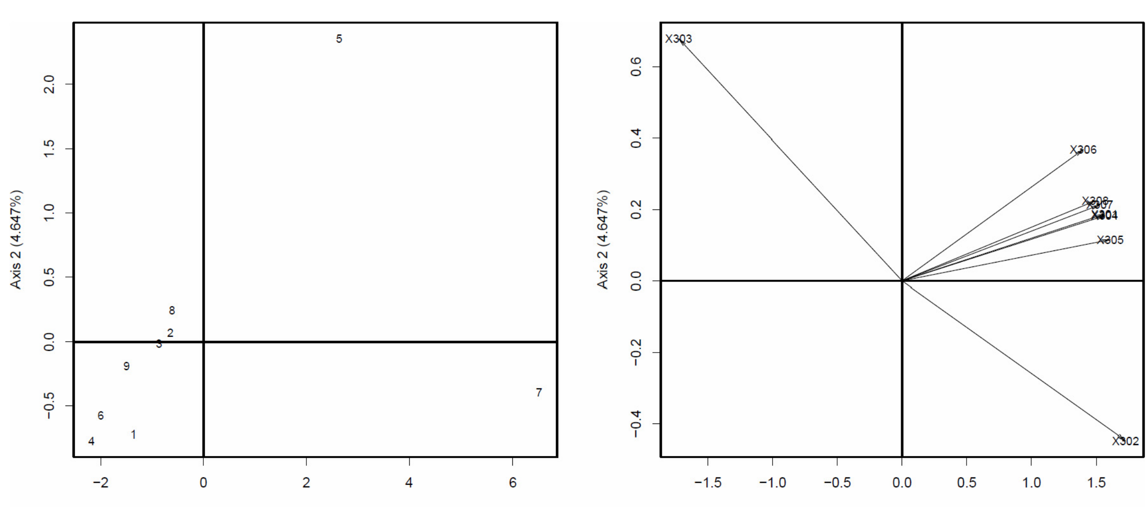

Fig. 2. (Left) Geographical regions (codes from Table 1) vs (right) GRI indicators (codes from Table 5).

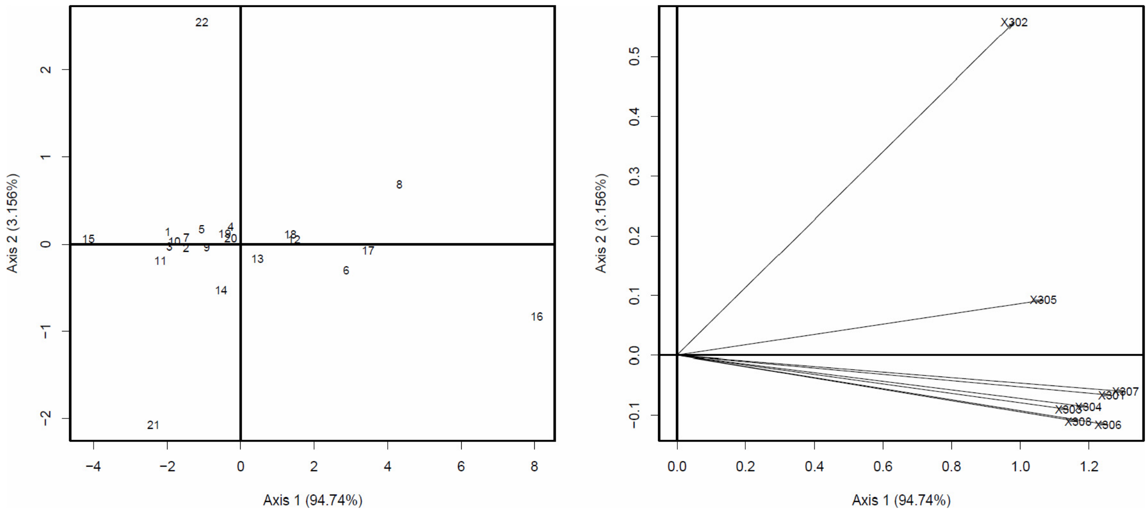

Fig. 3. (Left) Industries (codes from Table 1) vs (right) GRI indicators (codes from Table 5).

the second most important producer of natural gas and the third most important producer of liquid hydrocarbons (Shvarts et al., 2016). This issue has become so important that since May 2013 companies are required to disclose emissions information (i.e., accounting for direct and indirect greenhouse gas emissions and an emission reductions program) in their sustainability reports. Our findings are also in line with other prior literature (Lorenzoni and Pidgeon, 2006; Comyns, 2016) that identifies significant variations in corporate environmental disclosures among companies of different countries.

Fig. 3 shows that the industries of diversified financials, food and staples retailing, materials, media, retailing, semiconductors and semiconductor equipment, and software and services (codes 6, 8, 12, 13, 16, 17, and 18, respectively) are plotted in the right half-plane. In other words, these sectors pay more attention to the GRI environmental indicators, compared to the lower values of other industries, plotted in the left half-plane. These results are in line with previous studies that obtain similar findings. Particularly relevant is the materials sector, including companies in the oil, chemical, and mining industries. Jenkins and Yakovleva (2006) report that companies in this sector are more likely to report on environmental issues. The chemical industry is traditionally considered to have the most potential negative risks for humans and the environment. Hence, chemical companies have improved their environmental reporting practices mainly by focusing on how they implement processes to prevent potential environmental and human disasters.

5. Conclusions and avenues for future research

We build an index to measure relevant information on the environment for an international sample of companies from the Thomson Reuters Eikon database. This index allows reporting companies to evaluate and compare its results by sector and/or region, thus providing a means to confirm good behavior and improve bad behavior. The index also provides a tool to analysts and regulators as well as providing general information to the public. Our environmental index is a linear combination of the values of original numeric variables reported by each company and in the original categorical variables, which are transformed into numeric variables. Thus, we create a very reliable environmental index that helps both companies and policymakers to make decisions on environmental issues (Biscotti and D'Amico, 2016).

Because we adopt a global perspective, the index can be useful for explaining the values for each company in the sample. Companies with a value near zero behave in an average manner toward the environment relative to all companies in the sample. If the value is closer to 1 or −1, the company's environmental rating deviates from the average positively or negatively respectively, not more than 1 standard deviation. This result accounts for 68% of the sample companies. If the value is higher than 2 or lower than −2, the company's environmental policy deviates from the average value more than 2 standard deviations. These companies, which account for roughly 5% of the sample, stand out for their exceptionally higher or lower than the average behavior.

To make our results highly relevant, we analyze the extent to which environmental disclosure conforms to the internationally recognized standards in the GRI. In addition, we perform a between-groups analysis to examine the relation between geographical regions, activity sectors, and the GRI 300 sustainability reporting standards. The between-groups analysis of geographical regions is in line with previous findings that companies in Australia (a country in Oceania) are highly interested in certain environmental issues such as energy and materials. Australia places great importance on alternative sources of energy such as wind turbines, solar thermal, and solar photovoltaic, among others (Australian Academy of Science, 2009). In Russia, emissions are a very important issue because the country is on the world's largest producers of natural gas and liquid hydrocarbons (Shvarts et al., 2016). In fact, since May 2013 Russian companies are required to disclose emissions information in their sustainability reports.

Our analysis also shows that certain sectors such as materials pay more attention overall to the GRI 300 environmental indicators compared to other industries, which have lower values. In fact, according to Jenkins and Yakovleva (2006), companies in the materials sector, which includes the oil, chemical, and mining industries, are more likely than companies in other sectors to report on environmental issues. The chemical industry is traditionally considered to have the most potential negative effects on humans and the environment. Consequently, chemical companies have improved their environmental reporting practices primarily by focusing on how they implement processes to prevent potential environmental and human disasters. These results and conclusions are in line with previous environmental reporting studies that differentiate the sample by industry sectors.

Our index allows companies to increase transparency and to improve along key environmental aspects. The index also increases attention among researchers and the public to the distribution of environmental quality information, which is particularly relevant given that the GRI 300 will come into effect on July 1, 2018. Our results also have several interesting policy implications such as strengthening environmental legislation and related controls. The results provide a relevant policy criterion deciding where to distribute more or less awards or where to prioritize abatement and enforcement efforts among existing sources to positively impact environmental disclosure.

Although this study empirically explores for the first time the worldwide environmental information and builds an index to measure relevant information on the environment, further research is needed. First, the analysis can be carried out to develop comparable measures in the upcoming years to investigate the trajectory of each country or region relative to the situation described in this study. Also, additional analytical approaches may be applied to the issue. Second, measurement of environmental disclosure creates possibilities for researchers to analyze the relation of disclosure to other variables of interest to social scientists and policymakers, such as corporate governance and finance variables, voting behavior, and state environmental policies.

In a wider framework, to ensure greater alignment of future environmental behaviors, these policies and information should be approved at an international level through a wide implementation of a binding common legislation in numerous countries. Finally, it may also be helpful to introduce forward-looking policies, such as mandatory environmental education to form an effective culture of sustainable development.

References

Adams, C.A., Kuasirikum, N., 2000. A comparative analysis of corporate reporting on ethical issues by UK and German chemical and pharmaceutical companies. Eur. Account. Rev. 9 (1), 53–79.

Al-Tuwaijri, S.A., Christensen, T.E., Hughes, H.E., 2004. The relations among environmental disclosure, environmental performance, and economic performance: a simultaneous equations approach. Acco. Organ. Soc. 29 (5–6), 447–471.

Australian Academy of Science, 2009. Australia's Renewable Energy Future, December, 2009. Australia.

Bewley, K., Li, Y., 2000. Disclosure of environmental information by Canadian manufacturing companies: a voluntary disclosure perspective. Adv. Environ. Account. Manag. 1 (1), 201–226.

Biscotti, A.M., D'Amico, E., 2016. What are political leaders' environmental intentions? The impact of social identification processes and macro-economic conditions. Ecol. Econ. 129, 152–160.

Blacconiere, W.G., Patten, D.M., 1994. Environmental disclosures, regulatory costs, and changes in firm value. J. Account. Econ. 18 (3), 357–377.

Blacconiere, W.G., Northcut, W.D., 1997. Environmental information and market reactions to environmental legislation. J. Account. Audit Finance 12 (2), 149–178.

Boyce, J.K., Zwickl, K., Ash, M., 2016. Measuring environmental inequality. Ecol. Econ. 124, 114–123.

Brady, A., Honey, G., 2007. Corporate Reputation: Perspectives of Measuring and Managing a Principal Risk. The Chartered Institute of Management Accountants, London. http://www.cimaglobal.com.

Brammer, S., Pavelin, S., 2006. Voluntary environmental disclosures by large UK companies. J. Bus. Finance Account. 33 (7–8), 1168–1188.

Burrit, R.L., 2002. Environmental reporting in Australia: current practices and issues for the future. Bus. Strat. Environ. 11, 391–406.

Clarkson, P., Li, Y., Richardson, G., Vasvari, F., 2008. Revisiting the relation between environmental performance and environmental disclosure: an empirical analysis. Account. Org. Soc. 33, 303–327.

Comyns, B., 2016. Determinants of GHG reporting: an analysis of global oil and gas companies. J. Bus. Ethics 136 (2), 349–369.

Cormier, D., Magnan, M., Van Velthoven, B., 2005. Environmental disclosure quality: do firms respond to economic incentives, public pressures or institutional conditions. Eur. Account. Rev. 34 (1), 1–37.

Cormier, D., Magnan, M., 2015. The economic relevance of environmental disclosure and its impact on corporate legitimacy: an empirical investigation. Bus. Strat. Environ. 24, 431–450.

Cho, C.H., Patten, D.M., 2007. The role of environmental disclosures as tools of legitimacy: a research note. Account. Org. Soc. 32 (7–8), 639–647.

Dangelico, R.M., Pontrandolfo, P., 2010. From green product definitions and classifications to green option matrix. J. Clean. Prod. 18 (16–17), 1608–1628.

Deegan, C., Gordon, B., 1996. A study of the environmental disclosure practices of Australian corporations. Account. Bus. Res. 26 (3), 187–199.

Deegan, C., Samkin, G., 2000. New Zealand financial Accounting. McGraw-Hill, Manukau.

Dragomir, V.D., Cristina, M., 2009. Corporate governance in the European union: the implications for financial and narrative reporting. Interna. J. Bus. Econ. 9 (1), 53–64.

Fallan, E., Fallan, L., 2009. Voluntarism versus regulation lessons from public disclosure of environmental performance information in Norwegian companies. J. Accoun. Organizatio. Chan 5 (4), 472–489.

Fédération des Experts Comptables Européenes (FEE), 1995. Environmental Accounting, Reporting and Auditing: Survey of Current Activities and Developments within the Accountancy Profession. FEE, Brussels.

Freedman, M., Jaggi, B., 2005. Global warming, commitment to the Kyoto protocol, and accounting disclosures by the largest global public firms from polluting industries. Int. J. Account. 40, 215–232.

Gabriel, K.R., 1971. The biplot graphic display of matrices with applications to principal components analysis. Biometrika 58, 453–467.

Gabzdylova, B., Raffensperger, J.F., Castka, P., 2009. Sustainability in the New Zealand wine industry: drivers, stakeholders and practices. J. Clean. Prod. 17, 992–998.

Gallego-Álvarez, I., Vicente-Villardón, J.L., 2012. Analysis of environmental indicators in international companies by applying the logistic biplot. Ecol. Indicat. 23, 250–261.

Gifi, A., 1990. Nonlinear Multivariate Analysis. Wiley, Chichester.

Global Reporting Initiative, 2016. Consolidated Set of GRI Sustainability Reporting Standards, The Netherlands.

Gray, R., Javad, M., Power, D.M., Sinclair, C.D., 2001. Social and environmental disclosure and corporate characteristics: a research note and extension. J. Bus. Finance Account. 28 (3–4), 327–356.

Gray, R., Kouhy, R., Simon, L., 1995. Corporate social and environmental reporting: a review of the literature and a longitudinal study of UK disclosure. Account Audit. Account. J. 8 (2), 47–77.

Guthrie, J., Parker, L.D., 1990. Corporate social disclosure practice: comparative international analysis. Adv. Publ. Interest Account. 3, 159–176.

Hughes, S., Anderson, A., Golden, S., 2001. Corporate environmental disclosures: are they useful in determining environmental performance? J. Account. Publ. Pol. 20 (3), 217–240.

Institute of Chartered Accountants in England and Wales (ICAEW), 1992. In: Macve, R., Carey, A. (Eds.), Business, Accountancy and the Environment: a Policy and Research Agenda. ICAEW, London.

Jenkins, H., Yakovleva, N., 2006. Corporate social responsibility in the mining industry: exploring trends in social and environmental disclosure. J. Clean. Prod. 14, 271–284.

L'Hermier des Plantes, H., 1976. Structuration des Tableaux à Trois Indices de la Statistique (Thèse de Troisième Cycle). University of Montpellier, France.

Liu, X., Anbumozhi, V., 2009. Determinant factors of corporate environmental information disclosure: an empirical study of Chinese listed companies. J. Clean. Prod. 17 (6), 593–600.

Lorenzoni, I., Pidgeon, N., 2006. Public views on climate change: European and USA perspectives. Climatic Change 77, 73–95.

Meng, X.H., Zeng, S.X., Tam, C.M., 2001. From voluntarism to regulation: a study on ownership, economic performance and corporate environmental information disclosure in China. J. Bus. Ethics 116, 217–232.

Moneva, J.M., Llena, F., 2000. Environmental disclosures in the annual reports of large companies in Spain. Eur. Account. Rev. 9 (1), 7–29.

Monteiro, S.M., Aibar-Guzmán, B., 2010. Determinants of environmental disclosure in the annual reports of large companies operating in Portugal. Corp. Soc. Responsib. Environ. Manag. 17, 185–204.

Patten, D.M., 2002. The relation between environmental performance and environmental disclosure: a research note. Account. Org. Soc. 27 (8), 763–773.

Reverte, C., 2009. Determinants of corporate social responsibility disclosure ratings by Spanish listed firms. J. Bus. Ethics 88 (2), 351–366.

Reynolds, M., Yuthas, K., 2008. Moral discourse and corporate social responsibility reporting. J. Bus. Ethics 78, 47–64.

Richardson, A.J., Welker, M., 2001. Social disclosure, financial disclosure and the cost of equity capital. Account. Org. Soc. 26 (7), 597–616.

Scrieciu, S.S., 2007. Can economic causes of tropical deforestation be identified at a global level? Ecol. Econ. 62, 603–612.

Shi, T., 2004. Ecological economics as policy science: rhetoric or commitment towards an improved decision-making process on sustainability. Ecol. Econ. 48, 23–36.

Shvarts, E.A., Pakhalov, A.M., Knizhnikov, A.Y., 2016. Assessment of environmental responsibility of oil and gas companies in Russia: the rating method. J. Clean. Prod. 127, 143–151.

Vanhamme, J., Grobben, B., 2009. Too good to be true! the effectiveness of CSR history in countering negative publicity. J. Bus. Ethics 85, 273–283.

Wiseman, J., 1982. An evolution of environmental disclosure made in annual reports. Account. Org. Soc. 7, 553–563.

Zeng, S.X., Xu, X.D., Dong, Z.Y., Tam, V.W.Y., 2010. Towards corporate environmental information disclosure: an empirical study in China. J. Clean. Prod. 18 (12), 1142–1148.