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"Everything should be as simple as possible, but not simpler"(Einstein in Meadows 1998, p. 22)

Abstract

Eco-efficiency has emerged as a management response to waste issues associated with current production processes. Despite the popularity of the term in both business and government circles, limited attention has been paid to measuring and reporting eco-efficiency to government policy makers. Aggregate measures of eco-efficiency are needed, to complement existing measures and to help highlight important patterns in eco-efficiency data.
This paper aims to develop aggregate measures of eco-efficiency for use by policy makers. Specifically, this paper provides a unique analysis by applying principal components analysis (PCA) to eco-efficiency indicators in New Zealand.
This study reveals that New Zealand's overall eco-efficiency improved for two out of the five aggregate measures over the period 1994/95 to 1997/98. The worsening of the other aggregate measures reflects, among other things, the relatively poor performance of the primary production and related processing sectors. These results show PCA is an effective approach for aggregating eco-efficiency indicators and assisting decision makers by reducing redundancy in an eco-efficiency indicators matrix.

Keywords: Policy development; policy evaluation; Aggregate indices

Introduction

Eco-efficiency is a management response aimed at "curing" the "disease of wastefulness" associated with current production processes (Weizsäcker *et al.* 1997). The concept of eco-efficiency first entered academic literature in an article by Schaltegger and Sturm in 1990

(Schaltegger & Burritt 2000). However, Schmidheiny (1992) popularised the term, and subsequently the concept of eco-efficiency has gained in popularity and spread throughout the business world. Not surprisingly, eco-efficiency has received significant attention in the sustainable-development literature, including this journal (Brady *et al.* 1999; Business Council for Sustainable Development 1993; Choucri 1995; Cramer 1997; DeSimone *et al.* 2000; Metti 1999; Reith & Guirdy 2003; Schaltegger & Synnestvedt 2002; Weizsäcker *et al.* 1997)

Many authors have attempted to define eco-efficiency. For example, Williams (1999, p.37) defines eco-efficiency as 'endeavouring to get more from less for longer". Metti (1999, p83) states "eco-efficiency is simply creating more value with fewer materials and less water. One definition of eco-efficiency that is gaining increasing currency comes from the World Business Council for Sustainable Development (WBCSD):

"Eco-efficiency is reached by the delivery of competitively-priced goods and services that satisfy human needs and bring quality life, which progressively reducing environmental impacts and resource intensity throughout the life cycle, to a level at least in line with the earth's estimated carrying capacity" (DeSimone et al., 2000, p47).

Despite the range of interpretations, Hinterberger and Stiller (1998, p.275) note that all definitions have an obvious theme in common; "All concepts call for a more efficient use of natural resources." Beyond that clearly, the detail of eco-efficiency can be understood in a number of ways.

Schaltegger and Burritt (2000) suggest a distinction can be made between eco-efficiency as a concept and as a ratio figure, although the two are linked. The eco-efficiency concept is a relatively new derivation of 'efficiency'. Efficiency itself embodies the notion of "fitness or power to accomplish, or success in accomplishing, the purpose intended" (Simpson & Weiner 1989 / p. 84). Adding the 'eco-' prefix to efficiency makes the eco-efficiency concept distinct from the other efficiency concepts. The 'eco-' prefix focuses on the 'environment and relation to it.' (Barnhart 1998). Specifically, the prefix adds a lens to the 'success in accomplishing' components of the efficiency concept. Through this lens, 'success' is seen to extend beyond simply whether the goal is achieved or not, to encompass a concern for the impact on ‘ the environment and relation to it’ associated with the activity of achieving the goal. The WBCSD, for example promote the concept of eco-efficiency.

Often, in modern use of the term, eco-efficiency is measured using a ratio of useful outputs to inputs. This ratio derives from 19^{th} Century thermodynamics and its empirical work on thermal efficiency measures (Jollands 2003).

When applied to eco-efficiency, the ratio measures useful outputs (products, services etc) to environmental inputs (Schaltegger & Burritt 2000). This ratio (or derivatives thereof) has been employed in many eco-efficiency studies including Glauser & Muller (1997), Metti (1999) and Schaltegger and Burritt (2000). In this study, we also operationalise the eco-efficiency concept by way of a ratio.

A review of the eco-efficiency literature reveals several notable methodological gaps. One gap that is the focus of this paper is the limited attention paid to measuring and reporting eco-efficiency for government policy makers. A notable exception is the work being done in Germany by the Wuppertal Institute (Bringezu 2004) and the German Federal Statistics office (Hoh *et al.* 2001). This gap is all the more surprising, given the recent interest in eco-efficiency by many government policy agencies and intergovernmental organisations (Organisation for Economic Co-operation and Development 1998).

It is often argued that policy makers have specific requirements of indicators. Boisevert *et al.* (1998, p.106-107) summarise policy makers' requirements into two broad needs:

- Only a limited number of indicators should be used to convey the general state of the environment. Too many indicators can compromise the legibility of the information.
- Information should be presented in a format tailored to decision making. This requires the construction of indicators that reduce the number of parameters needed to give a precise account of a situation.

As a result of these specific requirements, many authors (for example Alfsen & Saebo 1993; Heycox 1999; Luxem & Bryld 1997; Opschoor 2000) argue that aggregate indices that meet the needs of decision makers are needed. Unfortunately, few researchers have heeded this call, particularly in relation to eco-efficiency.

This paper attempts to provide aggregate indicators for policy makers. Specifically, it aims to develop aggregate measures of eco-efficiency for use in national environmental policy. In doing so, the paper briefly canvases the issues surrounding aggregate indices in general. It then applies one aggregating method that has shown promise in other applications, principal components analysis (PCA), to New Zealand data to reveal trends in eco-efficiency between 1994/95 and 1997/98.

Aggregate indices - brickbats and bouquets

The relative strengths and weaknesses of aggregate indices are well documented (see for example Jollands, 2003). The main arguments can be summarised as follows.

Proponents of aggregate indices argue that indices assist decision makers by:

- reducing the clutter of too much information (Alfsen & Saebo 1993; Callens & Tyteca 1999; Heycox 1999).
- helping to communicate information succinctly and making patterns in the data easier to see (Cleveland *et al.* 2000).
- formalising the aggregation process that is often done implicitly.

Critics of aggregate indices offer equally persuasive arguments. They point out that

- aggregate indices rely on potentially distorting assumptions (Lindsey *et al.* 1997).
- it is difficult for aggregate indices to capture the necessary interrelationships within complex environment-economy systems (Gustavson *et al.* 1999).

- aggregation is often faced with the problem of adding together quantities measured in different units. This is particularly the case with the economy-environment interface. In this context Martinez-Alier *et. al.* (1998) argue that it is inappropriate to shoehorn such disparate values into one cardinal set.

The two contesting views regarding aggregate indices are not as starkly opposed as may first appear and are necessarily complementary. A high level of indicator aggregation is needed to intensify the awareness of economy-environment interaction problems. But, even given the advantages of aggregate indices, no single index can possibly answer all questions.

On balance, the most appropriate approach appears to be to use a judicious mix of detailed and aggregated indices, and to treat aggregate indices with particular care.

Approaches to developing aggregate indices

Given that aggregate indices do have a role to play, how can aggregate eco-efficiency indices be developed for New Zealand? Previous work by Jollands (2003) proposed a framework for developing aggregate indices. One of the most challenging and contentious steps in developing aggregate eco-efficiency indices is the setting of weightings needed for commensurating the various aspects of eco-efficiency (such as water use and energy use) that are measured in different units. Possible weighting schemes range from direct monetization, public opinion polls and cost of distance to target, to ecological pricing and statistical methods (Jesinghaus 1997).

Considerable debate exists about which weighting scheme to use. This paper investigates the use of a multi-variate statistical weighting approach, principal components analysis (PCA). PCA has received little attention in aggregate indicator literature in general and eco-efficiency literature specifically (with the notable exception of the work by Yu *et al.* (1998)).

The use of PCA offers several advantages. First, PCA is a useful alternative to the more "subjective" weighting systems like public opinion polls. PCA weights data by combining original variables into linear combinations that explain as much variation as possible. In this way, PCA provides a relatively “objective” approach to setting weights that is dictated by the data rather than the analyst. In effect, it “lets the data speak”.

Second, PCA is a useful tool for improving the “efficiency” of indicators (Callens & Tyteca 1999). A unique advantage of PCA is that it reports the amount of variance in the data that is explained by the resulting aggregate indices.

Finally, PCA is designed to reduce the dimensionality of data sets. However, PCA is not a panacea (Vega *et al.* 1998). In particular, PCA is limited to ex post analysis. It is not an appropriate tool for prospective investigations. Nevertheless, given the strengths of PCA, it would appear that the use of PCA could provide fertile ground for an inquiry into developing aggregate measures of eco-efficiency.

Method –a brief description of PCA

Principal components analysis reduces a number of variables to a few indices (called the principal components) that are linear combinations of the original variables (Heycox 1999 p.211; Manly 1994 p.12; Sharma 1996; Yu *et al.* 1998). PCA provides an objective way of ‘aggregating’ indicators so that variation in the data can be accounted for as concisely as possible.

PCA takes *p* variables $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p$ and finds linear combinations of these to produce principal components $Z_1, Z_2, \ldots Z_p$ (Manly 1994 p.78). Principal components are established by linear transformations of the observed variables (ε_i) under two conditions (Marcoulides & Hershberger 1997). The first condition is that the first principal component accounts for the maximum amount of variance possible, the second component that greatest amount of remaining variance, and so on. The second condition is that all final components are uncorrelated with each another. This lack of correlation is useful because it means that the indices are measuring different ‘dimensions’ in the data.

The process for conducting PCA is well documented in multivariate statistics literature, (see for example (Manly 1994; Sharma 1996). In general, there are seven standard steps in a principal components analysis: construct a data matrix, standardise variables, calculate the covariance (C) matrix[1], find eigenvalues and eigenvectors, select principal components, interpret the results and calculate scores.

Data used for PCA analysis

This study uses PCA to aggregate 14 eco-efficiency indicators for New Zealand (Table 1). These indicators were drawn from a matrix of 131 eco-efficiency indicators (measured as ecosystem service/dollar value added[2]) for 2 years by the 46 sectors of the New Zealand economy (see Table 1), calculated in earlier work by Jollands (2003). The base data used in this analysis were derived from the *Eco*Link database (McDonald & Patterson 1999). This database is in turn derived from Local Authority resources consent information (for point source discharge and extraction) and Statistics New Zealand. The eco-efficiency indicators were calculated by Jollands (2003) using an augmented inverse Leontief matrix (Hite & Laurent 1971). Consequently, these indicators measure total economy wide eco-efficiency. Regarding the pooling of the 2 years data, although the two years are not totally independent, it admissible to pool the data because this analysis does not involve significant testing. Further, pooling the data allows us to trace score changes from one year to the next using the same component structure.

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[1] This is a correlation matrix if variables have been standardised (Yu et.al. 1998)

[2] Strictly speaking the eco efficiency used here is the reciprocal of efficiency and sometimes referred to as 'intensity' (Patterson 1996). Consequently, some people refer to these measures as 'eco-intensities'.

Table 1: List of sectors of the New Zealand economy used in this analysis

Sector number	Sector name	NZSIC codes
1	Mixed livestock	11120, 11130, 11140
2	Dairy farming	11110
3	Horticulture	11150, 11170, 11190
4	Services to Agriculture	112000
5	All other farming	11160
6	Fishing and Hunting	13000
7	Forestry & Logging	12000
8	Oil and Gas Exploration	22000
9	Other mining	29000, 23000, 21000
10	Meat Products	31110
11	Dairy Products	311120
12	Manufacture of other food	31100, 31200, 31100
13	Beverage Manufacture	31300, 31400
14	Textile Manufacture	32000
15	Wood & Wood Products	33000
16	Paper products	34100
17	Printing & Publishing	34200, 83402
18	Other Chemicals	35200, 35500, 35600
19	Basic Chemicals	35100, 35300, 35400
20	Non-metallic Minerals	36000
21	Basic Metal Industries	37000
22	Fabricated Metals	38100
23	Equipment Manufacture	38200-38500
24	Transport Equipment	38400
25	Other Manufacturing	39000
28	Water works	41030, 42000
29	Construction	53000
30	Trade	61000-62000
31	Accommodation	63000
32	Road transport	71120-71150
33	Services to Transport	71160-71190
34	Water Transport	71200
35	Air Transport	71300
36	Communications	72000
37	Finance	81100-81200
38	Finance services	81491-82300 excl 81200
39	Insurance	81200
40	Real Estate	83100
41	Business Services	83200
42	Dwelling ownership	83122
43	Education	93100-93200
44	Community Services	93300-93400
45	Recreation Services	93900-94900
46	Personal Services	95000, 93500, 92030, 92011, 92012, 92020
47	Central Government	91010
48	Local Government	91020

The 14 indicators chosen for inclusion in the analysis are shown in table 2.

Table 2: Variables used in principal components analysis[3]

Variable	Code	Unit
Total water inputs	ε_1	$m^3/\$$ (sum of ground and surface water takes)
Land	ε_2	ha/$
Energy	ε_3	Emjoules/$[4]
Minerals	ε_4	Tonne/$
Water discharge	ε_5	$m^3/\$$ (sum of discharge to land and water)
Water pollutant – Total ammonia	ε_6	$m^3/\$$ (sum of discharge to land and water)
Water pollutant – Total Biological Oxygen Demand (BOD_5)	ε_7	$m^3/\$$ (sum of discharge to land and water)
Water pollutant – Total Dissolved Reative Phosphorous (DRP)	ε_8	$m^3/\$$ (sum of discharge to land and water)
Water pollutant – Total Nitrate	ε_9	$m^3/\$$ (sum of discharge to land and water)
Water pollutant – Total Kjeldahl nitrogen (TKN)	ε_{10}	$m^3/\$$ (sum of discharge to land and water)
Water pollutant – Total Phosporous (TP)	ε_{11}	$m^3/\$$ (sum of discharge to land and water)
Carbon dioxide (CO_2) emissions (energy related)	ε_{12}	Tonne/$
Methane (CH_4) emissions (energy related)	ε_{13}	Tonne/$
Nitrous Oxide (NO_2) emissions (energy related)	ε_{14}	Tonne/$

In selecting the 14 variables for inclusion in the analysis, we considered two issues. First, we considered the need for comprehensiveness and cross- representative ness against data availability, data quality and policy interest. Second, we considered the information value of the PCA. Clearly, including unequal numbers of variables (for e.g. including 6 water pollutant variables) for different media is likely to weight the principal component order in favour of those media with more variables. However, there are two compelling reasons for our approach. First the PCA gave very similar results regardless of whether equal numbers of variables were used or not. That is, the different analyses revealed similar principal component structures – the only difference being the component order. This change in order is not a significant issue, since it is the list of principal components (princs) that is useful rather than the ranking. The second reason for including an unequal number of variables for each environmental media is because of the information value of the results. Including all water pollutant variables in the analysis

[3] Note that total water inputs, water discharges and water pollutants refer to point source quantities only.
[4] Energy total adjusted for energy quality (see Patterson 1993).

revealed an interesting relationship that would have been overlooked had arbitrarily a single 'representative' water quality variable been arbitrarily selected (see the discussion of 'prin 4' below).

For each of the 14 variables, there were 92 observations (46 sectors by 2 years), which greatly exceeds the 3 to 1 ratio regarded as the minimum requirement in PCA to provide a stable solution (Grossman *et al.* 1991; Yu *et al.* 1998). Table 3 gives the mean value, standard deviation maximum and minimum for each of the 14 variables. The covariance matrix of the 14 variables was calculated from standardised data and, therefore, coincides with the correlation matrix (also shown in Table 3). Some clear eco-efficiency relationships can readily be inferred: for example there were high positive correlations (underlined values) between water discharges and minerals (r=0.89); the various water pollutants (r= 0.68 to 1.0); and energy and air emissions (r = 0.71 to 0.97).

Table 3: Mean, standard deviation and correlation matrix of eco-efficiency sub-indices selected for PCA

	Water input	Land	Energy	Minerals	Water discharge	Water pollutant Ammonia	Water pollutant BOD_5	Water pollutant DRP	Water pollutant Nitrate	Water pollutant TKN	Water pollutant TP	CO_2	CH_4	NO_2
Observations	n=92													
Mean	6.92E-02	2.68E-04	4.78E-06	9.61E-05	4.67E-02	8.00E-05	3.93E-04	5.08E-05	1.09E-05	4.87E-04	9.69E-05	3.16E-04	8.63E-08	1.57E-08
Std dev	3.23E-01	5.85E-04	5.08E-06	4.76E-04	1.22E-01	1.97E-04	1.26E-03	1.80E-04	5.08E-05	1.75E-03	2.75E-04	3.67E-04	1.32E-07	1.88E-08
Maximum	2.24E+00	343E-03	2.63E-05	3.41E-03	8.71E-01	1.11E-03	8.94E-03	1.29E-03	3.62E-04	1.25E-02	1.57E-03	1.84E-03	9.58E-07	1.12E-07
Minimum	1.56E-03	8.76E-06	3.73E-07	1.55E-06	2.40E-03	3.82E-06	2.50E-05	3.51E-06	2.97E-07	3.40E-05	4.69E-06	2.77E-05	7.28E-09	1.39E-09
Water in	1.00													
Land	0.06	1.00												
Energy	0.02	0.00	1.00											
Minerals	0.08	-0.06	0.05	1.00										
Water discharge	0.17	-0.05	0.06	0.89	1.00									
Water pollutant Ammonia	0.04	0.22	-0.07	-0.06	0.28	1.00								
Water pollutant BOD_5	0.08	0.04	-0.09	-0.04	0.37	0.83	1.00							
Water pollutant DRP	0.08	-0.01	-0.09	-0.04	0.37	0.81	0.99	1.00						
Water pollutant Nitrate	-0.01	0.28	-0.01	-0.03	0.01	0.41	0.09	0.05	1.00					
Water pollutant TKN	0.08	-0.01	-0.09	-0.04	0.37	0.79	0.99	1.00	0.10	1.00				
Water pollutant TPD	0.05	0.20	-0.05	-0.05	0.28	0.68	0.85	0.77	0.10	0.78	1.00			
CO_2	-0.03	-0.01	0.96	0.03	0.05	-0.07	-0.09	-0.09	-0.01	-0.09	-0.05	1.00		
CH_4	-0.05	0.07	0.71	0.02	0.01	-0.02	-0.03	-0.04	0.01	-0.04	0.02	0.67	1.00	
NO_2	0.04	-0.01	0.97	0.04	0.06	-0.06	-0.08	-0.08	0.00	-0.08	-0.04	0.94	0.57	1.00

Note: underlined values show relatively high correlation.

Results and Discussion

The PCA was performed using the PRINCOMP procedure of the SAS system (SAS Institute 1985), which standardises data to zero mean and unit variance. This standardisation is important in this study, given that the variables display widely different means and relatively large standard deviations (see Table 2). The eigenvalues and eigenvectors of the correlation matrix are given in Tables 4 and 5, respectively.

Table 4: Eigenvalues of the correlation matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	4.6720	1.2777	0.3337	0.3337
2	3.3943	1.5273	0.2425	0.5762
3	1.8670	0.5356	0.1334	0.7095
4	1.3314	0.3441	0.0951	0.8046
5	0.9872	0.2249	0.0705	0.8751
6	0.7623	0.2846	0.0545	0.9296
7	0.4777	0.2005	0.0341	0.9637
8	0.2772	0.1291	0.0198	0.9835
9	0.1481	0.0927	0.0106	0.9941
10	0.0554	0.0386	0.0040	0.9980
11	0.0169	0.0063	0.0012	0.9992
12	0.0106	0.0106	0.0008	1.0000
13	0.0000	0.0000	0.0000	1.0000
14	0.0000	0.0000	0.0000	1.0000

Table 5: Weights (eigenvectors) of the correlation matrix

	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7	Prin8	Prin9	Prin10	Prin11	Prin12	Prin13	Prin14
Water in	0.0487	0.0206	0.1584	0.1148	0.9477	-0.1857	0.1435	0.0206	-0.0353	-0.0379	0.0262	0.0450	0.0000	0.0000
Land	0.0511	0.0206	-0.1815	0.6386	0.1166	0.6679	-0.1663	-0.1951	0.1752	-0.0014	-0.0004	0.0007	0.0000	0.0000
Energy	-0.1147	0.5187	-0.0337	-0.0230	0.0329	-0.0308	-0.1244	0.0019	-0.0004	0.2148	-0.7626	0.2661	0.0000	0.0000
Minerals	0.0159	0.0659	0.6939	0.1892	-0.1654	0.0681	0.0202	0.0368	-0.0729	0.1099	0.2365	0.6091	0.0000	0.0000
Water discharge	0.1950	0.1216	0.6286	0.1191	-0.0875	0.0226	-0.0251	-0.0290	0.0627	-0.1279	-0.2479	-0.6682	0.0000	0.0000
Water pollutant Ammonia	0.4005	0.0779	-0.1262	0.1912	-0.0706	-0.1568	-0.0339	-0.3820	-0.7664	-0.0117	-0.0027	-0.0005	-0.0667	-0.1115
Water pollutant BOD_5	0.4501	0.0826	-0.0485	-0.1272	0.0054	0.0185	-0.0023	-0.0308	0.1617	0.0190	0.0277	0.0806	-0.4403	0.7370
Water pollutant DRP	0.4424	0.0763	-0.0301	-0.1733	0.0093	-0.0127	-0.0036	-0.2370	0.2374	0.0275	0.0342	0.0968	0.7970	0.0911
Water pollutant Nitrate	0.0887	0.0242	-0.1605	0.6483	-0.1870	-0.6193	0.0882	0.2195	0.2553	0.0034	-0.0021	0.0096	0.0586	0.0487
Water pollutant TKN	0.4429	0.0769	-0.0335	-0.1501	0.0020	-0.0453	0.0113	-0.1321	0.4094	0.0315	0.0374	0.1069	-0.3905	-0.6486
Water pollutant TPD	0.3889	0.0914	-0.0921	-0.0166	0.0200	0.2555	-0.0115	0.8285	-0.2350	-0.0216	-0.0050	-0.0050	0.1030	-0.1142
CO_2	-0.1138	0.5082	-0.0498	-0.0372	-0.0115	-0.0437	-0.1990	-0.0095	0.0259	-0.7944	0.2078	0.0911	0.0000	0.0000
CH_4	-0.0728	0.4117	-0.0785	0.0209	-0.0877	0.1689	0.8641	-0.0595	-0.0147	0.0770	0.1310	-0.0939	0.0000	0.0000
NO_2	-0.1069	0.4996	-0.0310	-0.0280	0.0628	-0.0836	-0.3737	0.0250	-0.0012	0.5332	0.4864	-0.2551	0.0000	0.0000

Five principal components retained

Several tests are available for determining how many principal components (PCs) to retain. Cattel's Scree plot of eigenvalues, the Jollife-amended Kaiser eigenvalue criterion and an examination of the proportion of variance accounted for by the principal components suggests retaining five PCs (which account for around 87% of the variation) (Table 3). Note that the order in which the principal components are listed in Table 3 reflects the order in which they are derived from the PCA. It does not necessarily reflect their relative importance in characterising eco-efficiency.

The five principal components

The first principal component (Prin1) accounts for 33.4% of the total variation in the data (Table 3). Algebraically, Prin1 is shown as:

$$Prin1 = 0.048\varepsilon_1+0.051\varepsilon_2-0.115\varepsilon_3+0.016\varepsilon_4+0.195\varepsilon_5+0.400\varepsilon_6+0.450\varepsilon_7+0.442\varepsilon_8+0.088\varepsilon_9+0.443\varepsilon_{10}+0.389\varepsilon_{11}-0.114\varepsilon_{12}-0.073\varepsilon_{13}-0.107\varepsilon_{14} \quad \textbf{Equation 1}$$

Where ε_1 to ε_{14} are the original eco-efficiency indicators used in the analysis.

Table 5 and the equation above show that Prin1 has high positive coefficients (weights) on ammonia water pollution (0.400), biological oxygen demand (BOD_5) (0.405), dissolved reactive phosphorous (DRP) (0.442), total kjeldahl nitrogen (TKN) (0.443) and total phosphorous (TP) (0.389); i.e., on all water pollutant indicators except nitrates[5]. Prin1 can be called water-pollutant intensity, with higher Prin1 scores indicating higher water pollutant intensity (m^3/\$). The prominence of water pollutants in this analysis is interesting, since the issue of greatest concern to New Zealanders is the pollution of New Zealand's freshwater resources (Ministry for the Environment 2001).

The second principal component, Prin2, accounts for a further 24% of the total variation in the data, and has high positive weights on energy (0.519) and air emission indicators (0.508, 0.412, 0.499 for CO_2, CH_4 and NO_2 respectively). Prin2 can be interpreted as energy and energy-related air emission intensity, with higher scores indicating higher energy and energy-related air emission intensities.

Prin3 accounts for a further 13% of the total variation. Compared to the first two principal components, the interpretation of Prin3 is less intuitive. It has large positive coefficients on mineral-input (0.694) and water-discharge (0.629) intensities. *Other mining* is a significant source of point-source water discharge in New Zealand. The dominance of the *other mining* (which includes iron sand mining) sector's water discharge intensity helps to explain the prominence of water discharge in Prin3. Given that mineral inputs 'drive' this principal component, this component could be interpreted as 'material intensity,' with higher scores indicating greater mineral-input and water discharge intensities. Interestingly the negative

[5] This appears to be because point source nitrate levels are closely linked to the *meat products* sector, which has a significant level of 'embodied' land. Therefore, the PCA analysis traces land and nitrate pollutants in a separate principal component.

coefficients on 11 of the 14 variables are likely to have a dampening effect on this component's scores.

The fourth principal component, Prin4, accounts for a further 9.5% of the total variation. Prin4 is highly participated by land intensity (0.639) and water pollutant (nitrate) (0.648). This is an interesting result, and one that could have been overlooked, had not all water pollutant variables been included in the analysis. The link between land and nitrate intensities is expected, and an analysis of the *meat products* sector helps to explain this link. The *meat products* sector is a significant source of point-source discharge of nitrates and accounts for approximately 96% of measured point-source nitrate discharges. Furthermore, this sector's total land intensity (ha/$) is second only to that of *mixed livestock*. That is, *meat product* outputs contain significant 'embodied' land. Given that the nitrates measured in this analysis derive from land, Prin4 can be interpreted to represent land intensities, with higher scores meaning higher land intensities.

The fifth principal component, Prin5, accounts for 7% of the total variation. Prin5 is dominated by water inputs[6], making interpretation of this component straightforward. Prin5 can be interpreted as water-input intensity, with higher scores meaning higher water-input intensities.

These five principal components are useful for decision makers. Not only do they summarise 92 x 14 points of data, but also they represent the most important dimensions of eco-efficiency from an explained variance point of view, given the available data (the components explain almost 90% of the variation in all 14 variables). The five principal components also meet *a priori* expectations, in that they summarise the important energy and material flows through the

[6] To both water 'suppliers' and water 'consumers' (see below).

economy that are covered in the analysis. Note, however, that data constraints mean that many environmental media are not covered in this analysis (for example, non-point source emissions). A fruitful area of future research would be to expand the PCA to cover a broader data set.

Aggregate scores for New Zealand

Individual sector scores for each principal component can be calculated by solving the principal component equations (such as Equation 1). The sector scores can be used to calculate overall scores for New Zealand for each principal component for each year[7]. The overall scores are measured in units of Prin*i* per $ of value added and are shown in Table 6 and Figure 1.

Table 6: Overall principal component scores for New Zealand, (Prin*i* /$), 1994/95 vs. 1997/98

	Prin1- Water pollutant intensity	Prin2 - Energy and air emissions	Prin3 - Material intensity	Prin4 - Land intensity	Prin5 - Water input intensity
1994/95	0.432	1.443	-0.200	0.462	-0.027
1997/98	0.467	1.629	-0.230	0.518	-0.034
Change from 1994/95 to 1997/98	8%	13%	-15%	12%	-24%

[7] The process of calculating the overall scores is as follows. First, sectoral scores are multiplied by final demand ($). These are summed and then divided by total New Zealand GDP to get a total score of Prin*i* per unit of value added.

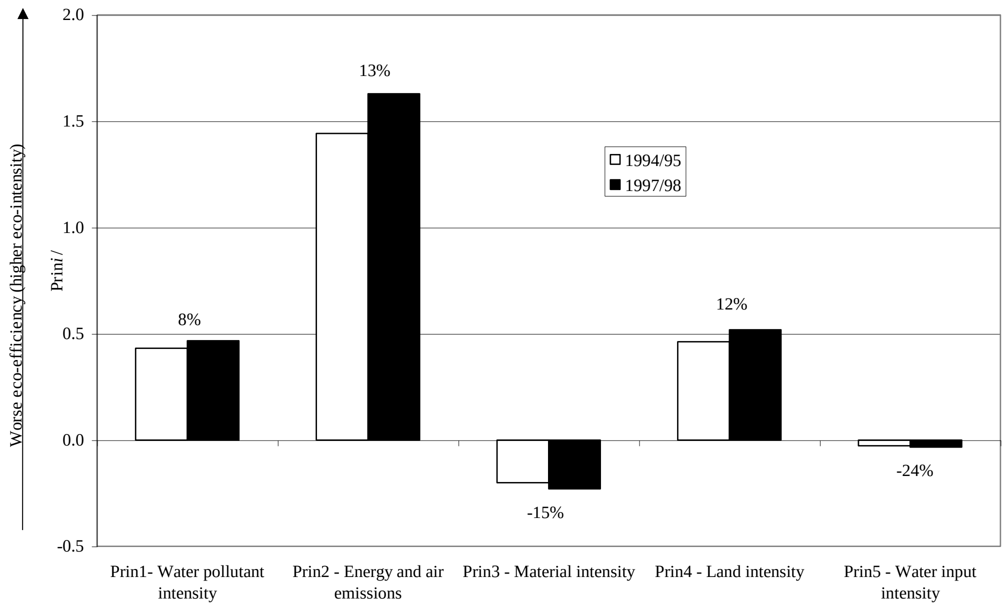

Figure 1: Total principal component scores for New Zealand (and percentage changes), (Prin*i* /$), 1994/95 vs. 1997/98

The overall scores indicate that over the period investigated (1994/95 to 1997/98), New Zealand's overall eco-efficiency improved (i.e. the relative score decreased) for two out of the five principal components (material intensity (Prin3) and water input (Prin5)). Over that period, New Zealand became less material intensive (the score decreased by about 15%) and less water input intensive (by about 24%).

The ability of PCA to provide decision makers with top-level indices over time is an important strength. Not only do these indices aid decision makers by providing a reduced number of indices, these PCA-estimated indices combine more information than any single original variable.

The results from the PCA can also be used to provide insights into the eco-efficiency and relative impacts of individual sectors in the economy. The following sections look at the principal component scores for each sector and also examine each component in more detail.

Sector eco-efficiency scores

Sectors showing poor eco-efficiency in multiple dimensions

PCA can help identify those sectors demonstrating poor eco-efficiency across most or all of the five important dimensions. For example, one sector has relatively high scores[8] across all five principal components (*water works*). This result appears counter intuitive since one would not expect the *water works* sector to have high material intensity. However, prin 3 (material intensity) also has a high coefficient on water discharge (volume). Since this sector processes and filters water for most other sectors, it is reasonable to expect a high score for this sector on water discharge (and therefore a high Prin 3 score). One sector has high scores on four principal components (*other mining,* which has high scores on all components except water input (Prin5)). In addition, four sectors show high scores on three principal components (Prin1, 2 and 4) simultaneously (*other farming, dairy farming, meat products* and *dairy products)*. The component scores for these sectors are shown in Figure 2.

[8] Defined in this instance as being 'greater than one.'

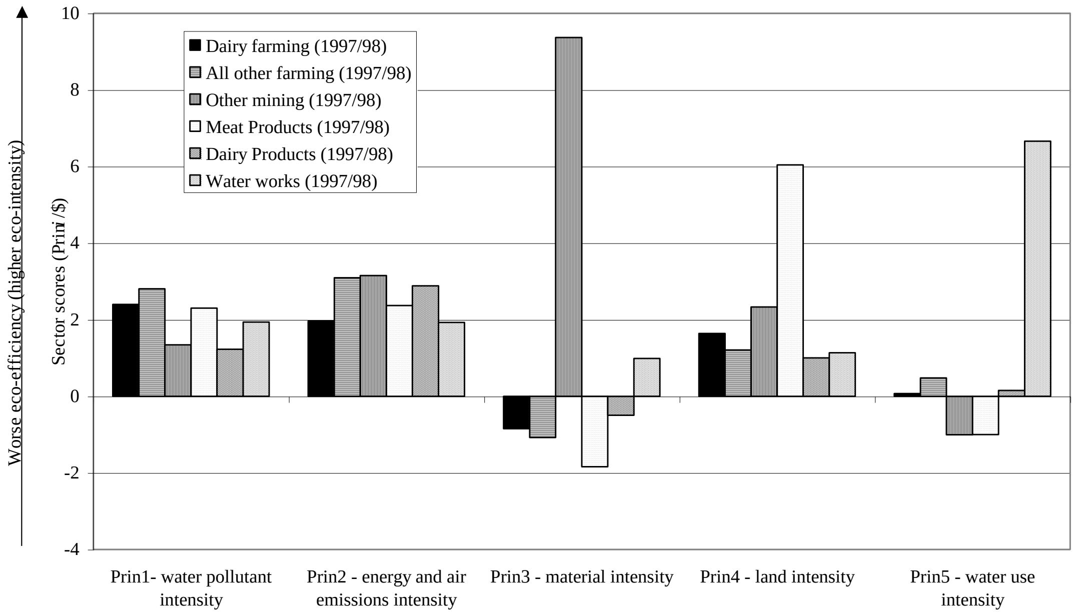

Figure 2: Diagram showing sectors with high scores[9] on three or more principal components

The high scores on these sectors indicate relatively 'poor' performance on an ecosystem service/dollar perspective. This analysis is useful, because it helps to identify those sectors that are relatively eco-intensive on several fronts. Consequently, these sectors may require broader policy attention than just a focus on one of the dimensions, as is the trend in New Zealand. (For example, the Energy Efficiency and Conservation Authority in New Zealand just focus on

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[9] Adjusted to remove the zero-mean standardisation.

energy efficiency, whereas for the sectors mentioned in this section, the focus needs to be broadened to overall eco-efficiency.)

Further insights into New Zealand's eco-efficiency are possible from an analysis of each principal component in turn.

Prin1 – water-pollutant intensity

Prin1 by definition explains the greatest amount of variation in the eco-efficiency indicator data of all the principal components. It is interesting to note that the pollution of New Zealand's freshwater resources is an issue of concern to New Zealanders (Ministry for the Environment 2001), giving this principal component added interest.

The overall score for Prin1 increased slightly (by 8%) over the analysis period, suggesting that New Zealand as a whole is increasing the amount of water pollution discharged per dollar of output (see Table 6 and Figure 1). This result is consistent with findings in New Zealand's State of the Environment report (Ministry for the Environment, 1997) that documents the increasing pressure on New Zealand's water ways over this period.

The *personal services* sector has the highest score on Prin1[10]. This sector is plotted against other relatively high Prin1 sector scores for 1997/98 in Figure 3.

The Prin1 scores for the *personal services* sector declined by 8% between 1994/95 to 1997/98, probably as a result of standard management practice to continually improve plant efficiency through capital replacement.

[10] The reason for this is the inclusion in the *personal services* sector of the 'sewerage and urban drainage' (NZSIC 92012) sector.

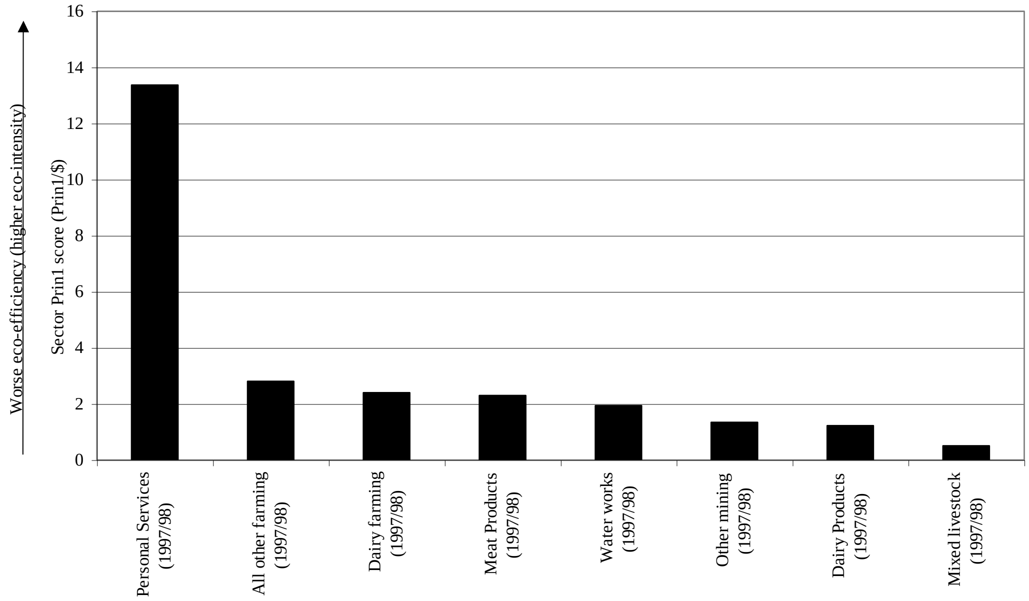

Figure 3: Sector scores on Prin1 (water pollutant intensity) for the most water-pollutant intensive sectors in New Zealand (1997/98)

Other sectors warranting attention from a Prin1 (water pollutant) perspective are *all other farming*, *dairy farming*, *meat products*, *water works*, and *other mining* (Figure 3). Prin1 scores for these sectors tended to increase, in line with trends in the underlying variables. Of particular note is the more than doubling of the *all other farming* sector's score. This shows a similar trend to this sector's original water-pollutant indicators, and because of the way the eco-efficiency indicators are calculated, this increase reflects the increased water pollutant intensities in those sectors with strong links to the *all other farming* sector: *basic chemicals* and *trade*.

This analysis is useful for policy and monitoring purposes in New Zealand. It suggests that monitoring of Prin1 (water pollutants) should focus on several sectors: *personal services*, *all other farming* (and associated sectors), *dairy farming*, *meat products*, *water works* and *other mining*.

Prin2 – energy and energy-related air emission intensity

Energy use and energy-related air emissions (CO_2, NH_4 and NO_2) are the focus of considerable policy attention at present. The presence of Prin2 in this analysis means that PCA can be used to add further weight to claims that this policy attention is well directed.

Those sectors scoring the highest on Prin2 are the usual energy-intensive suspects: *road transport*, *basic metal industries* and *paper manufacturing*. A plot of the scores for these sectors and other relatively high 'Prin2' scoring sectors is shown in Figure 4.

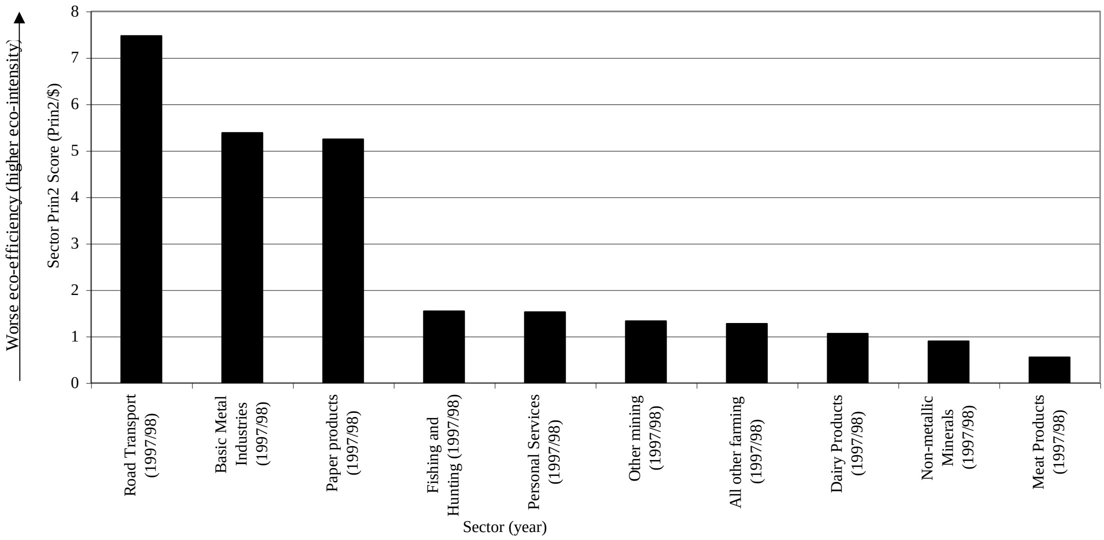

Figure 4: Highest sector scores on Prin2 – energy and energy-related air emission intensity (1997/98)

The total Prin2 score from 1994/95 to 1997/98 increased by 13%. Changes in the scores of the energy-intensive sectors (see Figure 4) over the analysis period followed a similar trend to that identified by an analysis carried out by New Zealand's Energy Efficiency and Conservation Authority (EECA) (2000).

It is encouraging to see that EECA, the agency responsible for monitoring energy efficiency in New Zealand, is focusing on these energy-intensive sectors (see for example Energy Efficiency and Conservation Authority 1995).

Prin3 – material intensity

This PCA has helped to highlight the important role of mineral inputs in the New Zealand economy. Specifically, there are important links between the *other mining* sector and *non-metallic minerals* and *basic metal industries*.

The *other mining*, *waterworks*[11] and *non-metallic minerals* sectors had the highest Prin3 scores. A plot of the score for these sectors and other relatively high Prin3 scoring sectors is shown in Figure 5.

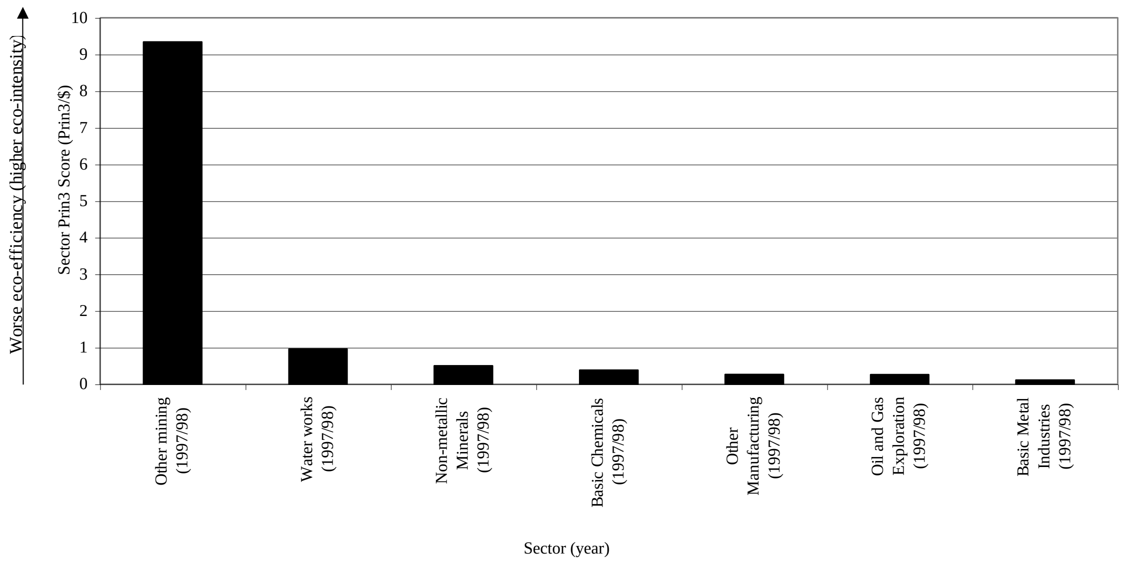

Figure 5: Highest sector scores on Prin3 – material intensity (1997/98)

Changes in these sectors' scores between 1994/95 and 1997/98 confirm findings in other analyses (Jollands 2003). Prin3 is highly participated by water discharged indicators, so it is not

[11] Because of the high water discharge component of this sector.

surprising to find that *waterworks* scores relatively highly on Prin3. The *waterworks* sector showed a decline in its Prin3 score (of around 20%). This follows a trend in the underlying indicators: water-discharge indicators declined by around 42 percent over the period.

Prin4 – land intensity

Land input is essential for all economic sectors. Furthermore, Prin4 is highly participated by nitrate pollutant. Nitrate pollution in waterways is of concern because nitrate is a significant source of eutrophication (McDonald & Patterson 1999).

The sectors with the three highest Prin4 scores are the *meat products*, *mixed livestock* and *other mining* sectors.

These sectors had increased Prin4 scores over the period, except *meat products*. The Prin4 score for the *meat products* sector decreased by 6%. This decrease follows a decrease in nitrate indicator of 4% and an increase in land intensity of 4%. The Prin4 score for the *mixed livestock* sector increased over the period, suggesting that this sector is becoming more land and nitrate-pollutant intensive. Data produced by Statistics New Zealand confirms that land intensity has increased for the mixed livestock sector (Statistics New Zealand 2004).

A useful feature of this PCA is its ability to highlight sectors warranting policy intervention. An analysis of sector scores suggests the two sectors warranting policy and monitoring attention are the *mixed livestock* and *meat products* sectors. These sectors are the most land and nitrate intensive, and the *meat products* sector in particular contributes a significant proportion of point-source nitrate pollutants.

Prin5 – water input intensity

This component is dominated by water inputs. Water is an essential ecosystem good and is required as an input (directly and indirectly) in all economics sectors. The highest scores on Prin5 were for the *other mining* and *meat products* sectors.

The high water input intensity of the *other mining* sector is primarily due to the titanomagnetite mining operation at Waikato Heads. Water is used to assist the transport of about 82kt of ore per week via an 18km pipeline to a steel mill. The *meat products* sector also has one of the highest water input intensities. Water is used in this sector primarily in cleaning and rendering. Scores on these sectors show that the *other mining* sector's Prin5 score increased (by 16%) while its water-input intensity increased by 18%. In contrast, the *meat products* sector's Prin5 score decreased.

Conclusion

Eco-efficiency has emerged as a management response to waste issues associated with current production processes. Eco-efficiency can be understood in terms of concept, or a ratio of useful output to environmental inputs. Despite the popularity of the term in both business and government circles, limited attention has been paid to measuring and reporting eco-efficiency to government policy makers. In particular, there is a need for aggregate measures of eco-efficiency to complement existing measures and help to highlight important patterns in eco-efficiency data.

This study investigated eco-efficiency through principal components analysis (PCA), a statistical technique that has shown promise but has had little attention for analysing eco-efficiency indicators. Conducting PCA on an eco-efficiency indicator matrix of two-years data over the 46 sectors in New Zealand revealed several strengths of the technique. First, PCA identified five important dimensions of the eco-efficiency data from an explained variance point of view: water pollutant, energy and energy-related air emissions, materials, land, and water input intensities. In doing so, PCA is able to reduce redundancy in the eco-efficiency indicator profile while providing results that are consistent with the findings of the more detailed matrix.

Second, PCA can provide the much sought-after 'aggregate' scores for each dimension (principal component). These scores supply condensed information for decision makers and provide an overall assessment of New Zealand's eco-efficiency trends.

Third, PCA helps to identify those sectors that are relatively 'eco-intensive' in several dimensions – thus providing a focus for policy and monitoring attention. These results are consistent with findings by other analyses conducted by the Ministry for the Environment, the Energy Efficiency and Conservation authority and Statistics New Zealand. In particular, the PCA conducted here identified several sectors as meriting special attention. These are listed in Table 7. One of the advantages of the PCA approach is that it can identify these sectors in a more 'parsimonious' manner.

Table 7: Sectors that merit special eco-efficiency policy focus in New Zealand by virtue of their relatively high principal component scores

	Focus sector	Change in sector score from 1994/95 to 1997/98
All Principal components (Prin1-5)	Waterworks	
Across 4 Principal components (Prin1,2,3,4)	Other mining	
Across 3 Principal components (Prin1,2,4)	Other farming	
	Dairy farming	
	Meat products	
	Dairy products	
Prin1 – water pollutants intensity	Personal services	Decrease
	Other farming	Increase
	Meat products	Decrease
	Other mining	Increase
	Waterworks	Increase
Prin2 – energy and energy-related air emissions intensity	Road transport	Increase
	Basic metals	Decrease
	Paper products	Decrease
Prin3 – material intensity	Other mining	Increase
	Waterworks	Decrease
	Non-metallic minerals	Increase
Prin4 – land intensity	Meat products	Decrease
	Mixed livestock	Increase
	Other mining	Increase
Prin5 – water use intensity	Other mining	Increase
	Meat products	Decrease

The PCA approach used in this study can provide aggregate indices for eco-efficiency. However, it is important to remember that PCA is essentially a tool for ex post analysis. It is not an appropriate tool for ex ante analysis. Nevertheless, this type of analysis warrants further investigation as a legitimate aggregation approach.

In conclusion, it is useful to draw on the pertinent message from Costanza (2000, p.342). "Even given [the] advantage of aggregate indicators, no single one can possibly answer all questions and multiple indicators will always be needed … as will intelligent and informed use of the ones we have". This conclusion goes without saying. Thus, aggregate indices provide a necessary but not completely sufficient, contribution to the debate of eco-efficiency issues, as well as the policy responses to those issues.

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