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Assessing redundancies in environmental performance measures for supply chains

Andrea Genovese[1], Jonathan Morris[1], Carmela Piccolo[2], S.C. Lenny Koh[1]

[1]Management School, University of Sheffield, Sheffield, UK

{a.genovese, j.c.morris, s.c.l.koh}@sheffield.ac.uk

[2] Department of Industrial Engineering, University of Naples "Federico II", Naples, Italy

carmela.piccolo@unina.it

Abstract

Incorporating environmental sustainability into production systems and supply chain management perspectives is a growing issue; this requires thorough efforts in measuring the environmental performance of such systems and benchmarking these against industry standards, through the usage of appropriate indicators.

The usage of environmental indicators in order to monitor and manage sustainability issues is an ongoing topic of debate and deliberation in the scientific community, which has generated the development of several methodological and conceptual approaches, often incorporated into Life Cycle Assessment frameworks, enabling the evaluation and monitoring of cumulative polluting impacts resulting across the whole product supply chain. In this field, the main challenge is to identify indicators to be employed in environmental assessments, in such a way that a precise account of sustainability issues is given without overloading end-users with overly complex and redundant information.

By utilising well-established environmental indicators measuring the sustainability performance of supply chains, this paper aims at critically assessing the amount of redundancy embedded in current performance measurement systems, also identifying the subset of environmental indicators that, if employed, could cover a wide amount of environmental impact categories without redundancies and providing decision-makers with a clear perspective.

Keywords: Environmental sustainability, Environmental Indicators, Principal Component Analysis

1. Introduction

The incorporation of environmental sustainability into production systems and supply chain management perspectives represents a timely issue. Regulatory requirements are a pressing concern for companies, particularly in the European Union (EU). For example, revised EU public procurement directives require robust certification as a proof that companies meet sustainability requirements set out in calls for tender (UNDP, 2003; UN Global, 2011). This is significant for many small and medium-sized enterprises (SMEs) that are often involved in supply networks of large multi-national enterprises that are increasingly applying more stringent sustainability requirements onto their vendors (UN Global, 2011); this requires thorough efforts in measuring the environmental performance of production systems and benchmarking these against industry standards, through the usage of appropriate indicators.

The usage of environmental indicators to monitor and manage sustainability issues is an ongoing topic of debate and deliberation in the scientific community (Veleva and Ellenbecker, 2001; Pozo et al. 2012). As a result of the lack of agreement on how to measure environmental issues and wider sustainability concepts, there has been a development of multiple methodological and conceptual approaches. These indicators link to the concept of sustainable development adopted by the United Nations from the 1987 World Commission on Economic Development (WCED 1987), defined as "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*" (Hansmann et al., 2012; Chichilnisky, 2012).

In terms of measuring environmental sustainability, Life Cycle Assessment (LCA) methodologies are becoming the most prevalent approaches, particularly in the specific field of supply chain management (Pozo et al., 2012). Life Cycle Assessment allows estimating cumulative impacts on the environment resulting from the entire supply chain, adopting a full product life cycle perspective; the advantage of LCA is that it can be adapted to take into account a wide range of environmental sustainability indicators. The main challenge lies in the identification of indicators that should be included in an environmental assessment, in such a way that relevant environmental impact dimensions are considered and a precise account of sustainability issues is given, without simultaneously overloading end-users with overly complex and redundant information (Jollands et al. 2004; Gaussin et al. 2013). In the current literature (to the best of our knowledge) there is a lack of studies performed on this topic, both at a general level and with reference to specific supply chains.

For this reason, by utilising well-established environmental indicators measuring the sustainability performance of product supply chains from the Ecoinvent database (Frischknecht et al., 2005; Weidema et al., 2013), this paper aims at identifying the subset of environmental indicators that, if employed, could cover a wide amount of environmental impact categories, while at the same time minimising information redundancies and providing decision-makers with a clear perspective.

The paper is structured as follows: Section 2 provides generalities on indicators and background information about their use in sustainability and related disciplines. Section 3 outlines the methodology that will be employed in the paper; Section 4 illustrates the analysis of the obtained results, while Section 5 presents a discussion of these. Then, some conclusions and directions for further research are drawn.

2. Background

2.1 Indicators and Composite Indicators

Indicators represent measures (both quantitative and qualitative) derived from observations of phenomena; as such, indicators can be utilised to keep track of performances of actors (for instance, companies, local authorities, countries) in a determined context (Saisana and Tarantola, 2002). When assessed at regular intervals, indicators can be particularly useful in identifying tendencies across dimensions and time; also, they can be utilised in benchmarking performances against given standards.

When multidimensional concepts and phenomena are to be evaluated (such as environmental sustainability) single indicators might fail to capture inherent complexities. Therefore, Composite Indicators (CIs) can be utilised. CIs are obtained bringing together (and often aggregating into a single synthetic measure) multiple indicators, based on a given underlying theoretical framework. CIs can be utilised for benchmarking and ranking activities (Saisana and Tarantola, 2002; OECD, 2008a); however, the construction of CIs should be carefully conducted, in order to avoid misrepresentations of monitored phenomena and, consequently, the formulation of misleading recommendations.

A crucial role in the construction of CIs is played by indicator selection. Indeed, as mentioned above, indicators' selection should be performed while carefully considering interrelationships among them, in order to avoid over-weight certain factors due the presence of highly correlated indicators (Saisana et al., 2005). As a general guidance, CIs should have the following characteristics:

- *Completeness*: Important indicators concerned with different dimensions of the phenomenon under investigation should be included.

- *Independence*: Indicators that are deemed to be less important or to be strongly correlated to other ones should be removed at a very early stage and not included in the selection. This would ensure that redundancy is kept at a minimum level, in such a way to avoid "double counting" issues.
- *Operationality*: It is important that data for each indicator can be collected in a straightforward way.
- *Parsimony*: An excessive number of indicators can lead to substantive efforts in data collection and assessment; also, communication of the results might be more difficult.

Therefore, statistical relationships among indicators should be verified, in order to select those which exhibit high degrees of independence (Jenkins and Cappellari, 2007; OECD, 2008a). OECD (2008a) also suggests that, when studying complex phenomena, parsimony in the number of indicators can be a desirable characteristic, in order to achieve transparency of interpretations and a manageable data collection process.

Thus, the use of multi-variate statistical techniques is suggested (Zhou et al., 2010) for minimising redundancies in CIs, which can arise as a result of high degree of collinearity (or correlation) between selected indicators and introduce an element of double counting. Examples of the adoption of similar procedures, aimed at verifying indicators selection and minimising redundancies, in both an a-priori (in the phase of construction of a CI) and an a-posteriori (once the CI has already been built, in order to suggest appropriate revisions) fashion, can be found in Bertuglia et al. (1994), Despotis (2005), Cherchye et al. (2008), Bruno et al. (2010).

It must be mentioned that also more complex methodologies (mainly based on optimisation approaches) have been developed for dealing with dimension and redundancies reduction when dealing with CIs. Brockhoff and Zitzler (2006) presented an approach based on the minimisation of an approximation error resulting from the elimination of sub-indicators. Similarly, Guillén-Gosálbez (2011) presented a Mixed Integer Linear Programming model addressing a similar problem and looking for dominant solutions (in terms of indicators to be eliminated), also reflecting on its practical implementation.

2.2 Environmental Indicators

In the current debate, environmental indicators are becoming essential instruments for measuring progress in tackling contemporary challenges, supporting policy evaluation and informing the public. Since the publication of the Brundtland Report (WCED, 1987), a wide body of literature dealing with the topic has been developed, both in practitioner and academic fields.

As a result, public interest in such indicators has risen both in policy forums and in the public debate; as sustainability issues are inherently multi-faceted, and environmental impacts can happen across a wide array of dimensions, many relevant indicators have been developed, usually combined in CI frameworks.

The identification of appropriate indicators is crucial for undertaking measurement and benchmarking programs. As a general requirement, ecological indicators should be able to capture the inherent complexity of the reference ecosystem (Dale and Beyeler, 2001); however, they should be designed in such a way their assessment and monitoring can be easily conducted on a continuous basis (Dobbie and Dail, 2013; Campos et al., 2015). Environmental metrics need to be relatively inexpensive to measure and easy to understand, in such a way to provide managers and policymakers with rigorous and cost-efficient information.

Notably, sources such as Ecoinvent (Weidema et al., 2013) collect a large amount of data that allows benchmarking the environmental profile of product supply chains across a variety of impact categories, collating together a variety of environmental indicators and calculation methodologies. While the availability of such wide datasets provides a valuable insight into the environmental impact of production systems, this data richness also leads to many challenges. Indeed, as mentioned above, one of the requirements of Composite Indicators for their practical usability is the selection of indicators, in such a way to avoid redundancies and promote manageable data collection activities.

For instance, in reporting their environmental performances at a country level, OECD member states are increasingly focusing on a reduced number of *key indicators*, selected from larger sets (OECD, 2008b).

Similarly, at a product supply chain level, it could be useful to identify a set of non-redundant relevant indicators (to be even combined in a CI framework) capable of capturing the impact of production and distribution systems on the environment. Many academic studies have been developed around the use of indicators and CIs for keeping track of the environmental performance of supply chains (see, for instance, McIntyre et al., 1998; Rahdari et al., 2015); however, in extant proposals, there is a large variation about the number and type of variables being considered, along with a lack of consensus about aggregation frameworks. The main contact point of most of the studies lies in the presence of Greenhouse Gas Emissions (commonly expressed in terms of *Carbon Emissions,* or *Carbon Emission equivalents*) as the main indicator of environmental impact of production systems (Sundarakani et al., 2010). However, while the significance and relevance of this indicator is clear (as it can be used as a proxy for energy and resources consumption), little or no evidence has been provided in order to understand how it correlates to other impact categories and if carbon emissions, by themselves, can explain a relevant quota of these wider impacts. Therefore, while the use of carbon emissions as an environmental indicator provides a figure that allows communicating environmental issues in a very synthetic way (avoiding overwhelming and confusing decision makers and the general public with complex CIs), legitimate questions about its representativeness of the whole spectrum of environmental issues may be raised.

Currently, the EcoInvent database includes 664 indicators (Weidema et al., 2013), related to several Lifecycle Analysis methodologies that have been developed in the literature, differing in terms of underlying principles. Table 1 details all the indicators categories embedded in the database, along with references providing methodological guidance related to their utilisation.

Indicators Category	**Related Publications**	**Total Indicators**
CML 2001	Guinée et al. (2001a, 2001b)	100
Cumulative Energy Demand (CED)	Frischknecht, et al. (2015)	8
Cumulative Exergy Demand (CExD)	Boesch et al. (2007)	10
Eco-indicator 99	Goedkoop and Spriensma (2000a and 2000b)	69
Ecological Footprint	Huijbregts et al. (2006)	4
Ecological Scarcity 1997	Brand et al. (1998)	7
Ecological Scarcity 2006	Frischknecht et al. (2006)	8
Ecological Scarcity 2013	Frischknecht et al. (2013)	19
Ecological Damage Potential (EDP)	Köllner and Scholz (2007 and 2008)	3
EDIP - Environmental Design of Industrial Products 1997	Hauschild and Wenzel (1997)	98
EDIP - Environmental Design of Industrial Products 2003	Hauschild and Potting (2005)	94
EPS - environmental priority strategies in product development	Steen (1999)	6
IMPACT 2002+	Jolliet et al. (2003)	18
IPCC 2001 (Global Warming)	Albritton and Meira-Filho (2001); IPCC (2001)	3
IPCC 2007 (Global Warming)	Forster et al. 2007	3
IPCC 2013 (Global Warming)	IPCC (2013)	2
ReCiPe (Midpoint and Endpoint approach)	Goedkoop et al. (2009)	195
TRACI	Bare (2004); Bare, et al. (2007)	9
USEtox	Rosenbaum et al. (2008)	8

Table 1 – Environmental Indicators from the Ecoinvent database (Ecoinvent, 2010; Weidema et al., 2013)

3. Materials and Methods

This study adopts Principal Components Analysis (PCA) in order to reduce the dimensionality of available environmental indicators and to provide valuable insight on the structure of environmental issues. Principal Components Analysis is a way of providing an objective approach to analysing and selecting suitable environmental sustainability indicators without relying on subjective judgement based on assumptions (Jollands et al. 2004). While, as mentioned above, more advanced methodologies have been developed, thanks to its integration in commercial software packages, PCA provides a widely accessible and inexpensive way to analyse dimension reduction issues; as such, as stated by Saisana et al. (2005), this approach can provide valuable help as a first step in order to assess and reduce redundancies within Composite Indicators frameworks.

3.1 Principal Components Analysis

The main aim of the procedure presented in this study is to reduce the volume of existing data related to environmental indicators, for obtaining a more manageable set of indicators. Dimensionality reduction methods are used to determine a subset of the original data, whilst maintaining the original structure.

Principal Components Analysis (PCA) is a multivariate technique; starting from a set of correlated variables $C=\{c_1, c_2, .., c_n\}$, PCA seeks to build a new set of uncorrelated artificial variables $U=\{u_1, u_2, .., u_n\}$. These artificial variables, known as the principal components, are obtained as linear combinations of the original variables, with the objective of obtaining a limited subset of components that are capable of explaining a large quota of the variance of the original dataset. This is useful for identifying redundant variables that can be removed, therefore reducing the level of complexity. For this reason, PCA seems particularly suitable to the research aims of this study.

In particular, the employed methodology can be articulated into the following steps.

Let C be a set of n indicators ($C= \{c_1,..,c_n\}$). First, a correlation analysis is performed, in order to assess the general level of redundancy in the initial dataset. In case of the detection of strong and significant level of correlation among the initial indicators, the second step of the procedure consists in the utilisation of Principal Component Analysis (PCA).

As explained, this step will transform the original, highly correlated, indicators into a set of new uncorrelated and orthogonal variables, preserving the maximum possible proportion of variation in the data set.

Considering the set C of n indicators, the n principal components U_k (k=1,..n) can be defined as:

$$U_k = b_{k1}c_1 + \ldots + b_{kj}c_j + \ldots + b_{kn}c_n$$

The generic weight b_{kj} represents the influence of indicator j on the component k. In particular, weights b_{kj} are "optimally" calculated through appropriate algorithms in order to maximise the amount of variance explained through a limited number of components and minimise the correlation level among the component themselves (Kim and Mueller, 1978a, 1978b). The objective is to produce the set of components that can better describe the observed variables, for the given set of data (for a more detailed explanation, see Stevens, 1986). Extracted components can be then ranked in descending order, according to the amount of the total variance explained (Bruno et al., 2010).

In order to choose a significant subset U' of principal components, many rules can be used. In this research, the *eigenvalue criterion* was adopted; in practice, the first $p<n$ components such that the associated eigenvalue is at least equal to 1 are selected (for detailed explanations, see Joliffe, 2002; OECD, 2008a).

It must be highlighted that, as principal components are linear combinations of the original indicators, they just represent artificial variables, which might lack physical meaning. As such, their usage does not represent by itself a practical reduction in terms of physical indicators.

For this reason the correlation matrix $R=\{r_{ij}\}$ between each indicator i ($i=1..n$) and each selected component j ($j=1..p$) is calculated. For each component $k \in U'$ we identify the 5 indicators with the highest value of correlation (commonly referred to as "loading") to the component itself. In this way, we identify the subset of indicators with the highest values of a r_{ik} for each $k \in U'$. These indicators can be seen as "core" indicators, as their usage (opposed to the usage of the whole set of original variables) can still explain a very significant amount of variance.

3.2 Materials and Samples

A ready-made source of Environmental Indicators is available from the Ecoinvent database (Weidema et al., 2013). This database has been developed as a cross-collaboration between several Swiss research institutions (including: ETH Zürich; ETH Lausanne; the Swiss Federal Laboratories for Materials Testing and Research; the Swiss Federal Research Station Agroscope Reckenholz-Tänikon) (Weidema et al., 2013). From this database, 664 environmental indicators were available for analysis. In order to minimise unnecessary redundancy in the dataset, a pre-processing step was performed, involving the following operations:

- In presence of indicators available in multiple versions, instances including long-term impacts were considered, discarding the ones excluding these. For instance, within the CML 2001 category, the 50 indicators are also available in a version that excludes long-term impacts (for a total of 100 indicators). As these two sub-categories would be hugely correlated, just the 50 indicators also including long-term impacts have been considered. A similar logic has been applied to all the categories.

- In presence of multiple versions of the same indicators (as a result of updated versions having been released), just the most recent ones have been considered. This has been the case, for instance, of EDIP 1997 and EDIP 2003 indicators (just the most recent version has been considered) (Hauschild and Potting, 2005)
- In presence of indicators computed across multiple perspectives (Egalitarian, Hierarchical, Individualistic), the Egalitarian version has been considered (as the most comprehensive one) (for more details, see Weidema et al., 2013). This logic has been applied, for instance, to the ReCiPe indicators.
- Indicators that already are linear combination of other indicators (i.e., ReCiPe Endpoint and Ecoindicator-99) have been excluded from the analysis, as their inclusion would trigger some obvious redundancies.

This pre-processing step has allowed reducing the number of indicators to be considered from 664 to 215; the whole list of indicators that were employed in the analysis is reported in Table A1, Appendix A.

Method	**Total Indicators**	**Considered Indicators**
CML 2001	100	50
Cumulative Energy Demand (CED)	8	8
Cumulative Exergy Demand (CExD)	10	10
Eco-indicator 99	69	0
Ecological Footprint	4	4
Ecological Scarcity 1997	7	7
Ecological Scarcity 2006	8	8
Ecological Scarcity 2013	19	19
Ecological Damage Potential (EDP)	3	3
EDIP - Environmental Design of Industrial Products 1997	98	0
EDIP - Environmental Design of Industrial Products 2003	94	47
EPS - environmental priority strategies in product development	6	6
IMPACT 2002+	18	18
IPCC 2001 (Global Warming)	3	1
IPCC 2007 (Global Warming)	3	1
IPCC 2013 (Global Warming)	2	2
ReCiPe (Midpoint approach)	195	18
TRACI	9	9
USEtox	8	4

Table 2 – Considered Environmental Indicators (Ecoinvent, 2010)

5 random samples of 1000 product supply chains were generated from the original Ecoinvent database, with the PCA procedure run on each of the samples. The purpose of generating these

samples was to ensure that identified components were consistent across a range of different product supply chains.

From the Ecoinvent database, it was possible to extract processes by their sub-categories, and examine how environmental indicators vary across these sectors. This exercise highlights how different industries with differing categories of supply chain processes experience different environmental considerations. These sub-categories chosen were: (i) Cement (involving 152 individual supply chains); (ii) Glass (involving 137 individual supply chains); (iii) Steel (involving 350 individual supply chains); (iv) Transport (involving 267 individual supply chains).

Details about the selected supply chains (both for the 5 random samples and the specific industrial sub-categories) can be retrieved in the supplementary materials file attached to this study.

4. Results

The outputs from Principal Components Analysis using both random samples and sector-specific samples highlight the very strong redundancy existing across the whole spectrum of the considered environmental indicators. All the analyses consistently point out that it is possible explaining the variance of the datasets by just employing a very limited number of *latent variables* identified through the usage of PCA. Details are provided in the following sub-paragraphs.

4.1 Random Samples Analysis

As a first step, a correlation analysis is performed, by computing, for each sample, the correlation coefficient for each pair of indicators. Table 3 reports, for each sample, the average correlation coefficient and the percentage of correlation coefficients larger than 0.800; it can be noticed that even this aggregated-level figure might suggest the presence of a high level of correlation across indicators, as the average correlation coefficients range from 0.722 (Sample 2) to 0.929 (Sample 1). Also, it can be shown that the percentage of correlation coefficients larger than 0.800 is strikingly high, apart from Sample 2.

	Random Sample				
	1	2	3	4	5
Average Correlation Coefficient	0.929	0.722	0.857	0.884	0.843
Percentage of Correlation Coefficients larger than 0.800	90.65	49.60	81.31	81.62	71.32

Table 3 – Average Correlation Coefficients for Random Samples

Such preliminary analysis seems to suggest that the 215 environmental indicators under analysis are characterised by a high level of redundancy. For verifying this hypothesis, Principal Component Analysis is performed.

The PCA results (Table 3) show a very consistent behaviour across the considered random samples. Even if a small variability is shown in terms of number of extracted components (from 3 to 7), in all the cases the first component accounts for a huge proportion of the variance in the dataset (from a minimum of 75.362% in the case of Sample 2, to a maximum of 95.075 in the case of Sample 1).

In particular, for Samples 1, 3 and 4, three components are extracted. For Samples 2 and 5, respectively 8 and 5 components are extracted; in both cases, the second component accounts for a slightly higher percentage of the variance explained (slightly over 10%) if compared to the remaining samples. Still, the gap between the variance explained by the first and the second component is huge; this confirms that considered environmental indicators are characterised by a huge level of redundancy.

Random Sample	Components Extracted	Eigenvalues		
		Eigenvalues	Variance (%)	Cumulative Variance (%)
1	1.1	204.412	95.075	95.075
	1.2	7.206	3.352	98.427
	1.3	1.994	0.927	99.354
2	2.1	162.027	75.362	75.362
	2.2	23.057	10.724	86.086
	2.3	9.056	4.212	90.298
	2.4	6.677	3.105	93.403
	2.5	5.480	2.549	95.952
	2.6	3.018	1.404	97.355
	2.7	2.857	1.329	98.684
	2.8	1.915	.891	99.575
3	3.1	191.679	89.153	89.153
	3.2	16.455	7.654	96.807
	3.3	5.067	2.357	99.164
4	4.1	196.183	91.248	91.248
	4.2	15.298	7.115	98.363
	4.3	1.457	.678	99.041
5	5.1	183.198	85.208	85.208
	5.2	24.705	11.491	96.699
	5.3	2.355	1.095	97.795
	5.4	1.564	.727	98.522
	5.5	1.320	.614	99.136

Table 4 – Components Extracted, Eigenvalues and Variance Explained for Random Samples

Table 5 provides further insight, by analysing the loadings of each component. Specifically, the correlation of each extracted component against selected indicators is shown. For the sake of simplicity, just extracted component needed to explain 95% of the variance are shown, along with the 5 most highly correlated indicators for each component. Therefore, this matrix can provide some further insights in terms of the physical meaning of the extracted components, correlating them with representative indicators.

Component	Random Sample									
	1		2		3		4		5	
1	Ecological Scarcity, Total, Total	1.000	EDIP2003, Global Warming, GWP 20a	.994	Ecological Scarcity 2013, Total, Water Pollutants	1.000	USEtox, Human toxicity, total	1.000	CML2001, Marine aquatic ecotoxicity, MAETP infinite	.999
	Cumulative Exergy Demand, Non-renewable energy resources, Nuclear	1.000	EDIP2003, Global Warming, GWP 100a	.994	CML2001, Terrestrial ecotoxicity, TAETP 20a	1.000	TRACI, Environmental impact, Ecotoxicity	1.000	CML2001, Malodours air, Malodours air	.998
	Cumulative Energy Demand, Non-renewable energy resources, Nuclear	1.000	CML2001, Global Warming, GWP 20a	.994	CML2001, Terrestrial ecotoxicity, TAETP infinite	.999	IMPACT 2002+ (Endpoint), Human health, Respiratory effects (inorganics)	1.000	CML2001, Photochemical oxidation (summer smog), MOIR	.998
	Ecological Footprint, Total, Nuclear	1.000	Ecological Scarcity 2013, Total, Global Warming	.994	IPCC 2013, Climate change, GWP 20a	.999	IMPACT 2002+ (Endpoint), Human health, Total	1.000	CML2001, Photochemical oxidation (summer smog), MIR	.998
	ReCiPe Midpoint (E), Ionising radiation, IRP_HE	1.000	CML2001, Global Warming, GWP 100a	.994	TRACI, Human health, carcinogenics	.999	Ecological Scarcity 2006, Total, Emission into air	1.000	EDIP2003, Land filling, Hazardous waste	.997
2			EPS 2000, Total, Emissions into water	.952	EDIP2003, Non-renewable resources, Nickel	.936	EDIP2003, Land filling, Bulk waste	.930	Ecosystem damage potential, Total, Linear, Land transformation	.992
			EDIP2003, Non-renewable resources, Mercury	.800	Ecological Scarcity 2013, Total, Mineral resources	.872	Cumulative Exergy Demand, Minerals, Non-renewable material resources, minerals	.927	EPS 2000, Total, Emissions into water	.826
			IMPACT 2002+ (Midpoint), Ecosystem quality, Aquatic eutrophication	.714	IMPACT 2002+ (Endpoint), Resources, Mineral extraction	.856	Ecological Scarcity 2013, Total, Mineral resources	.923	EDIP2003, Non-renewable resources, Mercury	.769
			Cumulative Exergy Demand, Wind,	.707	EDIP2003, Non-renewable resources,	.818	EDIP2003, Non-renewable resources,	.911	ReCiPe Midpoint (E), Natural land	.686

				Renewable energy resources, kinetic (in wind), converted		Nickel		Nickel		transformation, NLTP	
				Cumulative Energy Demand, Wind, Renewable energy resources, kinetic (in wind), converted	.707	ReCiPe Midpoint (E), Metal depletion, MDP	.805	EDIP2003, Non-renewable resources, Nickel	.899	IMPACT 2002+ (Midpoint), Ecosystem quality, Aquatic eutrophication	.662
	3			EPS2000, Total, Land occupation	.975						
				ReCiPe Midpoint (E), Urban land occupation, ULOP	.974						
				Ecological Scarcity 2013, Total, Land use	.974						
				IMPACT 2002+ (Endpoint), Ecosystem quality, Land occupation	.973						
				Ecological Footprint, Total, Land occupation	.901						
	4			EDIP2003, Non-renewable resources, Gold	.887						
				EDIP2003, Non-renewable resources, Silver	.868						
				EDIP2003, Non-renewable resources, platinum	.716						
				EDIP2003, Non-renewable resources, Palladium	.689						
				ReCiPe Midpoint (E), Human toxicity, HTPinf	.604						
	5			EDIP2003, Non-renewable resources,	.443						

				Iron							
				Ecological Scarcity 2013, Total, Heavy metals into water	.358						
				EDIP2003, Non-renewable resources, Gold	.358						
				EDIP2003, Human toxicity, Via soil	.337						
				Ecological scarcity 2006, Total, Emissions into surface water	.335						

Table 5 – Loadings against components

Component 1 across all of these random samples is consistently comprised of climate change (global warming potential) and ecological scarcity indicators; generally speaking, this component can be seen as providing a general assessment of the environmental impact of the considered supply chains. This is further stressed by Table 6, that provides the loadings against the first components extracted for each sample for one of the most popular environmental indicators, GWP 100a computed according to the CML 2001 methodology. It can be easily noticed that this indicator (indisputably the most utilised in the supply chain management literature to measure the sustainability of production systems) represents a good proxy for the first principal component extracted for all the random samples.

As regards the second components, it can be seen that, for all samples, these are largely correlated to indicators expressing non-renewable resource (NRR) impacts, including several metals and other critical materials.

	Extracted Component				
	1.1	2.1	3.1	4.1	5.1
CML 2001, Climate change, GWP 100a	1.000	0.994	0.992	0.995	0.995

Table 6 – Loadings against first principal components

4.2 Sub-Categories PCA Results

Also in this case, as a first step, a correlation analysis is performed, by computing, for each sub-category, the correlation coefficient for each pair of indicators. Table 7 illustrates, for each sub-category, the average correlation coefficient and the percentage of correlation coefficients larger than 0.800. As in the case of random samples, very high values in terms of average correlation coefficients are observed, ranging from 0.849 (Transport) to 0.985 (Steel). Also, it can be shown that the percentage of correlation coefficients larger than 0.800 is strikingly high across all sub-categories. Such preliminary analysis seems to suggest that the 215 environmental indicators under analysis exhibit a high level of redundancy. For verifying this hypothesis, Principal Component Analysis is performed.

In examining how the generated components vary across supply chain processes, PCA results (Table 8) still present similarities with the random sample with regards to the amount of variance accounted for by the first component (from a minimum of 88% for transport, to a maximum of 99.7% for cement), although the number of components extracted varies from 1 to 7. In the two instances where second components are extracted the amount of variance explained is below 5%, following the pattern established by the random sample where the gap between variance explained by the first and second component remains huge and confirms that even for specific supply chain processes there remains environmental indicators characterised by redundancy.

	Selected sub-categories			
	Cement	Glass	Steel	Transport
Average Correlation Coefficient	0.983	0.948	0.980	0.838
Percentage of Correlation Coefficients larger than 0.800	99.53	95.79	99.52	76.59

Table 7 – Average Correlation Coefficients for selected sub-categories

Industry	Components Extracted	Eigenvalues		
		Eigenvalues	**Variance (%)**	**Cumulative Variance (%)**
Cement	C.1	214.374	99.709	99.709
Glass	G.1	207.934	96.714	96.714
	G.2	4.278	1.990	98.703
	G.3	1.747	.812	99.516
Steel	S.1	213.735	99.412	99.412
Transport	T.1	188.284	87.574	87.574
	T.2	9.660	4.493	92.067
	T.3	8.064	3.751	95.818
	T.4	3.162	1.471	97.289
	T.5	2.236	1.040	98.329
	T.6	1.350	.628	98.957
	T.7	1.161	.540	99.496

Table 8 – Components Extracted, Eigenvalues and Variance Explained for Sampled Industries

By examining the sub-categories of supply chain processes (Table 9), it is shown that while climate change factors continue to dominate the components, the results obtained from the PCA highlight that different categories of supply chain processes have slightly differing patterns regarding environmental impacts. Again, for the sake of simplicity, the correlation of each extracted component needed to explain 95% of the variance is shown. For these processes this means that cement, glass, and steel have just one component each, whilst transport has three components. As with the random sample PCA, component 1 is consistently comprised of climate change (global warming potential) and ecological scarcity indicators, but differing results arise from running sector-specific processes compared to a random sample (as highlighted in Table 8).

The main similarity between the two sets of results is that component 1 still shows a strong link between impacts categories related to climate change and those relating to eco- and human health toxicity, and emissions into air and water. However, in the sector-specific results, strong loadings of non-renewable resources can be also retrieved in this 'climate change' component. Components 2 and 3 in the transport supply chain processes are concentrated around nonrenewable resources, critical metals, and ecosystem quality (component 2); and ecotoxicity indicators (component 3).

		Supply Chain Process							
		Glass		Steel		Transport		Cement	
Component	1	ReCiPe Midpoint (E), Freshwater ecotoxicity, FETPinf	1.000	TRACI, Human health, Respiratory effects, average	1.000	ReCiPe Midpoint (E), Human toxicity, HTPinf	.999	EDIP2003, Land filling, Bulk waste	1.000
		EPS2000, Total, Emissions into water	1.000	Ecological scarcity 1997, Total, Emission into top-soil/groundwater	1.000	CML 2001, Marine aquatic ecotoxicity, MAETP 20a	.998	Ecological footprint, Total, Total	1.000
		IMPACT 2002+ (Endpoint), Human health, Respiratory effects (inorganics)	1.000	EPS 2000, Total, Land occupation	1.000	EPS 2000, Total, Emissions into soil	.998	ReCiPe Midpoint (E), Photochemical oxidant formation, POFP	1.000
		CML2001, photochemical oxidation (summer smog), high NOx POCP	1.000	Ecological scarcity 2013, Total, Land use	1.000	TRACI, Environmental impact, Ecotoxicity	.998	Ecological scarcity 1997, Total, Deposited waste	1.000
		Ecological scarcity 2013, Total, Water resources	1.000	ReCiPe Midpoint (E), Urban land occupation, ULOP	1.000	Cumulative Exergy Demand, Minerals, Non-renewable material resources, minerals	.998	ReCiPe Midpoint (E), Environmental impact, Photochemical oxidation	1.000
	2					EDIP2003, Non-renewable resources, Gold	.876		
						EDIP2003, Non-renewable resources, Tantalum	.875		
						EDIP2003, Non-renewable resources, Silver	.802		
						EDIP2003, Non-renewable resources, Platinum	.777		
						EDIP2003, Non-renewable resources, Cadmium	.773		
	3					Ecological scarcity 2006, Total, Emission into groundwater	.915		
						CML 2001, Terrestrial ecotoxicity, TAETP 20a	.913		
						Ecological scarcity 2013, Total, Pesticides into soil	.911		
						CML 2001, Terrestrial ecotoxicity, TAETP 100a	.884		
						Ecological scarcity 2006, Total, Emission into top soil	.780		

Table 9 – Loadings against components

5. Discussion

There is a growing regarding the incorporation of indicators of environmental sustainability in production systems and supply chain systems in an effort to demonstrate pro-environmental behaviour, and to measure, monitor and take action in response to environmental challenges, often driven by regulation (for example EU legislation and the 2001 UN Global Compact) as well as from desires of companies to position themselves as environmentally sustainable (Genovese et al., 2014). Whilst methodologies such as LCA are well developed, with resources such as environmental indicator databases (e.g. Ecoinvent) enable the measurement of the performance of product supply chains across a variety of impact categories, the wideness and scope of the types of indicators (currently standing at 664) provided makes decision making difficult. For companies wishing (or being legislatively required) to measure environmental sustainability beyond a single measure of carbon emissions, the types and range of indicators available goes against the suggestions of Lorenz et al. (1999) stating that ecological measures shall be easy to implement and measure.

This research has established that while methodologies in academic literature are well-developed with regards to carbon emissions, moving beyond a carbon-centric accounting of supply chain environmental performance runs the risk of overloading end users with complex and often redundant information (Jollands et al., 2004 ; Gaussin et al. 2013). This is an area of research that to date is not as strongly developed.

The research in this paper highlights how a data reduction technique (Principal Components Analysis) across five random samples of supply chain processes listed in the Ecoinvent database consistently generates one component that accounts for over 75% of the variance between indicators being strongly correlated with CML 2001, Climate Change, GWP 100a environmental indicator ($r>0.993$). Given that this indicator is the most widely used in supply chain management literature (Koh et al., 2013), this decision is largely justified at the present moment in time given the findings of this paper. The use of PCA maintains the important characteristics of composite indicators, with regards to completeness – the total amount of variance explained by each of the first components across the sub-samples is above 75%; as regards redundancy, this has been greatly reduced, as sets with very limited amount of components (and, therefore, related indicators) can be considered. The use of a single indicator covering climate change impacts has strong implications for the operational capabilities of such an indicator.

Of note is that whilst creating four sub-samples based on specific supply chain processes does bring about similar results, increasing the amount of variance explained by the primary component, but contains the additional dimensions of ecosystem services, non-renewable resources, and ecotoxicity. This suggests that companies operating with specific supply chain processes may face additional environmental pressures not entirely covered by climate change indicators. The findings presented in this paper provide a generalised perspective for supply chain managers, but there still exists scope for discretion with what is being measured depending on company-specific circumstances.

6. Conclusions

The incorporation of performance management measures related to environmental sustainability for supply chains and production systems is becoming a pivotal issue, both in corporate practice and academic literature. Therefore, the deployment and usage of environmental indicators for monitoring and managing sustainability issues is an ongoing topic of debate and deliberation in the scientific community, which has generated several methodological and conceptual approaches. While a plethora of environmental indicators has been developed, the main challenge, for both academics and practitioners, is represented by the selection and identification of indicators to be considered in benchmarking processes, in such a way that relevant environmental impact dimensions and a precise account of sustainability issues are given without simultaneously overloading end-users with overly complex and redundant information.

In order to respond to this challenge, this research has employed Correlation Analysis and Principal Component Analysis for dimension reduction in environmental and sustainable supply chain management problems. By applying this methodology first to random samples of product supply chains and then to selected industries, this paper has clearly shown the existence of a striking redundancy in the current spectrum of environmental indicators. Therefore, it has been demonstrated how PCA can be effectively employed to identify a *core* of key environmental indicators that could be considered, in order to perform comprehensive environmental assessments without having to engage with unnecessary complex datasets.

Future researches could be devoted to further analyses based on primary data arising from real-world applications and to the utilisation of alternative approaches for dimension reduction, mainly based on optimisation techniques.

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Appendix A

The following Table A1 reports all the indicators employed in the analysis.

CML 2001	acidification potential	1	average European	kg SO2-Eq
		2	Generic	kg SO2-Eq
	climate change	3	GWP 500a	kg CO2-Eq
		4	lower limit of net GWP	kg CO2-Eq
		5	GWP 100a	kg CO2-Eq
		6	GWP 20a	kg CO2-Eq
		7	upper limit of net GWP	kg CO2-Eq
	eutrophication potential	8	average European	kg NOx-Eq
		9	generic	kg PO4-Eq
	freshwater aquatic ecotoxicity	10	FAETP infinite	kg 1,4-DC.
		11	FAETP 100a	kg 1,4-DC.
		12	FAETP 20a	kg 1,4-DC.
		13	FAETP 500a	kg 1,4-DC.
	freshwater sediment ecotoxicity	14	FSETP 100a	kg 1,4-DC.
		15	FSETP infinite	kg 1,4-DC.
		16	FSETP 20a	kg 1,4-DC.
		17	FSETP 500a	kg 1,4-DC.
	human toxicity	18	HTP 500a	kg 1,4-DC.
		19	HTP 20a	kg 1,4-DC.
		20	HTP 100a	kg 1,4-DC.
		21	HTP infinite	kg 1,4-DC.
	ionising radiation	22	ionising radiation	DALYs
	land use	23	competition	m2a
	malodours air	24	malodours air	m3 air
	marine aquatic ecotoxicity	25	MAETP 100a	kg 1,4-DC.

		26	MAETP 20a	kg 1,4-DC.
		27	MAETP 500a	kg 1,4-DC.
		28	MAETP infinite	kg 1,4-DC.
	marine sediment ecotoxicity	29	MSETP 500a	kg 1,4-DC.
		30	MSETP 20a	kg 1,4-DC.
		31	MSETP infinite	kg 1,4-DC.
		32	MSETP 100a	kg 1,4-DC.
	photochemical oxidation (summer smog)	33	EBIR	kg formed.
		34	MIR	kg formed.
		35	high NOx POCP	kg ethyle.
		36	low NOx POCP	kg ethyle.
		37	MOIR	kg formed.
	resources	38	depletion of abiotic resources	kg antimo.
	stratospheric ozone depletion	39	ODP 25a	kg CFC-11.
		40	ODP 5a	kg CFC-11.
		41	ODP 40a	kg CFC-11.
		42	ODP 15a	kg CFC-11.
		43	ODP 20a	kg CFC-11.
		44	ODP steady state	kg CFC-11.
		45	ODP 30a	kg CFC-11.
		46	ODP 10a	kg CFC-11.
	terrestrial ecotoxicity	47	TAETP 100a	kg 1,4-DC.
		48	TAETP 500a	kg 1,4-DC.
		49	TAETP 20a	kg 1,4-DC.
		50	TAETP infinite	kg 1,4-DC.
Cumulative Energy Demand	biomass	51	renewable energy resources, biomass	MJ-Eq
	fossil	52	non-renewable energy resources, fossil	MJ-Eq
	geothermal	53	renewable energy resources, geothermal, converted	MJ-Eq
	nuclear	54	non-renewable energy resources, nuclear	MJ-Eq

	primary forest	55	non-renewable energy resources, primary forest	MJ-Eq
	solar	56	renewable energy resources, solar, converted	MJ-Eq
	water	57	renewable energy resources, potential (in barrage water), converted	MJ-Eq
	wind	58	renewable energy resources, kinetic (in wind), converted	MJ-Eq
Cumulative Exergy Demand	biomass	59	renewable energy resources, biomass	MJ-Eq
	fossil	60	non-renewable energy resources, fossil	MJ-Eq
	metals	61	non-renewable material resources, metals	MJ-Eq
	minerals	62	non-renewable material resources, minerals	MJ-Eq
	nuclear	63	non-renewable energy resources, nuclear	MJ-Eq
	primary forest	64	non-renewable energy resources, primary forest	MJ-Eq
	solar	65	renewable energy resources, solar, converted	MJ-Eq
	water	66	renewable energy resources, potential (in barrage water), converted	MJ-Eq
	water resources	67	renewable material resources, water	MJ-Eq
	wind	68	renewable energy resources, kinetic (in wind), converted	MJ-Eq
Ecological footprint	Total	69	CO2	m2a
		70	Total	m2a
		71	land occupation	m2a
		72	Nuclear	m2a
Ecological scarcity 1997	Total	73	emission into air	UBP
		74	emission into top-soil/groundwater	UBP
		75	emission into water	UBP
		76	deposited waste	UBP
		77	use of energy resources	UBP
		78	radioactive waste	UBP
		79	Total	UBP
Ecological scarcity 2006	Total	80	emission into surface water	UBP
		81	emission into air	UBP
		82	natural resources	UBP
		83	emission into top soil	UBP

		84	Total	UBP
		85	emission into groundwater	UBP
		86	energy resources	UBP
		87	deposited waste	UBP
Ecological scarcity 2013	Total	88	Energy resources	UBP
		89	Global warming	UBP
		90	Radioactive substances into water	UBP
		91	Carcinogenic substances into air	UBP
		92	Main air pollutants and PM	UBP
		93	Radioactive substances into air	UBP
		94	Radioactive waste to deposit	UBP
		95	total	UBP
		96	Mineral resources	UBP
		97	Land use	UBP
		98	Heavy metals into water	UBP
		99	Non radioactive waste to deposit	UBP
		100	Pesticides into soil	UBP
		101	Heavy metals into soil	UBP
		102	POP into water	UBP
		103	Ozone layer depletion	UBP
		104	Water resources	UBP
		105	Heavy metals into air	UBP
		106	Water pollutants	UBP
Ecosystem damage potential	Total	107	linear, land use, total	points
		108	linear, land occupation	points
		109	linear, land transformation	points
EDIP2003	Acidification	110	acidification	m2
	Ecotoxicity	111	in sewage treatment plants	m3 waste .
		112	acute, in water	m3 water

		113	chronic, in soil	m3 soil
		114	chronic, in water	m3 water
	Eutrophication	115	separate N potential	kg N
		116	separate P potential	kg P
		117	combined potential	kg NO3-
		118	terrestrial eutrophication	m2
	global warming	119	GWP 100a	kg CO2-Eq
		120	GWP 500a	kg CO2-Eq
		121	GWP 20a	kg CO2-Eq
	human toxicity	122	via soil	m3 soil
		123	via air	m3 air
		124	via surface water	m3 water
	land filling	125	radioactive waste	kg waste
		126	slag and ashes	kg waste
		127	hazardous waste	kg waste
		128	bulk waste	kg waste
	non-renewable resources	129	Palladium	kg
		130	Silver	kg
		131	Iron	kg
		132	Molybdenum	kg
		133	Coal	kg
		134	Nickel	kg
		135	Antimony	kg
		136	Copper	kg
		137	Cadmium	kg
		138	Manganese	kg
		139	Tin	kg
		140	brown coal	kg
		141	Tantalum	kg

		142	Oil	kg
		143	Lanthanum	kg
		144	Aluminium	kg
		145	platinum	kg
		146	cobalt	kg
		147	zinc	kg
		148	gold	kg
		149	mercury	kg
		150	lead	kg
		151	natural gas	kg
		152	cerium	kg
	photochemical ozone formation	153	impacts on human health	person.pp.
	photochemical ozone formation	154	impacts on vegetation	m2.ppm.h
	renewable resources	155	wood	m3
	stratospheric ozone depletion	156	ODP total	kg CFC-11.
EPS 2000	Total	157	emissions into air	ELU
		158	total	ELU
		159	emissions into water	ELU
		160	land occupation	ELU
		161	emissions into soil	ELU
		162	abiotic stock resources	ELU
IMPACT 2002+ (Endpoint)	climate change	163	climate change	points
		164	total	points
	ecosystem quality	165	aquatic ecotoxicity	points
		166	land occupation	points
		167	total	points
		168	terrestrial ecotoxicity	points
		169	terrestrial acidification & nutrification	points
	human health	170	photochemical oxidation	points

		171	total	points
		172	respiratory effects (inorganics)	points
		173	human toxicity	points
		174	ionising radiation	points
		175	ozone layer depletion	points
	resources	176	mineral extraction	points
		177	total	points
		178	non-renewable energy	points
IMPACT 2002+ (Midpoint)	ecosystem quality	179	aquatic acidification	kg SO2-Eq
		180	aquatic eutrophication	kg PO4-Eq
IPCC 2001	climate change	181	GWP 100a	kg CO2-Eq
IPCC 2007	climate change	182	GWP 500a	kg CO2-Eq
IPCC 2013	climate change	183	GWP 20a	kg CO2-Eq
IPCC 2013	climate change	184	GWP 100a	kg CO2-Eq
ReCiPe Midpoint (E)	agricultural land occupation	185	ALOP	m2a
	climate change	186	GWP500	kg CO2-Eq
	fossil depletion	187	FDP	kg oil-Eq
	freshwater ecotoxicity	188	FETPinf	kg 1,4-DC.
	freshwater eutrophication	189	FEP	kg P-Eq
	human toxicity	190	HTPinf	kg 1,4-DC.
	ionising radiation	191	IRP_HE	kg U235-Eq
	marine ecotoxicity	192	METPinf	kg 1,4-DC.
	marine eutrophication	193	MEP	kg N-Eq
	metal depletion	194	MDP	kg Fe-Eq
	natural land transformation	195	NLTP	m2
	ozone depletion	196	ODPinf	kg CFC-11.
	particulate matter formation	197	PMFP	kg PM10-Eq
	photochemical oxidant formation	198	POFP	kg NMVOC
	terrestrial acidification	199	TAP500	kg SO2-Eq

	terrestrial ecotoxicity	200	TETPinf	kg 1,4-DC.
	urban land occupation	201	ULOP	m2a
	water depletion	202	WDP	m3
TRACI	environmental impact	203	ecotoxicity	kg 2,4-D-.
		204	photochemical oxidation	kg NOx-Eq
		205	global warming	kg CO2-Eq
		206	eutrophication	kg N
		207	acidification	moles of .
		208	ozone depletion	kg CFC-11.
	human health	209	non-carcinogenics	kg toluen.
		210	respiratory effects, average	kg PM2.5-.
		211	carcinogenics	kg benzen.
USEtox	ecotoxicity	212	total	CTU
	human toxicity	213	non-carcinogenic	CTU
		214	carcinogenic	CTU
		215	total	CTU