The usefulness of aggregate indicators in policy making and evaluation: a discussion with application to eco-efficiency indicators in New Zealand

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

Abstract

Aggregate indices can assist decision-making by summarising a complex array of information. However, little research has been conducted on aggregate environmental indicators. The purpose of this paper is to address the debate surrounding aggregate environmental indices. In doing so, the paper highlights the strengths and weaknesses of aggregate indices for use in decision-making. We conclude that aggregate indices do have a role in assisting decision makers, as long as they are not used in isolation from more detailed information.

The paper addresses several methodological issues that must be addressed when calculating aggregate indicators including selection of appropriate aggregation functions, weighting, and selecting variables for inclusion in the aggregation function. The methodological issues are applied to a case study of New Zealand data. Specifically, we apply principal components analysis (PCA) to eco-efficiency indicators. This case study reveals that PCA is an effective approach to aggregating eco-efficiency indicators. In doing so, we have identified an aggregation technique that is appropriate for increasing-scale indicators and can assist decision makers by reducing redundancy in the indicators matrix, while providing results that are consistent with the more detailed information.

Keywords: Policy development; policy evaluation; Aggregate indices; Principal components analysis; Eco-efficiency

Introduction

The ultimate aim of the *Economics and Environment Network* is to promote research, learning and better environmental policy. An important part of developing quality environmental policy is ensuring adequate attention is paid to providing accurate information to policy makers to assist their decision making. In this vein, indicators have become a popular decision support tool for environmental policy (United Nations 1995; Organisation for Economic Co-operation and Development 1998). However, the recent flurry of indicator-related activity has led some to argue that there is a danger of information overload. These authors argue that one way to assist policy-makers is to develop aggregate indices that summarise the information contained in the many environmental indicators. To date, little work has been done on developing aggregate environmental indicators. Hence, many authors (for example Alfsen and Saebo 1993; Walz, Block et al. 1996; Luxem and Bryld 1997; Heycox 1999; Opschoor 2000) suggest further research into indicators should focus on the development of highly aggregated indicators of the "environmental pressure that is associated with... the global material consumption of a national economy" (Billharz and Moldan 1997, p. 389).

Others are not so sanguine about the appropriateness of aggregate indicators (Bradbury 1996). The purpose of this paper is to address the debate surrounding aggregate environmental indices. In doing so, the paper highlights the strengths and weaknesses of aggregate indices. It then presents a framework to guide the development of aggregate indices. This framework provides an insight into several methodological issues that must be addressed when calculating aggregate indices. The paper applies this framework to eco-efficiency indicators in New Zealand using Principal Components Analysis (PCA). The analysis reveals that PCA effectively summarises and, therefore, reduces the redundancy in the matrix of eco-efficiency indicators.

Why aggregate indices?

It is often argued that those making decisions about environmental policy have specific requirements of indicators. Boisevert, Holec and Vivien (1998, pp. 106-7) summarise the nature of the demand for indicator information from decision makers as follows:

- 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 precise account of a situation.
- In the context of sustainable development, decision-makers are interested in the economy-environment interface. Indicators should therefore, concentrate on the interaction, rather than on just the environment itself.

Often, constructing environmental indicators that are useful for decision-makers cannot rely on scientific data as it stands. Rather, the challenge is to transform the data to produce condensed, or aggregate, information for decision makers. An alternative to a matrix of environmental indicators is some grand aggregate index[1] or indices. A grand index may be easier for decision-makers to use because it summarises important information in one or a few numbers.

The general preference for scalars (aggregate indices) or matrices (indicator 'profiles') is a controversial and long-standing methodological problem associated with the use of indicators. Essentially the debate centres on the amount of information that is lost in the simplification made possible by the index.

In an indicators matrix, the observer's eye scans the individual indicators and is implicitly asked to aggregate the indicators to form an overall impression of the issue of interest. Because the mathematical aggregation of different variables to form a single number does not occur, proponents of profiles see them as giving "less chance for misinterpretation or misunderstanding than aggregated indices" (Ott 1978, p. 26). People who are familiar with the complexities of monitoring environment-economy interactions generally prefer profiles and view the potential distortion occurring in an index as unacceptable.

[1] In this paper, the terms 'index' and 'indices' are used to refer to the aggregated indicators. The terms 'indicator' and 'subindex' are used as synonyms.

In contrast, when calculating an index, the aggregation process is carried out using a mathematical equation and not necessarily by the observer. This aggregation necessarily simplifies the information presented in the matrix of indicators. People who are removed from the measurement process have a greater willingness to accept the simplification, and potential distortion of information for the sake of obtaining an easy-to-understand, sometimes crude, picture of the environment.

Ecological economists have shown considerable interest in developing aggregate indices. This interest is demonstrated by the attention given to many aggregates including the:

- Index Of Sustainable Economic Welfare (ISEW) and the Genuine Progress Indicator (GPI) (see for example Daly and Cobb 1994; Stockhammer, Hochreiter et al. 1997; Hamilton 1999; Neumayer 2000);
- Ecological footprint (See articles in volume 32 (3) of Ecological Economics);
- Sustainable net benefit index (Lawn and Sanders 1999);
- Human development index (Neumayer 2001);
- Net national product (Adger and Grohs 1994);
- Pollution index (Khanna 2000);
- Unified global warming index (Fearnside 2002);
- Sustainable national income index (Gerlagh, Dellink et al. 2002);
- Index of Captured Ecosystem Value (Gustavson, Longeran et al. 2002).

However, within ecological economics, and beyond, there is ongoing debate on the appropriateness of aggregating indicators.

Strengths of aggregate indices

Proponents of indices argue that there are several necessary reasons for aggregation. The obvious benefit of an aggregate index is its production of a single or a few numbers. This makes using indices for decision making relatively straightforward. Aggregate indices assist decision-makers by reducing the clutter of too much information, thereby helping to communicate information succinctly and efficiently (Alfsen and Saebo 1993; Williams 1994; van den Bergh 1996; Callens and Tyteca 1999; Gustavson, Longeran et al. 1999; Heycox 1999). As Meadows (1998, p. 22) states "aggregation is necessary to keep from overwhelming the system at the higher levels of the hierarchy." Heycox (1999, p. 191) reflects this and states that "a complex, information-rich world requires frameworks that organise data to reveal succinct views and interrelationships."

An aggregation function formalises what is often done implicitly. Ultimately, when making a decision, the decision maker must go through a process of condensing information to make simple comparisons. Proponents of aggregate indices argue that it is better to make this process explicit through an aggregation function than relying on the implicit aggregation that inevitably happens using an indicator profile.

Weaknesses of aggregate indices

Critics of aggregate indices cite equally persuasive arguments. They argue that aggregate indices can lead to incorrect conclusions about policy performance. Development of the aggregation equation almost always requires more assumptions and arbitrary decisions than the design of a profile. Thus, aggregate indices are frequently criticised by scientists familiar with the data, who feel that the assumptions can lead to a loss of information (Meadows 1998, p. 22) and introduce serious distortions (Lindsey, Wittman et al. 1997). Critics caution that the distortions can lead the observer to misinterpret the data. As Meadows (1998, p. 4) states "if too many things are lumped together, their combined message may be indecipherable." However, it is important to note that "it is not that more detailed information is lost – usually it is possible to look at the details of how any aggregate indicator has been constructed – but rather that decision-makers are too busy to deal with these details" (Costanza 2000, p. 342).

If users are not careful and informed about their use of aggregate indices, they can be ignorant of the source of the numbers, how the numbers were aggregated, and the uncertainties, weights, and assumptions involved, etc. This again can lead to spurious conclusions.

One of the major limitations of aggregate indices is the manner in which the constituent variables to be included in the index are determined (Lohani and Todino 1984). Generally, the parameters are chosen on the basis of expert opinion. Critics argue that there is no single satisfactory method of selecting parameters. Therefore, an index is always in danger of missing important parameters. However, it is generally not feasible or practical to monitor the hundreds of potential environmental variables.

Another problem with aggregate indices is that it is difficult for them to capture the interrelationships between individual variables (Lohani and Todino 1984). Gustafsson (1998, p. 259) warns against reductionistic views, encouraged by aggregate indices. Physical processes that occur in the economy-environment interactions are so complex and interdependent. And, often a stress on one part of the system affects other system elements as well. It is unrealistic to expect aggregate indices or a single index to capture this complexity.

In reality, the two views regarding aggregate indices are not as black and white as may appear. In fact, they are necessarily complementary. A high level of indicator aggregation is necessary in order to increase the awareness of economy-environment interaction problems. But, even given the advantages of aggregate indices, no single index can possibly answer all questions. Multiple indicators will always be needed, as will intelligent and informed use of the ones we have (Costanza 2000). Nevertheless, it can be argued that aggregate indices do have a role in assisting policy development and evaluation.

Methodological considerations for aggregating environmental indicators

Given that aggregate indices have a role in informing policy makers, the question remains, what can be done to ensure that high quality aggregate indices are produced?

The aggregation process

A significant gap in theory relating to aggregate indices is the lack of a framework to guide aggregation. A generic framework is shown below (see Figure 1). This framework can be applied to the estimation of aggregate environmental indices. Several of the steps are outlined in more detail below.

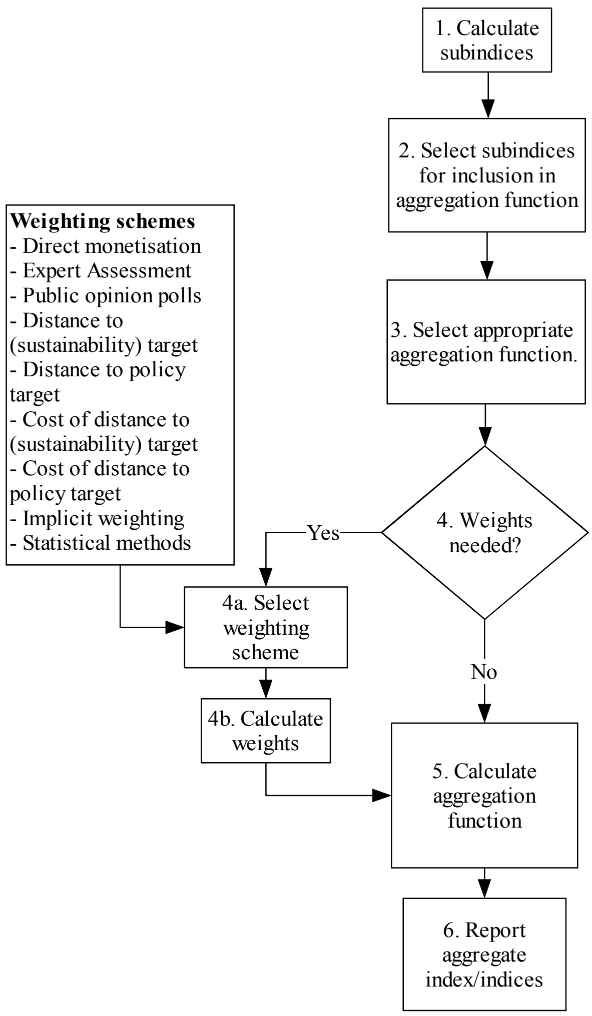

Figure 1: A generic process for calculating aggregate indices

Selection subindices for inclusion in aggregation

After the subindices are calculated, the second step is to select variables for inclusion in the aggregation function.

The selection of the variables for inclusion in aggregation is a contentious issue and must be approached with some caution (Lohani and Todino 1984). Several considerations dictate the variable selection. First, the range of the subindices should provide a cross-sectional representation of the principal factors of interest. In the context of environmental indicators this suggests a need for a representative coverage of ecosystem services for which data are available (Yu, Quinn et al. 1998).

Second, the problem of 'multicolinearity' should be addressed by eliminating those variables that are correlated (Yu, Quinn et al. 1998). A standard test for this is the correlation coefficient. For example, variables that are highly correlated with one another can be considered substitutes. By including only one subindex from a highly correlated set and excluding the others, one not only accounts for the trend in the variables, but also achieves parsimony in the data matrix.

Finally, and perhaps most importantly, there is a need to balance the need for data parsimony with relevance to purpose. For example, often there is policy interest in both energy and CO_2 emissions. Obviously, these are correlated. However, if decision makers require an aggregate that reports both CO_2 and energy, the analyst (often implicitly) considers the balance between policy relevance and statistical integrity.

Selection of appropriate aggregation function

There is considerable debate over the most appropriate method for aggregating subindices. Aggregation functions usually consist either of a (Ott 1978, p. 50):

- summation operation, in which individual indicators (or subindices) are added together
- multiplication operation, in which a product is formed of some or all of the subindices, or

- maximum or minimum[2] operation, in which just the maximum subindex or minimum subindex respectively is reported.

Several aspects must be considered when choosing the most appropriate aggregation function. First, the functional form of subindex is important. Subindices can be either of an increasing or decreasing-scale form. In increasing-scale subindices higher values are regarded as a ‘worse’ state than lower values. In decreasing-scale subindices, higher values are associated with ‘better’ states than lower values.

The second aspect to consider when selecting the most appropriate aggregation function is the strengths and weaknesses of the aggregation function itself. Ott (1978) identifies two potential problems with aggregation functions:

- an overestimation problem, where the aggregate index *I*, exceeds a critical level, say 100, without any subindex exceeding that critical level.
- an underestimation problem, where an index *I* does not exceed a critical level, say 100, despite one or more of its subindices exceeding that critical level.

These two problems are particularly an issue with dichotomous subindices (where subindices take on just two values - such as acceptable or not acceptable). The most appropriate aggregation function will minimise one or both of the overestimation and underestimation problems.

Another aspect to consider when selecting the most appropriate aggregation function is the parsimony principle. That is, when competing aggregation functions produce similar results with respect to overestimation and underestimation, the most appropriate function will be that which is the ‘simplest’ mathematically. In other words, simple mathematical functions are preferred over complex functions.

[2] Algebraically shown as $I=\max\{\varepsilon_1, \varepsilon_2, \ldots \varepsilon_i,\ldots \varepsilon_n\}$ or $I=\min\{\varepsilon_1, \varepsilon_2, \ldots \varepsilon_i,\ldots \varepsilon_n\}$ respectively

Finally, an aggregation approach is successful if all assumptions and sources of data are clearly identified, the methodology is transparent and publicly reported, and the index can readily be disaggregated to the separate components and no information is lost (Hammond, Adriaanse et al. 1995).

The challenge of setting the weights

A significant challenge with most aggregation functions is how to select the appropriate weights needed for commensuration. A number of methods can help to establish weights. Jesinghaus (1997, p. 84) suggests eight alternative weighting schemes for valuing environmental pressure: direct monetisation, expert assessment and impact equivalents, public opinion polls, distance to (sustainability) target, distance to (policy) target, cost of distance to sustainability target, cost of distance to policy target and implicit weighting.

Statistical methods are a ninth category that can be added to Jesinghaus's list of weighting schemes. Statistical methods offer an alternative to more 'subjective' systems of setting weights. Statistics provides a multivariate technique, principal components analysis[3] (PCA) that is useful for setting weights in the context of multi-dimensional environmental data.

There is still considerable debate among experts about which weighting system to use. While each approach has merits, one advantage of PCA over many others is its relative 'objectivity'. Unfortunately, PCA has received little attention to date in indicator aggregation literature in general and eco-efficiency literature specifically. Possible reasons for this include a lack of statistical skills among the indicators fraternity and/or a lack of linking of PCA with the need for aggregate indices.

[3] Other 'interdependence'-type multivariate techniques appropriate for metric variables are factor analysis and cluster analysis. These are not appropriate for use in the context of setting weights. For a detailed discussion of these techniques, refer to Sharma (1996).

Application: calculating aggregate eco-efficiency indices for New Zealand using principal components analysis

The following section applies the methodological insights identified above to an area of interest in New Zealand; eco-efficiency. Specifically we use PCA to calculate aggregate eco-efficiency indices.

Step 1 of the generic aggregation process (Figure 1) has already been covered in previous work[4]. The next step is to select variables for inclusion in the aggregation function for calculating eco-efficiency indices. The set of variables used for this analysis are shown in the table below:

Table 1: Final variables used in principal components analysis[5]

[4] Specifically, eco-efficiency intensities were calculated for New Zealand for 1994/95 and 1997/98 following the method outlined by Hite, J. and E. A. Laurent (1971). "Empirical Study of Economic-Ecologic Linkages in a Coastal Area." Water Resources Research **7**(5): 1070-1078.

The method provided indicators estimated across 46 sectors of the New Zealand economy. For each sector, three groups of intensities were estimated for each year covering direct, indirect and total system-wide requirements. Within each group, several ecosystem services were measured; water inputs, minerals, energy, water discharges, water and air pollutants.

[5] Note that total water inputs, water discharges and water pollutants refer to point source quantities only.

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/$[6]
Minerals	ε_4	Tonne/$
Water discharge	ε_5	m^3/$ (sum of discharge to land and water)
Water pollutant – Total ammonia[7]	ε_6	m^3/$ (sum of discharge to land and water)
Water pollutant – Total BOD_5	ε_7	m^3/$ (sum of discharge to land and water)
Water pollutant – Total 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 TKN	ε_{10}	m^3/$ (sum of discharge to land and water)
Water pollutant – Total TPD	ε_{11}	m^3/$ (sum of discharge to land and water)
CO_2 emissions (energy related)	ε_{12}	Tonne/$
CH_4 emissions (energy related)	ε_{13}	Tonne/$
NO_2 emissions (energy related)	ε_{14}	Tonne/$

For each of these 14 variables, there were 92 observations. This exceeds the 3 to 1 ratio, which could be regarded as a rule-of-thumb for the minimum requirement in PCA to provide a stable solution (Grossman, Nickerson et al. 1991; Yu, Quinn et al. 1998).

Table 2 summarises the mean value and standard deviation of the 14 variables used in this PCA. The covariance matrix of the 14 variables was calculated from standardised data and, therefore, coincides with the correlation matrix (also shown in

[6] Energy total adjusted for energy quality (see Patterson, M. G. (1993). "Approaches to Energy Quality in Energy Analysis." International Journal of Global Energy Issues, Special Issue on Energy analysis **5**(1): 19-28.

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[7] Note that water pollutants measure only point source discharges. Also note that, while it appears the data set is weighted in favour of water pollutants, this is not necessarily the case. All water pollutants were retained for 3 reasons:

- The water pollutants are different in their impact on the environment, and together they add to the picture of environmental impact of economic activity
- Water pollution issues are currently high on the public agenda in New Zealand
- There is no accurate way of aggregating these pollutants into a single figure.

Table 2 below). Some clear eco-efficiency relationships can readily be inferred: high and positive correlation (underlined values) can be observed 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 2: Mean, standard deviation and correlation matrix of eco-efficiency subindices 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 TPD	CO_2	CH_4	NO_2
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
Observations	92	92	92	92	92	92	92	92	92	92	92	92	92	92
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.

Following Figure 1, the next step is the selection of an appropriate aggregation function. It can be shown that the linear-weighted sum aggregation function is most suited to increasing-scale eco-efficiency indicators (see Jollands 2003). This is because:

- the (unweighted) linear sum is not appropriate for aggregating indicators measured in different units (i.e. the variables are incommensurable)
- although the weighted linear sum does incur an underestimation region, it is less than that incurred by the weighted product aggregation function
- the weighted product function is less parsimonious than the weighted sum
- the maximum operator aggregation function is not sensitive to fine gradations of eco-efficiency.

One approach to setting weights in linear weighted-sum aggregation functions is through the use of PCA (see Appendix 1 for a brief description). Specifically, PCA can provide a rigorous alternative weighting scheme for aggregating eco-efficiency indicators for situations where:

- the analyst wishes for a less 'subjective' weighting scheme than others mentioned above
- comparative static observations are acceptable or useful
- the original variables are increasing scale and highly correlated
- there are sufficient observations to provide a stable solution
- many aspects of the environment are considered at once and there is limited or no information on relative environmental criteria.

Calculation of the aggregation function for eco-efficiency in New Zealand using principal components analysis

PCA was used to estimate aggregate eco-efficiency indices for New Zealand. These indices significantly reduce the redundancy in the 262 by 46 eco-efficiency intensities matrix estimated in previous analyses (Jollands 2003). The PCA was performed using the PRINCOMP procedure of the SAS system (SAS Institute 1985). An important point to note is that the PRINCOMP procedure used here standardises data to zero mean and unit variance. Standardisation of the data is important in this study given that the variables display widely different means and relatively large standard deviations (see

Table 2 above). The eigenvalues and eigenvectors of the correlation matrix are given in Table 3 and Table 4, respectively.

Table 3: 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 4: 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 the eigenvalues suggests retaining four PCs. On the other hand, the Jollife-amended Kaiser eigenvalue criterion suggests retaining five PCs. Similarly, examining the proportion of variance accounted for by the principal components also suggests retaining five PCs (which account for around 87% of the variation).

On balance, the first five principal components were selected, and account for 87.5% of the total variation (Table 3). Before a discussion of the principal components in more detail, it is important to note that the order in which the principal components are listed reflects the order in which are they are derived from the PCA. It does not necessarily reflect their relative importance in characterising eco-efficiency.

The five principal components described

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

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

Equation 1

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

Table 4 and the equation above show that Prin1 has high positive coefficients (weights) on ammonia water pollution (0.400), BOD_5 (0.405), DRP (0.442), TKN (0.443) and TPD (0.389). That is, on all water pollutant multipliers except nitrates[8]. 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

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

concern to New Zealanders is also the pollution of New Zealand's freshwater resources (Ministry for the Environment 2001).

The second principal component, Prin2, accounts for a further 24.25% of the total variation in the data, and is highly participated by energy (0.519) and air emission multipliers (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% (Table 3) of total variation. Compared to the first two PCs, the interpretation of Prin3 is less intuitive. It has large positive coefficient loadings 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. It is the dominance of the *other mining* (which includes iron sand mining) sector's water discharge intensity that helps to explain the prominence of water discharge in Prin3. Given that it is the mineral inputs that 'drive' this principal component, this component could be interpreted as 'material intensity,' with higher scores indicating greater mineral-input and water discharged intensities. An interesting characteristic of this 'material intensity' component is the dominance of negative coefficients on 11 out of the 14 variables. These negative factors are likely to have a dampening effect on this component's scores.

The fourth principal component 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). 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 is second only to *mixed livestock*. That is, the products of the *meat products* sector contain a large degree of '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 accounts for 7% of the total variation. Prin5 is dominated by water inputs[9] making the 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. They summarise 46 x 14 points of data. They also represent the most important dimensions of eco-efficiency from an explained variance point of view given 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 many of the important energy and material flows through the economy.

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)[10]. Using the sectoral scores it is possible to calculate overall scores for New Zealand for each principal component for each year[11]. The overall scores are measured in units of Prin*i* per $ of value added and are shown in Table 5 and Figure 3.

How to interpret the scores

These scores (and particularly the negative scores) may at first appear counterintuitive. However, they are a result of the form of the principal component function (often with negative coefficients)[12]. The scores (both negative and positive) show relative magnitude, in

[9] To both water 'suppliers' and water 'consumers' (see below).
[10] Note that SAS, by default, undertakes PCA using data that is standardised for unit variance and zero mean. While this is necessary for the PCA, it can make interpretation of PCA scores problematical. This is particularly the case with the zero-mean adjustment, which prevents calculation of percentage change in PCA scores and can lead to counterintuitive high negative scores. Consequently, the scores reported below have been adjusted to remove the zero-mean standardisation.
[11] 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.
[12] Remember that a condition imposed by PCA is that the squares of the components of each eigenvector (i.e. the weights) sum to one, so the sign is arbitrary.

terms of Prin*i*/$ at a point in time on the rational-number[13] scale. The higher the score, the higher the magnitude of the Prin*i*/$ for the sector or the economy.

An illustration helps to clarify how these scores are interpreted. Consider the *mixed livestock* sector. Figure 2 shows this sector's scorers for the five principal components in 1994/95 and 1997/98.

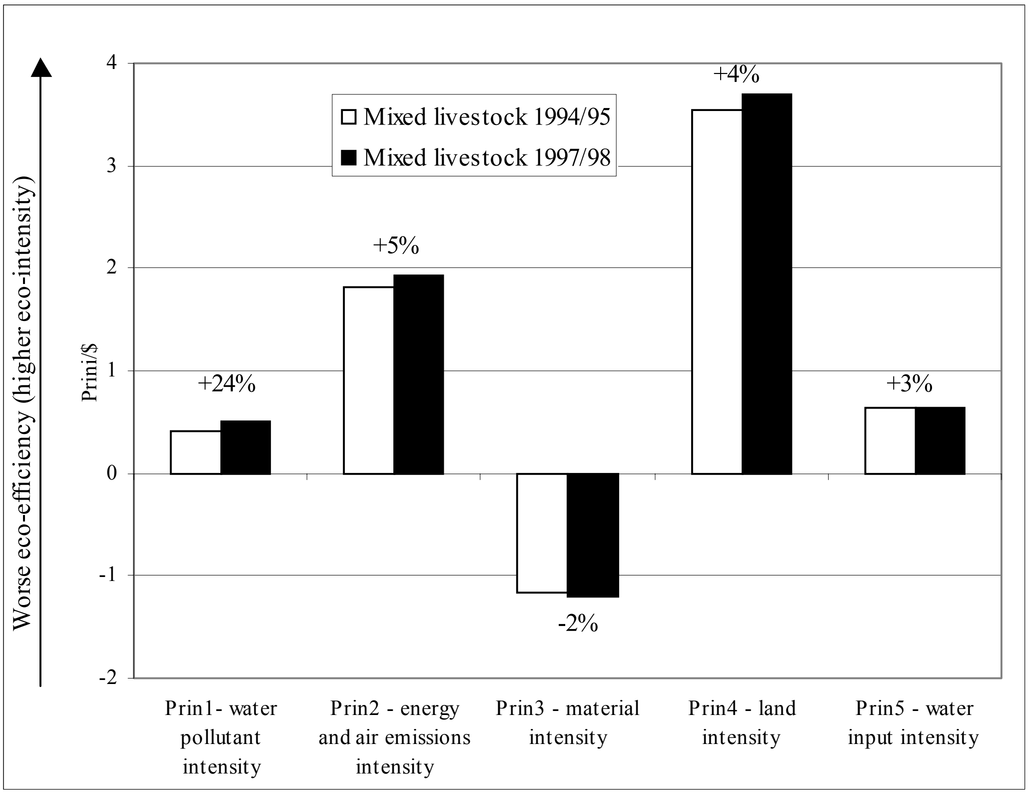

Figure 2: An illustration of how to interpret the principal component scores (and percentage changes) using the *mixed livestock* sector

Figure 2 shows that the scores for the *mixed livestock* sector changed slightly over the period. From Figure 2 it can be seen that the sector's intensities increased for all principal components except material intensity. For example, land and water-input intensities increased by 4% and 3% respectively. In contrast, the sector became less material intensive (the relative score decreased by 2%). Note that the negative score on Prin3 does not imply the sector uses a negative amount of material input for dollar of output.

[13] From negative infinity to positive infinity.

Note also that no conclusions can be made about the relative magnitude of the different principal components. This is because each principal component (by definition) measures a different aspect of the sector's ecosystem service intensity. As such, each principal component is measured in different, incommensurable units.

Scores for New Zealand

The same reasoning can be used for understanding the economy-wide scores in Table 5 and Figure 3.

Table 5: 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%

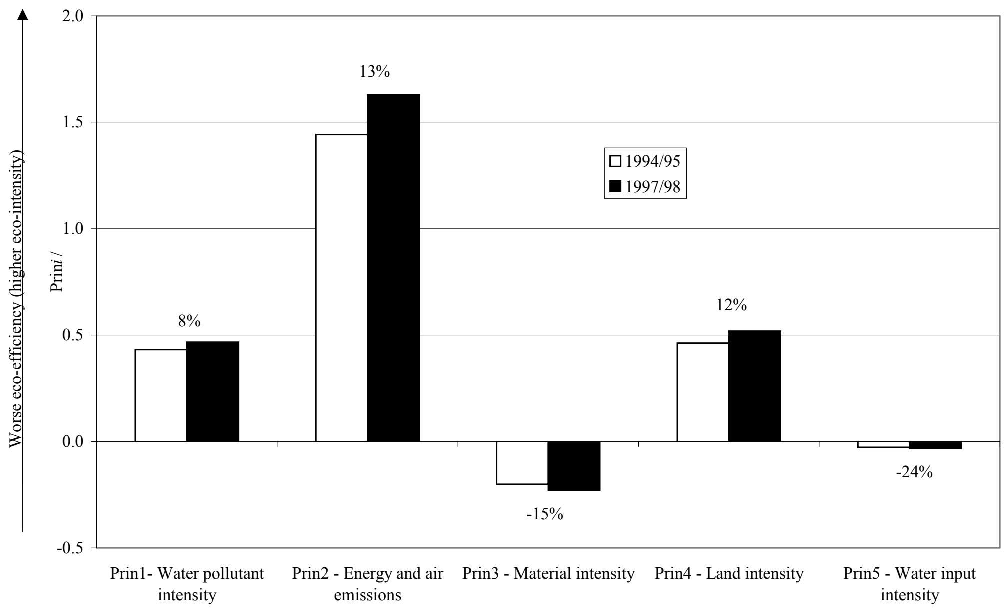

Figure 3: Graph of total principal component scores for New Zealand (and percentage changes), (Prin*i* /$), 1994/95 vs. 1997/98

These scores indicate that New Zealand's overall eco-efficiency improved (i.e. decreased relative score) for two out of the five principal components: material intensity (Prin3) and water input (Prin5). Over the period, New Zealand became less material intensive (the score decreased by about 15%) and less water input intensive (by about 24%)[14].

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.

[14] Noted that while this PCA has reduced the number of variables to five principal components, it fails to provide the much-sought-after single overall index (whether this is a wise pursuit is another matter). If a single index was considered useful, it could be calculated by multiplying the percentage change in each principal component by some 'importance' or 'impact' weighting. One way to determine these weights could be through a survey of expert opinion.

Sector eco-efficiency scores

Sectors showing poor eco-efficiency in multiple dimensions

PCA can also help identify those sectors that demonstrate poor eco-efficiency across all five important dimensions. An examination of the principal component scores reveals one sector as having relatively high scores[15] across all five principal components (*water works*) and one sector that scores highly on four principal components (the *other mining* sector has high scores on all components accept 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 4.

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

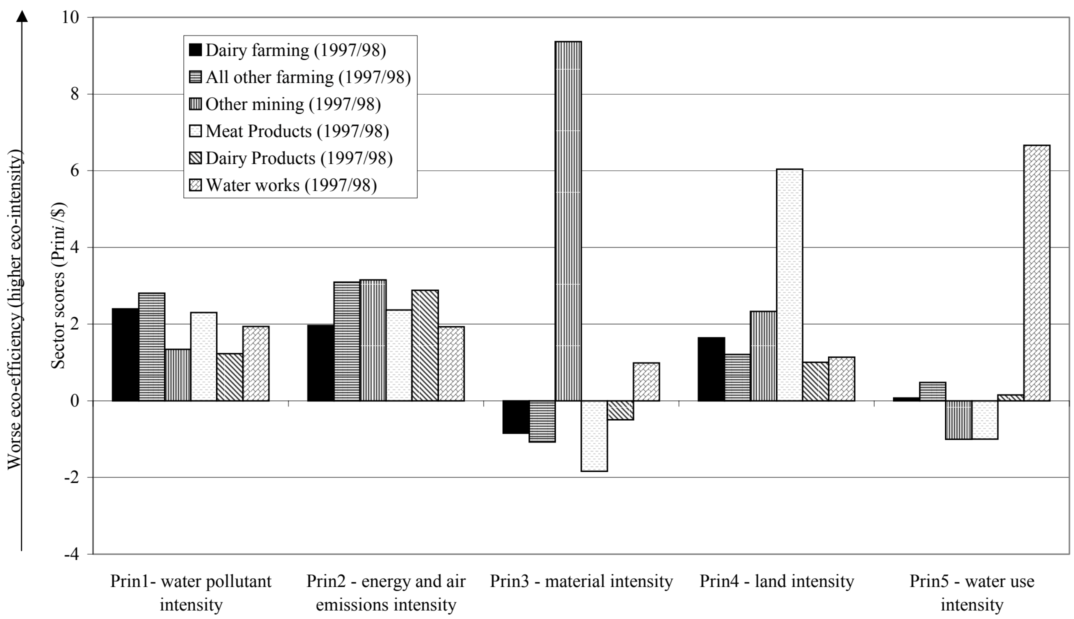

Figure 4: Diagram showing sectors with high scores[16] on three or more principal components

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

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

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 *energy* efficiency, whereas for the sectors mentioned in this section there is a need to extend this to 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 multiplier data of any of the principal components. The fact that the pollution of New Zealand's freshwater resources is an issue of concern to New Zealanders (Ministry for the Environment 2001) gives this principal component added importance.

The overall score for Prin1 increased slightly (by 8%) over the analysis period. This suggests New Zealand as a whole is increasing the amount of water pollution discharged per dollar of output (see Table 5 and Figure 3).

The *personal services* sector has the highest score on Prin1[17]. This sector is plotted against other relatively high Prin1 sectoral scores for 1997/98 in Figure 5. The *personal services* sector scores are low on the other principal components. A graph of the *personal services* sector's scores shows the dominance of the Prin1 score compared with the relatively low scores for the other four principal components (see Figure 6).

The Prin1 scores for the *personal services* sector declined from 1994/95 to 1997/98 by 8% (Figure 5), probably as a result of standard management practice to continually improve plant efficiency through capital replacement.

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

Other sectors warranting attention from a Prin1 (water pollutant) perspective are *all other farming*, *dairy farming*, *meat products*, *water works*, and *other mining.*

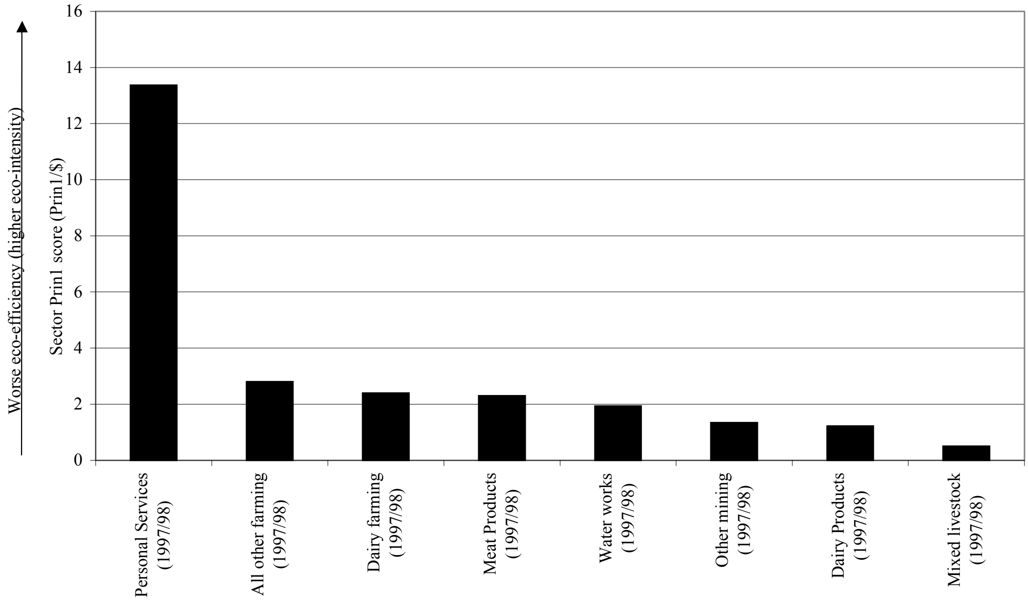

Figure 5: Sectoral scores on Prin1 (water pollutant intensity) for the most water-pollutant intensive sectors in New Zealand (1997/98)

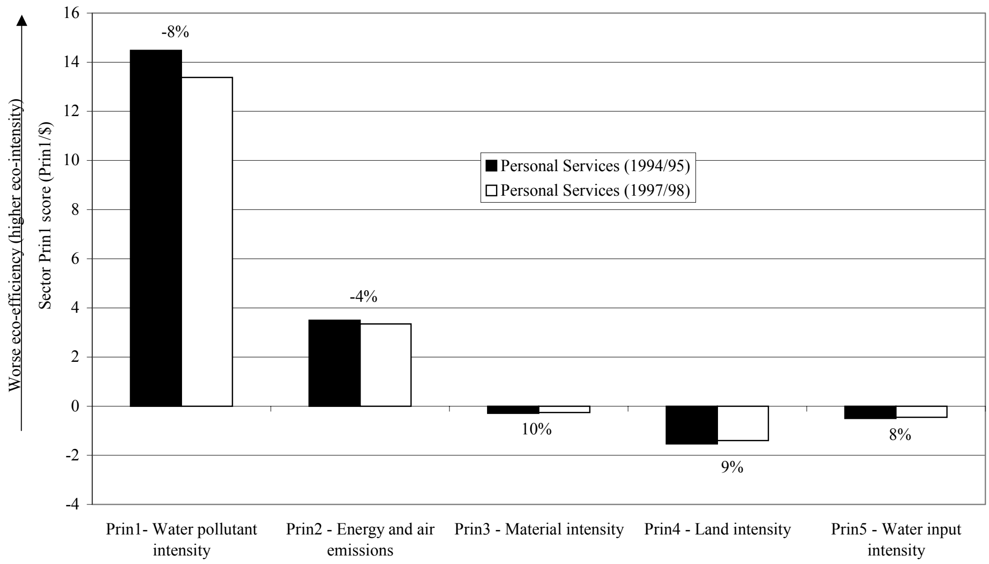

Figure 6: Diagram of five principal components (and percentage change) for the *personal services* sector in New Zealand (1994/95 vs. 1997/98)

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 reflects a similar trend to this sector's original water-pollutant multipliers. The point-source water pollutant multiplier for this sector is almost entirely indirect. Therefore, this increase reflects the increased water pollutant intensities in those sectors with strong links to the *all other farming* sector as shown in the inverse Leontief matrix: *basic chemicals* and *trade*.

This analysis is useful for policy and monitoring purposes. 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

The second principal component explains 24% of the variation in the eco-efficiency data. Energy use and energy-related air emissions (CO_2, NH_4 and NO_2) are the focus of considerable policy attention at present. The prominence of Prin2 in this analysis adds further weight to the claim 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 7.

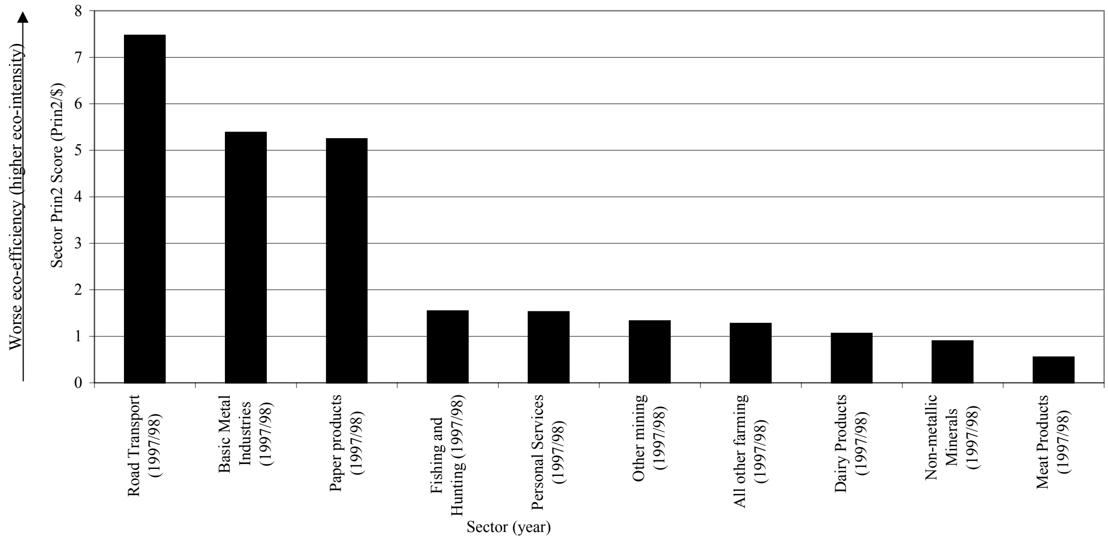

Figure 7: Highest sectoral scores on Prin2 – energy and energy-related air emission intensity (1997/98)

The change e total Prin2 score from 1994/95 to 1997/98 increased by 13%. Changes in the scores of the energy nsive sectors over the analysis period followed a similar trend to that identified by CA (2001). The *road transport* sector showed an increase in Prin2 scores of around 5% (that is, declining, or 'worsening' eco-efficiency). In contrast, the *basic metal industries* and *paper manufacturing* sectors showed declining Prin2 scores (that is, 'improving' eco-efficiency).

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

Prin3 – material intensity

The material intensity principal component explains 13.3% of the variation in the eco-efficiency data. Mineral inputs are an essential input into many aspects of the New Zealand economy. Specifically, an examination of the inverse Leontief matrix shows that there are important links between the *other mining* sector and *non-metallic minerals* and *basic metal industries*.

The sectors with the highest Prin3 scores are the *other mining*, *waterworks*[18] and *non-metallic minerals* sectors. A plot of the score for these sectors and other relatively high Prin3 scoring sectors is shown in Figure 8.

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

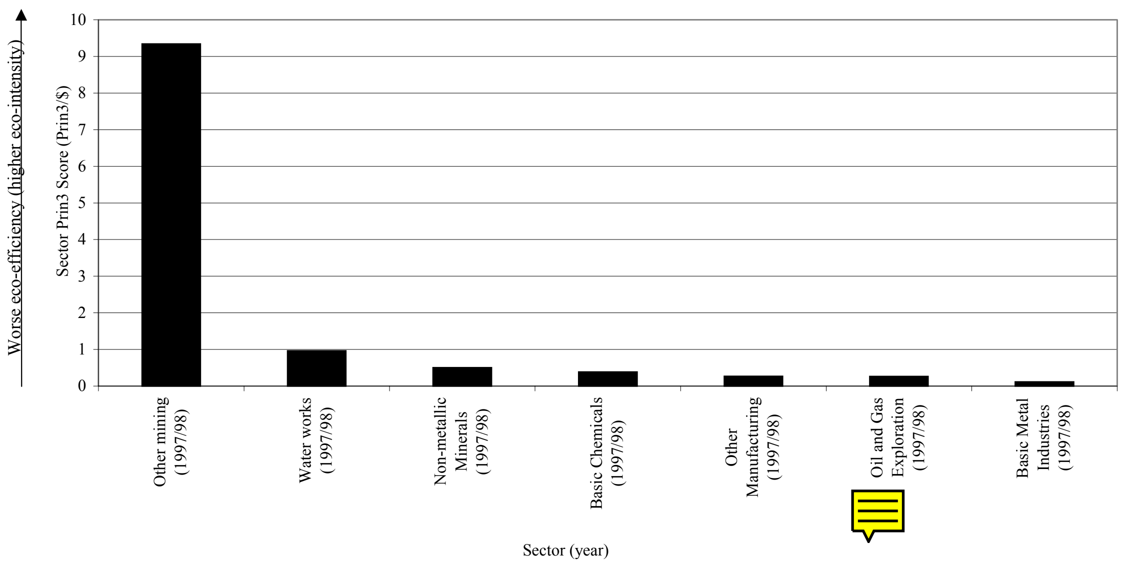

Figure 8: Highest sectoral scores on Prin3 – material intensity (1997/98)

Changes in these sectors' scores over the 1994/95 to 1997/98 period confirm findings in other analyses (Jollands 2003). The *other mining* sector recorded an increased Prin3 score of around 20%. In like manner, the *non-metallic minerals* sector recorded an increase in its Prin3 score of around 24 percent. Total water discharge multipliers for this sector also increased by 31%.

Prin3 is highly participated by water discharged multipliers. Consequently, it is not surprising to find that *waterworks* scores relatively highly on Prin3. The *waterworks* showed a decline in its Prin3 score (of around 20%). This follows a trend evident in the underlying indicators; water-discharge total-requirement multipliers declined by around 42 percent over the period.

Prin4 – land intensity

Prin4 – land intensity explains 9.5% of the variation in the eco-efficiency data. Land input is essential for all economic sectors. Furthermore, Prin4 is highly participated by the nitrate pollutant. Nitrate pollution in waterways is of concern because nitrate is a significant source of eutrophication (McDonald and Patterson 1999).

The sectors with the three highest Prin4 scores are the *meat products*, *mixed livestock* and *other mining* sectors. A plot of the score for these sectors and other relatively high Prin4 scoring sectors is shown in Figure 9.

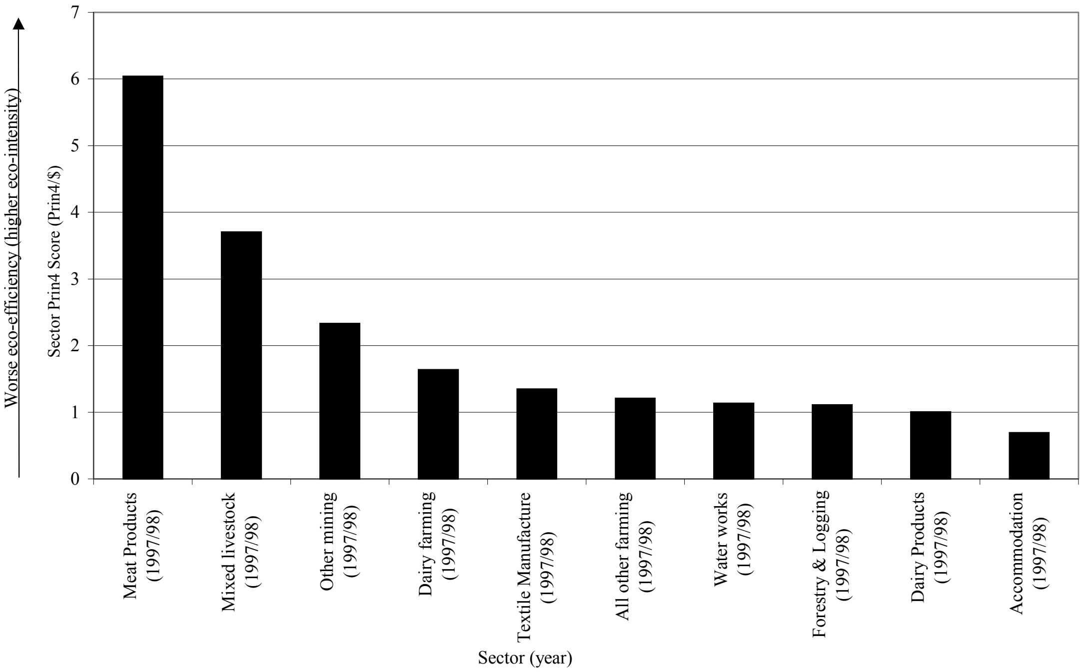

Figure 9: Highest sectoral scores on Prin4 – land intensity (1997/98)

The five highest scoring Prin4 sectors recorded increased scores over the period, except *meat products*. The Prin4 score for the *meat products* sector decreased by 6%. This follows a decrease in nitrate multiplier of 4% and an increase in land intensity of 4%.

The Prin4 score for the *mixed livestock* sector increased by 4% over the period. This suggests that this sector is becoming more land and nitrate-pollutant intensive. Indeed, base calculations show this sector's land and nitrate multipliers (total requirements) grew by 4% and 23% respectively. Similarly, the Prin4 score for the *dairy farming* sector increased by 7%.

An analysis of Figure 9 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

Prin5 explains 7% of the variation in the eco-efficiency multiplier matrix used in this principal components analysis. 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[19] (see Figure 10).

[19] Note that in this analysis it was decided to change the sign of the SAS-generated sectoral scores for the following reasons. *Waterworks* received the largest positive score in the SAS output while *other mining* received a high negative score. However, *waterworks* is not strictly a water 'user,' but rather a 'supplier.' In contrast, *other mining* is a water user.
The SAS-generated scores allocate positive signs in the eigenvector arbitrarily (remember that PCA is conducted under the condition that the square of the eigenvector elements must equal 1). Signs are, by default, allocated by SAS such that the largest scores are positive. While this is usually appropriate, in this case it would be useful for water 'users' (such as *other mining*) to have positive scores rather than water 'suppliers' (*waterworks*). Therefore, it was decided that it was appropriate to change the signs to improve the usefulness of the sectoral scores. Note that changing the signs does not affect the ranking of the sectoral scores, merely the interpretation.

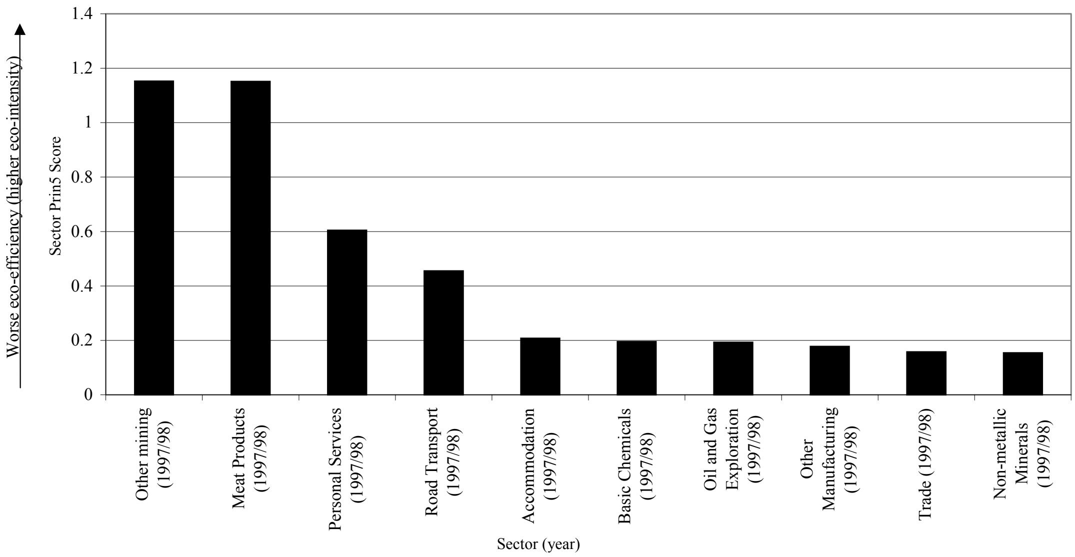

Figure 10: Highest sectoral scores on Prin5 – water-input intensities for water users (1997/98)

The dominance of the *other mining* sector is consistent with changes in the individual variables. The *meat products* sector also has one of the highest water input multipliers. Scores on these sectors show that the *other mining* sector's Prin5 score increased (by 16%) while its water-input multiplier increased by 18%. In contrast, the *meat products* sector's Prin5 score and multipliers decreased.

Conclusion

A matrix of eco-efficiency indicators gives a multi-dimensional picture of eco-efficiency in New Zealand. In the context of a decision-maker's preference for concise information the matrix can prove to be too cumbersome. Despite the limitations of aggregate indices, aggregate measures can provide a useful complement to other forms of information. What is needed is a framework for condensing information into aggregate indices (Dahl 2000).

One aggregation function that has shown promise but had little attention in analysing eco-efficiency indicators is principal components analysis. Conducting PCA on the eco-efficiency indicator matrix has 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 is able to provide the much sought-after 'aggregate' scores for each dimension (principal component). This supplies condensed information for decision-makers and provides 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. In particular, the PCA conducted here identified the following sectors that merit special attention (see Table 6). One of the advantages of the PCA approach is that it is able to identify these sectors in a more 'parsimonious' manner.

Table 6: 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

A PCA approach has demonstrated an ability to provide aggregate indices for eco-efficiency. As such, this approach warrants further investigation as a legitimate aggregation approach.

In conclusion, it is useful to draw on the pertinent message from Costanza (2000, p. 342 brackets added). "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. Aggregate indices are a necessary but not sufficient condition for promoting better decision making and, ultimately, better environmental policy.

Appendix 1:A brief description of Principal Components Analysis

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

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

The expectation when conducting PCA is that correlations among eco-efficiency variables (ε_{ij}) are large enough so that the first few principal components account for most of the variance. If this is the case, “no essential insight is lost by applying the first few principal components for further analysis or decision-making, and parsimony and clarity in the structure of the relationships are achieved” (Yu, Quinn et al. 1998).

A principal components analysis starts with data on p variables (such as water use per $ of value added) for n individuals (or in the case of eco-efficiency, sectors). The first principal component is then the linear combination of the variables $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p$ (Manly, 1994, p. 78) weighted by some constant γ_{ij} where i is the principal component number and j is the variable number.

$$Z_1 = \gamma_{11}\varepsilon_1 + \gamma_{12}\varepsilon_2 + \ldots \gamma_{1p}\varepsilon_p \qquad \textbf{(Equation 2)}$$

that varies as much as possible for the observations. However, because var(Z_1) can be increased by choosing any set of values for $\gamma_{11}, \gamma_{12}, \ldots \gamma_{1p}$, a restriction that $\gamma_{11}^2 + \gamma_{12}^2 + \ldots + \gamma_{1p}^2 = 1$ is also imposed.

In order to use the results of PCA it is useful to understand the nature of the equations themselves. In fact, a PCA just involves finding the eigenvalues of the sample covariance matrix (**C**) (see below). The variances of the principal components are the eigenvalues (λ) of the matrix **C**. Assuming that eigenvalues are ordered as $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \lambda_p \geq 0$, then λ_i corresponds to the *i*th principal component

$$Z_i = \gamma_{i1}\varepsilon_1 + \gamma_{i2}\varepsilon_2 + \ldots \gamma_{ip}\varepsilon_p \qquad \textbf{(Equation 3)}$$

In particular, var(Z_i)= λ_i and the constants $\gamma_{i1}, \gamma_{i2}, \ldots \gamma_{ip}$ are the elements of the corresponding eigenvector, scaled so that the sum of γ_i^2 equals 1 (Manly 1994, p. 79). An important property of the eigenvalues is that they add up to the sum of the diagonal elements (the trace) of **C**. That is,

$$\lambda_1 + \lambda_2 + \lambda_3 + \ldots \lambda_p = c_{11} + c_{22} + \ldots c_{pp} \qquad \textbf{(Equation 4)}$$

As c_{ii} is the variance of ε_i and λ_i is the variance of Z_i, this means that the sum of the variances of the principal components is equal to the sum of the variances of the original variables. Therefore, in a sense, the principal components account for all of the variation in the original data (Manly 1994, p. 80). The eigenvalue for a principal component indicates the variance that it accounts for out of the total variances (Manly 1994, p. 81). 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[20].

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[20] Construct a data matrix, standardise variables, calculate **C** matrix, find eigenvalues and eigenvectors, select principal components, interpret the results and calculate scores.

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