EVALUATING NATIONAL ENVIRONMENTAL SUSTAINABILITY: PERFORMANCE MEASURES AND INFLUENTIAL FACTORS FOR OECD-MEMBER COUNTRIES FEATURING CANADIAN PERFORMANCE AND POLICY IMPLICATIONS

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ABSTRACT

This research reviews five studies that evaluate national environmental sustainability with composite indices; performs uncertainty and sensitivity analyses of techniques for building a composite index; completes principal components factor analysis to help build subindices measuring waste and pollution, sustainable energy, sustainable food, nature conservation, and sustainable cities (Due to its current importance, the greenhouse gases (GHG) indicator is included individually as another policy measure.); analyses factors that seem to influence performance: climate, population growth, population density, economic output, technological development, industrial structure, energy prices, environmental governance, pollution abatement and control expenditures, and environmental pricing; and explores Canadian policy implications of the results.

The techniques to build composite indices include performance indicator selection, missing data treatment, normalisation technique, scale-effect adjustments, weights, and aggregation method. Scale-effect adjustments and normalisation method are significant sources of uncertainty inducing 68% of the observed variation in a country's final rank at the 95% level of confidence. Choice of indicators also introduces substantial variation as well. To compensate for this variation, the current study recommends that a composite index should always be analysed with other policy subindices and individual indicators. Moreover, the connection between population and consumption indicates that per capita scale-effect adjustments should be used for certain indicators. Rather than ranking normalisation, studies should use a method that retains information from the raw indicator values.

Multiple regression and cluster analyses indicate economic output, environmental governance, and energy prices are major influential factors, with energy prices the most important. It is statistically significant for five out of seven performance measures at the 95% level of confidence: 37% variance explained on the environmental sustainability performance composite indicator out of 73%, 55% (of 55%) on the waste and pollution subindex, 20% (of 70%) on the sustainable energy subindex, 5% (of 100%) on the sustainable cities subindex, and 55% (of 81%) on the GHG indicator. Energy prices are relevant to Canadian policy; increasing prices could substantially improve Canada's performance. Policy makers should increase energy prices through a carbon pricing strategy that is congruent with the ecological fiscal reform advanced by the National Round Table on the Environment and the Economy.

Keywords: sustainable development; composite indices; environmental policy; environmental governance; energy prices; Canada

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LIST OF ACRONYMS

AIC	Akaike's Information Criterion
AIC_C	Akaike's Information Criterion corrected for sample size
AGPI	Alberta Genuine Progress Indicator Accounting Project
ANOVA	ANalysis Of VAriance
CBC	Conference Board of Canada
EKC	environmental Kuznets curve
EPG	Environmental Performance Grade
EPI	Environmental Performance Index
EPR	Environmental Performance Rank
ESDI	Environmental Sustainable Development Initiative
ESI	Environmental Sustainability Index
ESPCI	environmental sustainability performance composite index
ESPI	environmental sustainability performance indicator
FBC	Fraser Basin Council
GHG	greenhouse gas
GOC	Government of Canada
GPI	Genuine Progress Indicator
GPI Atlantic	GPI Atlantic Natural Resource and Environmental Accounts
GVA	gross value added
ISIC	International Standard Industrial Classification
MEA	Millennium Ecosystem Assessment
NCPS	nature conservation policy subindex
NRTEE	National Round Table on the Environment and the Economy
OECD	Organisation for Economic Co-operation and Development
PAC	pollution abatement and control
PCA	principal components analysis
PCFA	principal components factor analysis
PSR	pressure-state-response
SCPS	sustainable cities policy subindex
SEPS	sustainable energy policy subindex
SFPS	sustainable food policy subindex
SSCC	squared semi-partial correlation coefficients

TAI	Technology Achievement Index
toe	tonnes of oil equivalent
UN DESA	United Nations Department of Economic and Social Affairs
UN DP	United Nations Development Programme
VOC	volatile organic compound
WEF	World Economic Forum
WPPS	waste and pollution policy subindex
WWF	World Wide Fund

GLOSSARY OF TERMS

Akaike's Information Criterion, corrected for sample size: Akaike's Information Criterion (AIC) balances predictive power of a regression equation with parsimony of independent variables. In essence, AIC penalises a model for adding too many explanatory variables. AIC corrected for sample size (AIC_C) should be used when n/k is less than 40, where n is the number of observations and k is the number of parameters in the regression equation including the constant (intercept). As n gets large, AIC_C converges to AIC.

Association: A term that describes a general relationship between two measured quantities, no matter the quantities' measurement scale—nominal, ordinal, interval, or ratio—that renders them statistically dependent.

Cluster Analysis: Based on a single characteristic or on multiple characteristics, cluster analysis classifies large sets into subgroups with similar characteristics using multivariate techniques. The classification aims to reduce the dimensionality of a data set by exploiting the similarities (or dissimilarities) between subgroups. Termed either agglomerative or divisive, hierarchical clustering techniques are stepwise procedures that combine, or divide, objects into groups. Non-hierarchical techniques have the number of clusters specified prior to analysis, as with the *k*-means clustering method.

Coefficient of Multiple Determination, R^2: A statistic for the goodness of fit of the estimated multiple regression equation. The coefficient can be interpreted as the proportion of the variation in the dependent variable that is explained by a combination of independent variables.

Correlation: A statistic that gauges the linear relationship that may occur between two interval- or ratio-scaled quantities. These quantities can be random variables or observed data values assumed to contain random measurement error. Note, despite the similarities between correlation and association, correlation is a narrower term.

Dependent Variable: The variable that is being predicted or explained by a group of independent variables, also referred to as a criterion variable. The dependent variable is denoted by y.

***F*-test:** An F-test is any statistical test in which the test statistic has an F-distribution, a continuous probability distribution, under the null hypothesis. Analysts often use this test when comparing statistical models that have been fit to a data set. The test identifies the model that best fits the population from which the data were sampled. F-tests mainly arise when the models have been fit to the data using least squares.

Independent Variable: The variable that is doing the predicting or explaining of a dependent variable, also referred to as a predictor or explanatory variable. The independent variable is denoted by x.

Monte Carlo Simulation: An analytical technique in which one runs a large number of simulations. These simulations use random or quasi-random distributions to represent uncertain variables; each run selects values from these distributions for inputs. The distribution of output results infers which outcomes are most likely given the uncertainties in the input variables. Known for its casinos, the name comes from the city of Monte Carlo.

Multicollinearity: The term used to describe the level of correlation among the independent variables. Multicollinearity is the capacity for the other variables to explain all or a portion of a given variable in the analysis. Increasing multicollinearity complicates the interpretation of an analysis because interrelationships among the variables make detecting the effect of any single variable more difficult. The term multicollinearity indicates either that the correlations have surpassed an arbitrary cut-off level, making multiple regression analysis inadvisable, or it descriptively refers to the level of correlation (e.g., high, medium, low).

Multiple Regression: A data-analytic procedure, based on least squares criterion, involving two or more independent variables and a single dependent variable. The analysis determines the linear relationship between the independent variables and the dependent variable. Non-linear relationships may also be analysed with multiple regression, but additional complications arise. To avoid confusion since the current research uses linear regression, no further explanation of non-linear regression is provided.

Partial Regression Coefficient: The value specified in the regression equation with which an analyst multiplies the independent variable to predict dependent variable scores. Each independent variable has its own, unique, coefficient. Partial coefficients represent the effects of a predictor after partialling out the effects of all other independent variables. There are two forms of these coefficients: raw and standardised, which are raw values converted to z-scores.

Principal Components Analysis (PCA): A methodology that is used to identify linear functions that explain the theoretical maximum amount of total variance in a correlation matrix. PCA parsimoniously partitions the total variance of the data structure into primary elements, thus defining the underlying dimensionality of the variable set. The number of linear functions that explains all the variance is the rank, or true dimensionality, of the variable set.

Principal Components Factor Analysis (PCFA): A methodology related to PCA. Similar to PCA, PCFA describes a set of variables in terms of a smaller number of components, also referred to as factors. However, this methodology diverges from PCA in that PCFA retains fewer components (or factors) through application of stopping criteria (Kaiser's Rule or the scree test). The methodology also enhances the ability to interpret the nature of the retained components (or factors) with a technique known as rotation that loads the variables onto the components in different ways. The different patterns of loads that emerge often provide insight into the nature of the component.

***p*-value:** The probability, when the null hypothesis is true, of obtaining a sample result that is at least as unlikely as what is observed. The *p*-value is often called the observed level of significance.

Semi-Partial Correlation Coefficient: A coefficient, also referred to as a part correlation coefficient, that indicates, on a scale from -1 to 1, the degree and direction of linear relationship between two variables (the dependent variable and a single independent variable). The effects of one or more of the other variables have been removed from the single independent variable.

Squared Semi-Partial Correlation Coefficient: This value indicates the proportion of variance in the dependent variable explained by a single independent variable after variance shared with the other predictors has been removed from the single independent variable.

Suppression: Suppression occurs when the sum of the squared semi-partial correlation coefficients is greater than the coefficient of multiple determination. Suppression is a combination of three different aspects: redundancy, enhancement, and suppression. Both enhancement and suppression variables increase the magnitude of the explained variation of a dependent variable. They do this by removing, or suppressing, variation not associated with the dependent variable in one or more of the other explanatory variables. Redundant variables decrease the variation explained for a dependent variable and should be excluded from the analysis. However, both enhancement and suppression variables are desirable because they increase the explained portion of a dependent variable's variance.

***t*-test:** A *t*-test is any statistical hypothesis test in which the test statistic follows a Student's *t* distribution if the null hypothesis is true. The *t*-distribution is a probability distribution used to estimate the mean of a normally distributed population when the sample size is small.

Uncertainty and Sensitivity Analyses: Uncertainty analysis focuses on how variation in input data affects the whole while sensitivity analysis apportions the effects. Uncertainty analysis focuses on how the input data engenders uncertainty throughout the structure and final value. Sensitivity analysis assesses how the different sources of variation qualitatively and quantitatively affect the final value.

Ward's Method: A hierarchical procedure where the similarity metric used to join clusters is calculated as the sum of squares between the two clusters summed over all variables. Ward's method has the tendency to produce clusters of approximately equal size.

Wilkes's Lambda: A multivariate test statistic that expresses the proportion of unexplained variance in the dependent variables. Wilkes's lambda is a general test statistic used in multivariate tests for differences of means among more than two groups.

***z*-score:** A value found by dividing the difference between the data value and the mean by the standard deviation s. A z-score is referred to as a standardised value and denotes the number of standard deviations a data value is from the mean.

CHAPTER 1:
PLANNING FOR ENVIRONMENTAL SUSTAINABILITY

The publication of the *Brundtland Report* increased awareness among national governments about alternate forms of economic development (World Commission on Environment and Development 1987). International attention is now focusing on sustainable economic development, an approach that explicitly acknowledges the inherent limits of the environment. Countries are attempting to decouple environmental degradation from socio-economic activities, thereby achieving a more sustainable trajectory for growth and development. To achieve environmental sustainability, policy makers must overcome several planning challenges arising mainly from innate uncertainties. Much of the uncertainty confronting policy makers comes from a lack of information about underlying natural systems, as well as the impacts on these systems of management decisions. A planning process that does not take into account uncertainties is likely to formulate inefficient and ineffective policies that may misdirect environmental protection efforts, thereby wasting valuable resources that society could employ elsewhere to better effect.

To mitigate the effects of uncertainties, policy makers require more and better information about various aspects of environmental performance. The current study partially addresses this informational void. First, the current research assesses measurement techniques of five studies that use performance indicators and composite indices as proxies to quantify underlying aspects of environmental sustainability. Composite indices combine a set of individual indicators into an easily comparable single value. Assessing these techniques is timely since such studies are marred with inconsistent results (i.e., widely varying performance ranks for the same country), which provides less credence for policy recommendations. Understanding the nature of the differences among studies provides valuable information about appropriate measurement techniques. Next, the current study evaluates the importance of factors that are emerging from the literature as influencing national environmental sustainability. Finally, Canadian policy implications of the findings are explored.

By using the same set of indicators, the current study builds on the work done by one of the five reviewed studies, Gunton et al. (2005). The author of the current study was also director of research for the Gunton et al. (2005) study, prepared by the Sustainable Planning Research Group in the School of Resource and Environmental Management at Simon Fraser University as an independent evaluation of Canada's environmental performance. The research team, a multidisciplinary team of 14 researchers (see Acknowledgements), completed a twice peer-reviewed final report that included experts in the private, public, and non-governmental organisation sectors.

During the earlier study, questions arose about the causes of the dissimilar findings among studies and about the appropriateness of using a single-value composite index as the only policy measure. Consideration progressed from these causes to speculation about the factors that might be affecting a country's environmental sustainability. These questions and considerations provide the impetus for much of the current research. Thus, the Gunton et al. (2005) study forms a foundation for the current research by providing the basic indicator set, albeit with minor alterations to accommodate the specific goals of the current research. These changes are detailed in the Environmental Sustainability Performance Indicator section.

The review of these studies catalogues the different decisions that affect the final value of each study's composite index. To compare dissimilar entities such as countries, only one method is available for an analyst to build a composite index, but the method requires several decisions about the individual techniques one employs (Nardo et al. 2005). The method starts with selecting a set of performance indicators with the aid of a guiding conceptual framework and then deciding how to treat missing data. Next, an analyst must decide on the scale-effect adjustments to use to be able to compare indicators across countries of different sizes. Once these steps are completed, the performance indicators are normalised to a common measurement scale so that individual indicators may be compared and aggregated. Finally, the weights and method of aggregation are selected for combining the individual indicators into a composite index.

These different decisions provide the framework for the uncertainty and sensitivity analyses that quantify the affect each decision has on a country's final rank on a composite index. These results help clarify why findings differ among studies, as well as provide insight into how analysts should formulate and interpret environmental policy measures. Of course, these results also clearly demonstrate techniques for using the Gunton et al. (2005) indicator set effectively as policy measures. Explaining environmental performance, as determined by the value of policy measures, involves analysing the relationships the measures have with influential factors thought to account for observed differences. Results from regression and cluster analyses of these relationships determine the important factors as well as their corresponding contributions to explaining performance on the policy measures.

Knowledge about important factors' relationships with, and contributions to, the various policy measures helps identify policy opportunities. Policy makers can leverage the strongest influences to formulate policies that are more effective. Indeed, the current study uses Canada as an exemplar to illustrate how policy makers may apply these results to design environmental management policies. Countries that are members of the Organisation for Economic Co-operation and Development (OECD), of which Canada is one, are the geographical units of analysis for the current research.

Using a national perspective to evaluate environmental performance has both advantages and disadvantages. Many environmental problems cross national boundaries to impact neighbouring countries, such as air and water contamination caused by migratory waste and pollution, or habitat protection concerns for species at risk that have natural ranges that cross borders. These types of problems are addressed most effectively at the national level of governance, often requiring a national government's legislative mandate and resources. However, relying on national averages can miss or trivialise locally important environmental issues. Moreover, an international agenda may influence national environmental efforts, thus focus might shift from issues relevant to Canada. In the earlier study that developed the indicator set used by the current research, Gunton et al. (2005) assess several Canadian frameworks to maintain a relevant context.

The rest of this chapter examines why the current research is important, what the author did to accomplish it, and how the thesis is organised. First, a discussion of strategic environmental management demonstrates the importance of suitable measures of policy effectiveness. The next section details how the research was performed by presenting the research plan, research questions, hypotheses, objectives, the guiding conceptual framework, and the individual performance indicators. The final section presents an overview description of subsequent chapters.

1.1) STRATEGIC ENVIRONMENTAL MANAGEMENT

Policy makers may mitigate the effects of uncertainties by promoting continuous learning with a strategic approach to environmental management (U.S. National Academy of Science 1999). The best continuous learning processes for providing further information to policy makers incorporate two feedback loops, rather than one: double-loop learning as opposed to single-loop learning (fig. 1.1). Policy makers use information from single-loop learning to initiate change within the planning process so as to improve performance, while they use information from double-loop learning to adjust the process itself by altering various governing variables (Argyris and Schon 1978). The double-loop learning cycle questions the values and assumptions behind various aspects of the planning process so that policy makers may change them, thus altering the framework of the process itself. Essentially, the single-loop learning cycle describes how the planning process produces the desired outcomes or results, whereas the double-loop learning cycle examines why these outcomes are desired.

The planning process starts with initially defining goals and objectives, or redefining if incorporating newly acquired information. During step 1, policy makers delineate the management scope, synthesise existing knowledge, and explore alternative visions of management outcomes. In step 2, various policy options are developed that will fulfill the articulated goals and objectives. Policy makers then determine a set of assessment criteria that assess the likelihood each option has to achieve goals and objectives (step 3). Next, each policy option is evaluated with these criteria (step 4) to help select the one preferred for achieving the goals and objectives (step 5). After implementing the preferred option (step 6), desired outcomes are monitored to determine the effectiveness of the preferred policy option (step 7). After comparing actual outcomes to forecasts, underlying reasons for any differences are noted so that practices, objectives, and forecasting techniques may change to reflect newly acquired knowledge (single-loop learning). New understanding leads to problem redefinition in a cycle of continuous learning designed to ameliorate the effects that uncertainty has on a country's environmental management efforts.

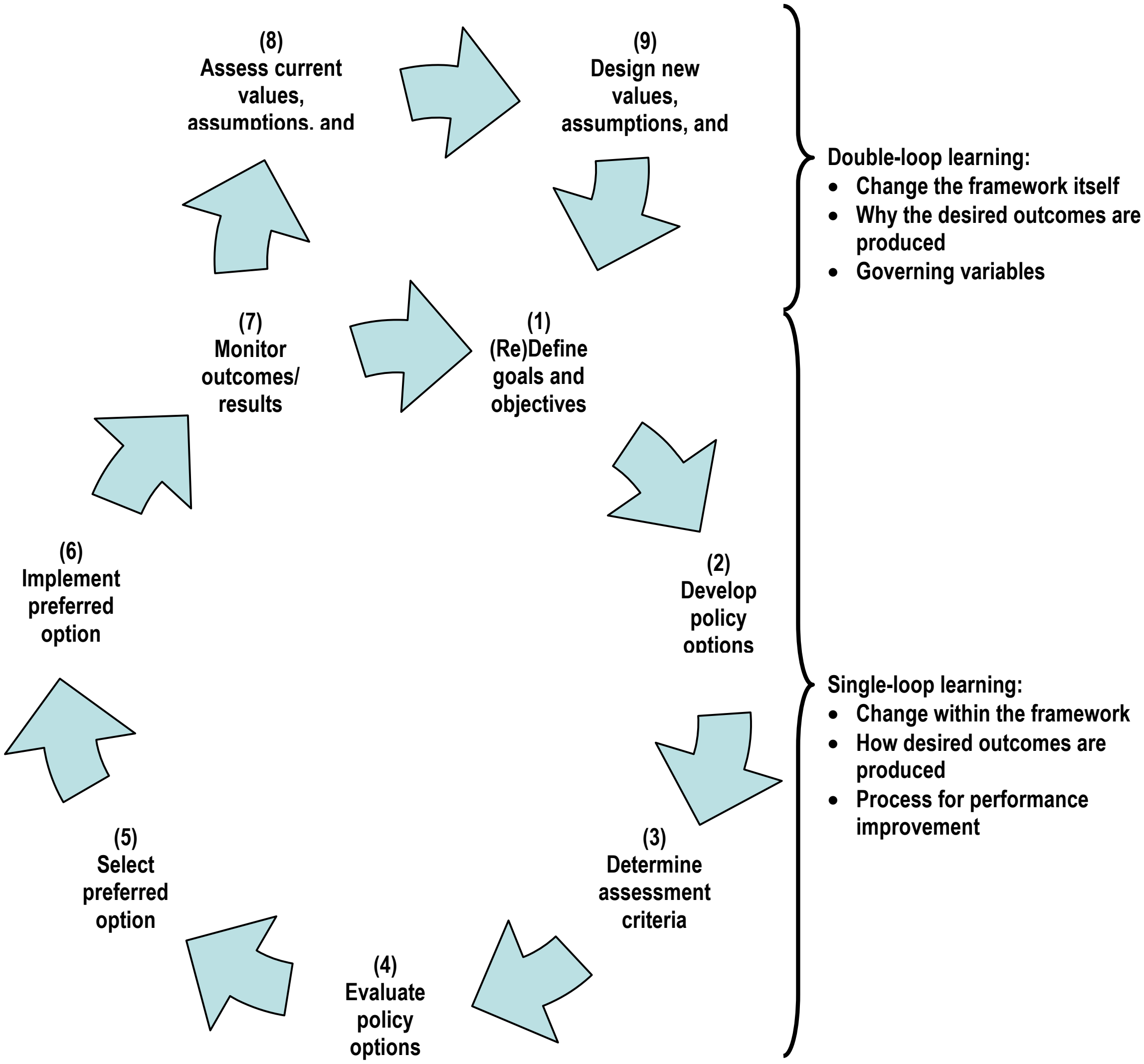

Figure 1.1: The single- and double-loop learning planning cycles that promote continuous process improvements for strategic environmental management

However, well-developed, single-loop learning systems may keep a country on an inappropriate trajectory if underlying value judgments and assumptions are unable to be re-examined. Policy makers start double-loop learning when they question or assess such elements of a planning process (step 8) (Argyris and Schon 1978). If policy makers are unable to review these elements, they also will be unable to substantially modify, or replace, goals and objectives (step 9), potentially keeping a country's environmental management efforts on an inappropriate trajectory. In the absence of such a capacity, a country could perfect its environmental management system without improving its environmental quality because it can not reassess incorrect initial goals and objectives. Clearly, policy makers may further reduce the effects of uncertainty on a country's environmental management efforts by actively reassessing the appropriateness of established goals and objectives.

Critical to both single- and double-loop learning is the capacity of the process to acquire and integrate new information. For single-loop learning, policy makers gain new information and knowledge by monitoring a set of indicators linked to process outcomes and results. With double-loop learning, policy makers gain new knowledge both by monitoring indicators and by scanning sources from outside the planning process during reassessment of process goals and objectives. Monitoring relevant indicators enables a comparison between actual outcomes with expected goals and targets. Disparities between expected and observed outcomes signal policy makers to evaluate the effectiveness of management actions to improve process performance, and to question the relevance of articulated goals and objectives to establish different ones.

Comparisons between expected and actual outcomes provide the basis for adaptive management by identifying deficiencies that require adjustment. With each iteration, new understanding helps shape further policy action. Consequently, acquiring new knowledge by measuring indicators allows policy makers to learn continually about the systems that are management efforts targets. Each policy adaptation offers a country an opportunity to improve its environmental management efforts. Clearly, indicators that gauge expected policy outcomes fulfill an important role crucial to the effective functioning of strategic environmental management.

Moreover, recent best practices guidelines for strategic environmental management support the importance of indicators (table 1.1; Gunton and Joseph 2007; Ellis 2008). Of particular interest for the current research is the monitoring and reporting component, which forms an environmental performance evaluation system. Such a system determines performance by tracking systematically through time a series of indicators representing key environmental sustainability variables. Besides providing the ability to assess progress towards achieving goals, tracking indicators also provides information for communicating with the public.

Table 1.1: Best practices guidelines for strategic environmental management planning

GUIDELINE	DESCRIPTION
Comprehensive goals and targets	Goals should be set that cover all aspects of sustainability and include measurable short-, medium-, and long-term targets with timelines.
Effective strategy	Strategies should quantifiably show how sustainability targets will be met.
Integration	The strategic environmental management actions should be integrated sectorally and spatially.
Governance and leadership	Responsibility for developing management actions should reside with the most senior levels of government and responsibility for implementation should be clearly delineated.
Progress monitoring and reporting	There should be regular, independent public reporting to assess progress in implementing strategies and achieving targets.
Adaptive management	There should be mandatory adjustments to plans to address deficiencies identified in monitoring.
Stakeholder participation	Development, implementation, and monitoring should be collaboratively managed through permanent and institutionalized multi-stakeholder processes.
Legal framework	The process and requirement for planning should be enshrined in legislation.

Source: Gunton and Joseph 2007; Ellis 2008

The ability to track aspects of environmental sustainability would greatly aid a country's efforts at improving its environmental record (United Nations Department of Economic and Social Affairs (UN DESA) 2006; OECD 2005a; UN DESA 2002; OECD 2001b; OECD 2001c; Cherp et al. 2004; Dalal-Clayton and Bass 2002; Pinter et al. 2005; World Wide Fund[1] (WWF) 2006). International frameworks for sustainable development from OECD and UN recognise the importance of indicators for measuring policy performance (table 1.2). In the early 2000s, the OECD Development Assistance Committee and UN DESA each developed guidelines to assist countries in formulating national strategies for sustainable development (OECD 2001c; UN DESA 2002). Both frameworks based their guidelines on a number of key principles such as broad consultation, country ownership, and realistic targets.

Obviously, the management principle regarding indicators and targets is most relevant for the current research. The presence of quantitative indicators in national sustainable development strategies partially mitigates the discrepancies that occur between intentions and reality. Quantitative, rather than qualitative, indicators are preferred for measuring environmental performance for two reasons. First, qualitative data may be subjective, which increases the difficulty of

[1] Formerly World Wildlife Fund.

comparisons across units of analysis or through time. Second, such data also limit the type of analytical techniques a researcher may use, as well as decrease the likelihood of obtaining significant results because error bands and confidence intervals expand as the data set becomes more qualitative. However, qualitative data are sometimes the only way a researcher can document certain phenomena. On the other hand, quantitative data are perfectly suitable for statistical analysis; therefore, such indicators more easily identify and assess trade-offs among the economic, environmental, social, and institutional dimensions of sustainable development (OECD 2005a; UN DESA 2002). Moreover, Cherp et al. (2004) regard the presence of performance indicators as a positive gauge of the effectiveness of national sustainable development strategies in their assessment framework. In short, "what gets measured gets managed!"

Table 1.2: OECD and UN DESA frameworks of national strategies for sustainable development

MAIN PRINCIPLES	OECD	UN DESA
Policy integration	Integrate economic, social and environmental objectives Comprehensive and integrated strategy	Integrate economic, social and environmental objectives Link different sectors
Intergenerational timeframe	Consensus on long-term vision.	Shared strategic and pragmatic vision Link short term to medium/long term
Analysis and assessments	Base on comprehensive and reliable analysis Build on existing processes and strategies	Anchor in sound technical and economic analysis Build on existing mechanisms and strategies
Indicators and targets	Targeted with clear budgetary priorities	Realistic, flexible targets
Co-ordination and institutions	High-level government commitment and influential lead institutions	Strong institution or group of institutions spearheading the process
Local and regional governance	Link national and local levels	Link national, regional and global levels
Stakeholder participation	Effective participation People centred	Access to information for all stakeholders Transparency and accountability Partnerships among government, civil society, private sector and external institutions
Monitoring and evaluation	Incorporate monitoring, learning, and improvement	Integrated mechanisms for assessment, follow up, evaluation and feedback

Source: OECD 2001c; UN DESA 2002

Several recent efforts at assessing environmental sustainability involve some form of common denominator that aggregates many indicators into one value, a composite index. Composite indices are useful constructs for policy analysis because they can simplify complex systems, making them easier to interpret than an array of many indicators (Nardo et al. 2005). Composite indices are also valuable for estimating multi-dimensional concepts such as environmental sustainability (Nardo et al. 2005). For both reasons, composite indices are useful for setting policy priorities. Moreover, easier interpretation also means easier communication because laypersons are more likely to understand a single composite index value with less effort than an array of separate indicator values.

In contrast to these strengths, composite indices also have several limitations. Inappropriate policies may result from ignoring difficult to quantify dimensions of performance. The highly aggregated results also provide opportunities for misinterpretation and simplistic policy conclusions (Nardo et al. 2005). Moreover, as the results of the current research demonstrate, composite indices are highly variable depending on the assumptions made during their construction. As such, construction techniques need to be as transparent as possible.

While composite indices are useful for setting priorities, controversy surrounds recent efforts to evaluate environmental sustainability performances. By using different objectives, indicators, and weighting and aggregation methods, several recent studies produce significantly different performance ranks for Canada (Boyd 2001; Conference Board of Canada 2004; Gunton et al. 2005; WWF 2006; Esty et al. 2008; reviewed in chapter 2). A comparison of Canada's rank from each of these studies using a common set of 23 OECD-member countries that occur across all studies displays a large range (table 1.3). The common set excludes Iceland, Czech Republic, Hungary, Poland, Slovak Republic, Turkey, and Luxembourg. Canada's rank within these 23 countries varies from 8th (top 10) to 22nd (next to last). Indeed, the main message from these combined results may be how aptly they illustrate that different methods produce different results. Clearly, several issues confound efforts for measuring national environmental sustainability performance, warranting further study.

Table 1.3: Comparing the results of environmental performance studies using Canada's performance rank

STUDY	CANADA'S RANK*
Environmental Performance Index 2008	8
Conference Board of Canada 2004	8
Gunton et al. 2005	21
World Wide Fund 2006	21
Boyd 2001	22

* Canada's rank is out of 23 OECD-member countries that occur across all studies; the common set excludes Iceland, Czech Republic, Hungary, Poland, Slovak Republic, Turkey, and Luxembourg

1.2) RESEARCH STRUCTURE

This section discusses the structure of the current research. The section first details the various components of the research plan, then presents research questions, hypotheses, and objectives. This section next reviews the conceptual framework that helps to develop and to organise performance indicators and influential factors that affect national environmental sustainability. Lastly, the section discusses the set of environmental sustainability performance indicators (ESPIs) the current study uses, briefly summarising the selection process and the alterations from the original set of the Gunton et al. (2005) study.

RESEARCH PLAN

The current study has three components. The first component reviews five studies that use composite indices to evaluate national environmental sustainability. For researchers to build a composite index that compares dissimilar entities such as countries, only one method is available, but it requires several decisions about the individual techniques one employs (Nardo et al. 2005). This review assesses the various techniques each study uses to construct a composite index for measuring and ranking a country's environmental performance. Such techniques include individual performance indicators that quantify different aspects of environmental sustainability, missing data treatment, normalisation technique, scale-effect adjustments, weights, and aggregation method. These elements provide the basis for uncertainty and sensitivity analyses using input-output Monte Carlo simulations that examine the variation each element induces in the value of a country's composite index and its corresponding final rank. These findings provide a unique contribution of the current research.

The results of the uncertainty and sensitivity analyses offer two benefits. These results clarify how differences among studies arise, and they provide insight into an appropriate approach for measuring national environmental performance. Because the current research uses the same ESPIs, these results also clearly demonstrate techniques for using the Gunton et al. (2005) indicator set effectively as policy measures. In addition to the overall index, the environmental sustainability performance composite index (ESPCI), the current research also uses principal components factor analysis to develop a series of subindices that determine performance on specific environmental policy areas. The other policy measures are waste and pollution, sustainable energy, sustainable food, nature conservation, and sustainable cities. Due to its current importance as an international environmental issue, the current research also includes the greenhouse gas emissions indicator individually as another policy measure. The reader is cautioned to remember that changes in the value of these sustainability indices do not necessarily constitute a change in sustainability. Rank ordering calculated indices establish relative frameworks for evaluating a country's environmental sustainability performance across the noted policy areas.

The second component of the current study assesses the reasons for observed differences among OECD-member countries' environmental performances on the various policy measures. As a first step towards determining their importance, influential factors thought to help shape national environmental performance are culled from the literature. The compiled factors are climate, population pressure (computed as both growth and density), economic output, technological development, industrial structure, energy prices, environmental governance, pollution abatement and control (PAC) expenditures, and environmental pricing. Analysing the relationships these factors form with the policy measures determine their importance in each area. The combined results of regression and cluster analyses identify the important factors, as well as their corresponding contributions to explaining performance on the policy measures. In effect, a triangulation process that combines a literature review with the findings of two analytical techniques identifies the significant influential factors for each policy measure. These findings provide a second unique contribution of the current research.

The third component of the current study applies the results from the other two components. This component examines the policy implications of these findings for Canada and develops options for improving Canadian environmental performance. Applying the findings to an exemplar demonstrates the value of the current research. OECD-member countries, of which Canada is one, are the units of analysis for the current research, designed to answer or achieve the following research questions, hypotheses, and objectives.

RESEARCH QUESTIONS

Q_1: How can a policy maker best measure a country's environmental sustainability progress and performance? And, what are significant areas of uncertainty in measurement and ranking methods?

Q_2: How do influential factors—ungovernable, semi-governable, governable—affect a country's environmental sustainability performance? And, what are potential implications for policy makers?

HYPOTHESES

H_1: Countries' ranks for environmental sustainability performance will depend, in part, on the measurement techniques selected for evaluation.

H_2: Countries' environmental sustainability performances will depend, in part, on influential factors, either ungovernable, semi-governable, or governable.

OBJECTIVES

1. Compare environmental performance studies to gain insight into the various approaches, perspectives, issues, methods, and findings (among other factors) involved with assessing a country's environmental sustainability efforts using indicators and composite indices. The review situates the current study within the literature.
2. Impute and aggregate ESPIs according to techniques recommended by the OECD *Handbook on Constructing Composite Indicators: Methodology and User Guide* (Nardo et al. 2005), as well as subsequently rank OECD-member countries' performances on the overall composite index, ESPCI, and each of the subindices measuring various environmental policy areas.
3. Perform uncertainty and sensitivity analyses using different normalisation methods, missing data treatments, scale-effect adjustments, weights, and aggregation methods to estimate the sources of uncertainties in the inputs, as well as the magnitude of effect each source produces.

4. Complete multiple regression and cluster analyses of the relationships between the policy measures and influential factors. These analyses determine the important factors for each policy measure, as well as their relative contributions to explaining performance on each.

CONCEPTUAL FRAMEWORK

Indicators and factors are most useful when developed and organised around a guiding framework. A general framework for generating sets of indicators does not exist (Pinter et al. 2005; OECD 1993; Walmsley 2002), but a widely used model is the OECD's pressure-state-response (PSR) framework (OECD 1993). This framework is adapted from Rapport and Friend's (1979) earlier 'stress-response' model that distinguishes between indicators of environmental change (stress) and those of environmental conditions (response to the stress), a distinction that helps explain environmental change. Stresses may be natural processes, such as flooding or volcanic eruptions, or humans and their activities, such as harvesting resources or generating wastes. Responses to such stresses include changes to underlying inventories of natural resources like forests, fish, and non-renewable resources, or changes to quality of life aspects like air, water, food, or health. The Rapport and Friend model unrealistically attempts to link, on a one-to-one basis, each environmental stress with a corresponding environmental change or response. Thus, the model is data intensive and may become unusable due to missing or low-quality data. Conversely, the OECD PSR framework does not attempt to specify these interactions between activities and the environment, preferring a more general approach.

The logic of the PSR framework follows a cause-effect relationship between pressures and the state of the environment allowing for societal and institutional responses. A PSR framework categorises indicators as pressure, state, or response. Pressures on the environment arise from human production and consumption activities that deplete natural resources and generate waste and pollution. These pressures have deleterious impacts on the state of a country's environment. Society then responds to changes in pressures or state of the environment with policies intended to prevent or mitigate environmental degradation (OECD 1993).

The best indicators gauge the state of the environment because they send the most direct signal regarding the health of ecosystems. The next best indicators track environmental pressures as proxies for the state of the environment and ecosystem health. The stronger the causal mechanism between a pressure and the underlying state, the better the indicator. Finally, indicators quantifying policy responses are least favoured for tracking environmental sustainability because they are somewhat removed from the status of ecosystem health. Although, certain policy-response indicators are highly relevant because they do strongly signal the state of an ecosystem. For example, the proportion of protected area in a country indicates the extent to which a country conserves its natural habitat.

Like the Gunton et al. (2005) and Conference Board of Canada (CBC) (2004) studies, the current research uses a PSR structure, albeit modified to incorporate influential factors that interact with environmental pressures and societal responses (fig. 1.2). The conceptual framework serves two purposes. First, it provides an organising schema that helps to determine the relevancy of individual indicators and to communicate the nature of each performance indicator. The next section further explains the selection process, as well as explains the connections between the current research and the earlier Gunton et al. (2005) study. Of the 26 indicators used in the current research, two are 'state,' three are 'response,' and the rest are in the 'pressure' category (refer to table 1.4).

The second purpose that the conceptual framework serves is to introduce the idea that influential factors affect a country's state of the environment. These factors are aspects of a country's circumstances that help explain its environmental performance. They may be ungovernable, semi-governable, or governable according to the degree of control a country's policy-making arena exerts over them. Indeed, one may conceive of a continuum with wholly ungovernable factors at one end and wholly governable factors at the other end, in between are factors with various proportions of the two extremes. Such a continuum may be divided into three categories: factors that are largely ungovernable, factors that contain relatively large proportions of both ungovernable and governable elements, and factors that are largely governable. This distinction is particularly relevant when examining the policy implications of the findings. Figure 1.2 symbolises this distinction by altering the societal response arrows whereby solid lines represent responses that are more effective, dashed lines represent responses that are less effective, and no lines represent the absence of effective responses.

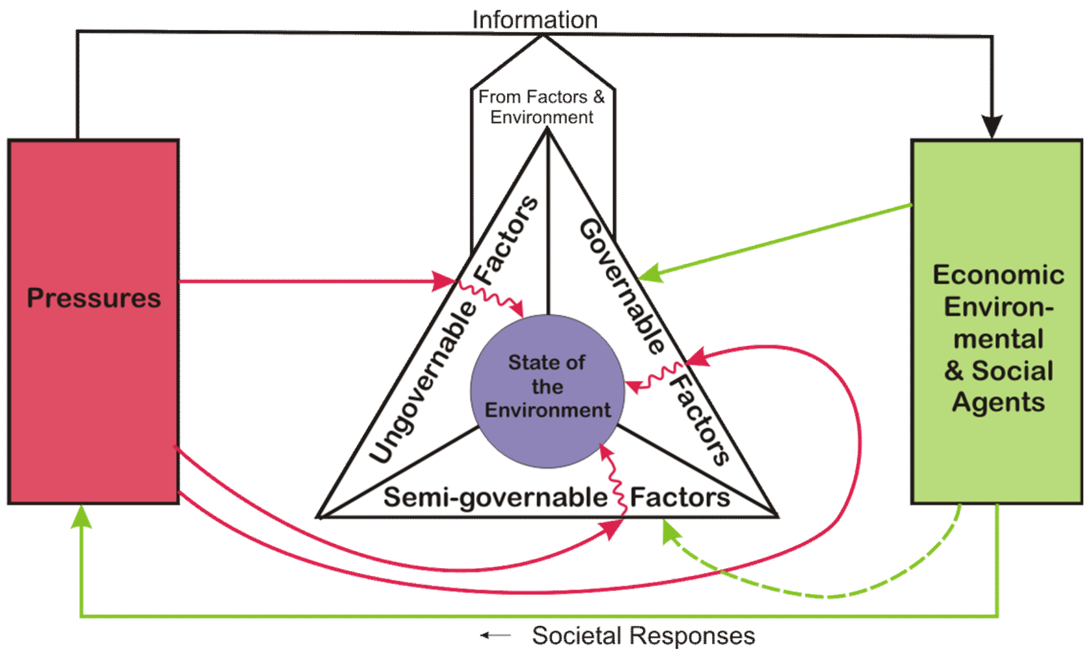

Figure 1.2: Overarching guiding conceptual framework for the current study

Completely ungovernable factors are the least amenable to government policy actions because they are largely outside a country's sphere of influence. As such, they are relatively inflexible characteristics of a nation that are not easily manipulated. The Government of Canada (GOC) refers to such factors as 'national circumstances' that significantly influence a country's production, consumption, and usage of energy, as well as subsequent pollution-emission patterns (Canada 2001). In contrast, completely governable factors are open completely to policy levers; such factors are influenced primarily by government fiat. Semi-governable factors possess large proportions of both ungovernable and governable elements, meaning such factors are somewhat intractable to government intervention but still possess many governable features. Those semi-governable factors with larger proportions of governable elements are obviously more amenable to policy interventions than those factors with larger proportions of ungovernable elements. Again, the distinction regarding a factor's governability is only important for the policy implications of the findings. Including influential factors in the conceptual framework introduces the idea that circumstantial elements may affect a country's environmental performance.

The factors culled from the literature review in chapter 4 are climate, population pressure (computed as both growth and density), economic output, technological development, industrial structure, energy prices, environmental governance, PAC expenditures, and environmental pricing. Climate is an ungovernable factor, while population growth and density, economic output, technological development, and industrial structure are semi-governable factors. Finally, energy prices, environmental governance, PAC expenditures, and environmental pricing are governable factors.

ENVIRONMENTAL SUSTAINABILITY PERFORMANCE INDICATORS

The current study uses the same basic set of indicators as Gunton et al. (2005). To develop the list of indicators, Gunton et al. (2005) review the following 10 environmental reporting methodologies.

1. *OECD Environmental Performance Reviews for Canada* (OECD 1995; 2004)
2. *Canada vs. the OECD: an Environmental Comparison* (Boyd 2001)
3. *Alberta Genuine Progress Indicator Accounting (GPI) Project* (Anielski 2001)
4. *GPI Atlantic Natural Resource and Environmental Accounts* (Colman 2001)
5. *Environmental Trends in British Columbia* (B.C. 2002)
6. National Round Table on the Environment and the Economy (NRTEE) Sustainability Indicators Project (NRTEE 2003)
7. David Suzuki Foundation *Sustainability within a Generation* Framework (Boyd 2004)
8. Fraser Basin Council (FBC) *State of the Fraser Basin Report* (FBC 2004)
9. CBC *Potential and Performance Review* (CBC 2004)
10. Yale Environmental Sustainability Index (ESI) (Esty et al. 2005)

The current research updates this list of indicator frameworks by replacing ESI with the most recent Yale Environmental Performance Index (EPI) (Esty et al. 2008), as well as adding the Gunton et al. (2005) study and a recent WWF *Living*

Planet Report (WWF 2006). Appendix A describes these 12 indicator frameworks.[2] The 12 selected studies include ones done by international agencies focusing on multiple country assessments because they are most likely to include best practices of member countries. Also included are a number of evaluative frameworks from independent research organisations, as well as several frameworks included to reflect the Canadian context. Subsequently, appendix B compiles and evaluates each indicator for inclusion. The current study includes indicators that satisfy these five criteria.

1. **Relevance:** Does the proposed indicator capture a pertinent aspect of environmental sustainability?
2. **Measurability:** Is the phenomenon being appraised by the proposed indicator able to be reliably quantified with current techniques?
3. **Relationship:** Does the proposed indicator exhibit any a strong relationship or overlap with other indicators?
4. **Soundness:** Is the underlying data for the proposed indicator obtained with established and accepted methods?
5. **Coverage:** Do underlying data sources for the proposed indicator provide sufficient spatial coverage of the OECD countries for inclusion in the study?

These appendices summarise and replicate the process Gunton et al. (2005) use to select their performance indicators. Readers interested in further details about the selection of individual performance indicators may consult this earlier study.

Quality data are only available for 29[3] of the initial list of 37 indicators compiled by Gunton et al. (2005). Appendix B notes and section 3.5 Limitations of the Uncertainty and Sensitivity Analyses further discusses the eight indicators excluded for data coverage reasons. To reflect the research objective of

[2] Chapter 2 reviews the techniques that five of these 12 studies use to construct their respective composite indices.

[3] The OECD's Environmental Data Compendiums (e.g., OECD 2005b) supply data for 29 of the 37 indicators selected by Gunton et al. (2005) for international comparisons. OECD data undergo a due diligence assessment to ensure accuracy, reliability, and comparability of data. Member countries provide information to the OECD Secretariat through a questionnaire; a substantial internal data quality review occurs on compiled information before member countries conduct their own external review of the data. The internal assessment compares and harmonises the data with other national and international sources. On completion of the external review, the secretariat incorporates country comments through further review and updating of the data tables, which are then ready for inclusion in subsequent policy analyses.

explaining environmental performance, the current study further adjusts this list of 29 indicators to arrive at the final list of 26 (table 1.4). The current study recasts two indicators as factors and removes a third entirely. Chapter 4 identifies the policy-response indicators environmental pricing and PAC expenditures as influential factors because they explain, rather than gauge, environmental outcomes. That is, they are independent variables as opposed to dependent variables. For the purposes of the current research, influential factors are independent variables and indicators of environmental outcomes are dependent variables. Such treatment of performance indicators is common in the literature. For example, the Yale EPI treats indicators in such a way for regression analyses (Esty et al. 2008), while GOC uses this perspective when arguing that `natural circumstances` affect a country's environmental performance (GOC 2001).

The current research also removes official development assistance (ODA) from the list of performance indicators. This indicator reflects a country's contribution to international sustainability, rather than to its domestic sustainability, thus ODA more tangibly affects receiving countries' environmental performances rather than donor countries'. While efforts to improve international environmental sustainability do affect a country's national environmental sustainability, such impacts are indirect, only exerting effects through linkages. Again, with a research objective of explaining national environmental performance on the policy measures, it is important to keep the performance indicators focused on a national perspective.

This list of indicators (table 1.4) is both relevant to measuring environmental sustainability performance, and, perhaps more critically, strongly supported by high-quality data. Consequently, these 26 indicators form a solid basis for constructing a series of indices measuring various areas of environmental sustainability performance, and for conducting an uncertainty and sensitivity analyses, providing a unique contribution of the current research. However, one should note that these indicators and the corresponding composite indices formed from them might not adequately appraise sustainability.

Table 1.4: Environmental sustainability performance indicators

INDICATOR	MEASUREMENT VARIABLE	CATEGORY
1. Energy Consumption	Tonnes oil equivalent (toe) per capita	Pressure
2. Energy Intensity	toe/U.S.$1,000 GDP	Pressure
3. Water Consumption	Cubic metres of water consumption per capita	Pressure
4. Greenhouse Gas Emissions	Tonnes CO_2 equivalent emissions per capita	Pressure
5. Electricity From Renewable Resources (w/ hydro)	% electricity from renewable resources (w/ hydro)	Pressure
6. Electricity From Renewable Resources (w/out hydro)	% electricity from renewable resources (w/out hydro)	Pressure
7. Sulphur Oxides	Kilograms sulphur oxides emitted per capita	Pressure
8. Nitrogen Oxides	Kilograms nitrogen oxides emitted per capita	Pressure
9. Volatile Organic Compounds	Kilograms volatile organic compounds emitted per	Pressure
10. Carbon Monoxide	Kilograms carbon monoxide emitted per capita	Pressure
11. Ozone-Depleting Substances	Kilograms ozone-depleting substances emitted	Pressure
12. Municipal Waste	Kilograms municipal waste generated per capita	Pressure
13. Recycling	% material recycled from municipal waste	Response
14. Nuclear Waste	Kilograms nuclear waste per capita	Pressure
15. Municipal Sewage Treatment	% population with sewage treatment	Response
16. Pesticide Use	Tonnes pesticide used per square kilometre of	Pressure
17. Fertiliser Use	Tonnes fertiliser used per square kilometre of	Pressure
18. Livestock	Sheep equivalents per square kilometre of arable and grassland	Pressure
19. Number Species at Risk	Number species at risk	State
20. % Species at Risk	% known species at risk	State
21. Protected Areas	% land designated as protected	Response
22. Forest Harvested	Cubic metres timber harvested per square	Pressure
23. Forest Harvest to Growth Ratio	Timber harvested to forest growth ratio	Pressure
24. Fisheries Harvest to Primary Production Ratio	Tonnes fish harvested per tonne of primary production in exclusive economic zone	Pressure
25. Fisheries Harvest to World Harvest	% world catch	Pressure
26. Distance Travelled	Thousand vehicle-kilometres travelled per capita	Pressure

Source: Gunton et al. 2005

1.3) THESIS ORGANISATION

Chapter 2 is primarily a literature review. It describes five studies that quantify national environmental performance of multiple countries using a cross-sectional approach. Cross-sectional comparisons yield reference points, or benchmarks, based on each jurisdiction's performance relative to other jurisdictions'. Most importantly, the selected studies provide a representative sample of potential methods, which provides an effective framework for the subsequent uncertainty and sensitivity analyses.

Chapter 3 presents the results of the uncertainty and sensitivity analyses. The discussion of the input-output Monte Carlo-based uncertainty and sensitivity analyses of the current research emphasise the decision points, identified in chapter 2, that occur when constructing policy composite indices. These decision points are responsible for introducing variability into the results. Chapter 3 explores the important sources of variation identified by the current analysis, the analytical limitations of the findings, and recommended construction techniques for composite indices. Moreover, chapter 3 contains the principal components factor analysis used to group the individual ESPIs into the subindices for measuring other environmental policy areas. Also presented are the calculated policy subindex scores for each OECD-member country. The results of the uncertainty and sensitivity analyses help answer the first research question and provide information for evaluating the first hypothesis regarding measurement techniques influencing a country's performance rank. As such, these results provide one of the unique contributions of the current research.

Chapter 4 is also primarily a literature review. It discusses factors thought to influence a country's environmental performance. This chapter discusses each factor's association with various aspects of environmental sustainability, as well as describes the metric used to represent each influential factor in subsequent regression and cluster analyses. Chapter 4 also includes a discussion of other factors considered but ultimately excluded from further analysis.

Chapter 5 presents the results of several analyses that determine the most important factors shaping a country's environmental performance on the policy measures. Specifically, the results of Akaike's Information Criterion, multiple regression analysis, and cluster analysis, are discussed. In conjunction, these results answer the second research question and provide information for evaluating the second hypothesis, which both focus on influential factors that consistently affect a country's environmental performance. Estimating how the influential factors account for different environmental performances among OECD-member countries is a unique contribution of the current research.

Chapter 6 delves into the policy implications for Canada that arise from the findings of the current research. A series of sensitivity analyses that alter the value of pertinent factors for policy areas in which Canada currently is underperforming illustrates options for improving Canadian environmental performance. Included among the policy measures is the greenhouse gas (GHG) emissions indicator because climate change is an important environmental issue that deserves separate treatment. This chapter determines the key main influential factors for improving Canada's environmental performance, assesses the impacts of these key factors on Canada's performance on important environmental policy measures, compares the main influential factors to drivers of GHG emissions, and describes potential Canadian policy implications. Providing these policy options is another unique contribution of the current research.

Chapter 7 presents the conclusions and recommendations arising from the current study. It marshals evidence from the findings, specifically chapters 3, 5, and 6, to evaluate hypotheses tested by this investigation, answer research questions, and propose areas for future research.

CHAPTER 2:
EVALUATING ENVIRONMENTAL SUSTAINABILITY

This chapter reviews five studies that assess national environmental sustainability. Each study uses a set of performance indicators formulated into a composite index to rank countries. Recall that only one method is available for an analyst to build a composite index for comparing dissimilar entities, but the method requires several decisions about the individual techniques one employs (Nardo et al. 2005). The method starts with selecting a set of performance indicators with the aid of a guiding conceptual framework and then deciding how to treat missing data. Next, an analyst must decide on the scale-effect adjustments to use to be able to compare indicators across countries of different sizes. Once these steps are completed, an analyst normalises the performance indicators to a common measurement scale so that individual indicators may be compared and aggregated. Finally, an analyst selects the weights and method of aggregation for combining the individual indicators into a composite index.

The five studies are:

1. *Canada vs. the OECD* (Organisation for Economic Co-operation and Development) (Boyd 2001)
2. *Performance and Potential 2004-2005: Key Findings, How Can Canada Prosper in Tomorrow's World?* (Conference Board of Canada (CBC) 2004)
3. *Canada's Environmental Performance: an Assessment* (Gunton et al. 2005)
4. *Living Planet Report* (World Wide Fund (WWF) 2006)
5. Yale 2008 Environmental Performance Index (EPI) (Esty et al. 2008)[4]

The researcher selected these studies for several reasons. They form a representative sample of potential methods described by the *OECD Handbook on Constructing Composite Indicators: Methodology and User Guide* (Nardo et al. 2005), which provides the framework for the uncertainty and sensitivity analyses that follow. These studies were also selected because they provide regular evaluations of environmental performance of multiple countries using a cross-

[4] These five studies are part of the 12 studies that have their indicator frameworks reviewed in appendix A.

sectional approach. Regular evaluations are important because they support the development of data sources and testing methodology, while cross-sectional comparisons of multiple countries yield reference points, or benchmarks, based on each jurisdiction's performance relative to other jurisdictions'. Thus, policy makers are able to incorporate aspects of successful practices from benchmarks (best performers) into new policies by using refined data sources and methodologies to gauge a jurisdiction's performance by comparing it with the benchmarks (best performers).

The sample of reviewed studies provides a useful framework for evaluating the effects of alternative techniques on final performance ranks with subsequent uncertainty and sensitivity analyses. The first section of this chapter discusses how each of the five studies constructed its respective composite index, while the second section highlights the differences by contrasting the various techniques each uses. These areas of contrast are the basis of the uncertainty and sensitivity analyses detailed in chapter 3.

2.1) STUDIES EVALUATING ENVIRONMENTAL PERFORMANCE

The studies examined in this section have general methodological similarities as well as differences (table 2.1). All studies use a national perspective for the unit of analysis, and all incorporate aspects of environmental sustainability. On a technical note, most of the studies also use some form of linear aggregation for the performance indicators, as well as equal weights. On the other hand, the studies each use different indicator selection techniques, although data quality and availability issues limited indicator selection across all studies. Normalisation methods that convert indicators to a common scale and varying mixtures of scale-effect adjustments that allow comparison of different sized countries also differ across the studies. Notably, one study, the Yale EPI (Esty et al. 2008), imputed missing data and performed a sensitivity analysis by altering several elements in table 2.1.

CANADA VS. THE OECD: AN ENVIRONMENTAL COMPARISON

Prepared by the Eco-Research Chair of Environmental Law and Policy at the University of Victoria, *Canada vs. the OECD* assesses Canada's environmental record (Boyd 2001). The goal of *Canada vs. the OECD* is to provide accurate, independent information about Canada's environmental track record in comparison to other OECD-member countries. *Canada vs. the OECD* uses a time-series analysis and a cross-sectional methodology to compare Canada's environmental performance with other OECD-member countries, using 25 environmental indicators in 10 categories (see appendix A). The time-series analysis reports the percent change in each indicator over two decades from 1980 to 1999 to give an indication of progress, or lack thereof, towards sustainability. The cross-sectional comparison ranks Canada's environmental performance for each indicator relative to other OECD-member nations. The study also compares Canada's progress over the past two decades with the rest of the OECD.

Table 2.1: Comparing several recent environmental performance review exercises

ASPECT	BOYD 2001	CBC 2004	GUNTON ET AL. 2005
Scope	Environmental sustainability	Separate treatment of sustainability elements with focus on the environment	Environmental sustainability
Unit of Analysis	OECD countries	Subset of OECD countries	OECD countries
Indicator Selection	Author's selection as representative of major environmental concerns Data quality/availability	Compiled from PSR framework; final selection through evaluation by 3 criteria Data quality/availability	Compiled from 10 frameworks; final selection through evaluation by 4 criteria Data quality/availability
Missing Data	Average around missing value	Average around missing value	Average around missing value
Scale-Effect Adjustments	Per capita basis Per unit GDP Total population Number of known species	Number of known species Per unit populated land area Per capita basis Per unit GDP Per unit land area (various types)	Per capita basis Per unit GDP Total electricity consumption Total waste generated Total population Per unit land area (various types) Number of known species Total world fisheries catch
Normalisation Method	Ranking	Standardisation[a]	Ranking Distance to reference country[b]
Weighting Method	Equal weights	Equal weights	Equal weights
Aggregation Method	Simple mean	Simple mean	Simple mean
Sensitivity Analysis	None	None	None

a = Standardisation converts values to a common scale with a mean of 0 and standard deviation of 1 by subtracting the mean from the observation and dividing the result by the standard deviation of the variable (also known as *z*-scores)'

b = Distance to reference country quantifies the relative position of a given indicator value with regard to a reference country, in this case the best performer for a given indicator.

Continued on next page

Table 2.1—*Continued*

ASPECT	WWF 2006	ESTY ET AL. 2008
Scope	Biodiversity; Ecological footprint	Environmental sustainability
Unit of Analysis	About 2/3 of countries worldwide, including 28 OECD countries for footprint analysis	About 2/3 of countries worldwide, including 29 OECD countries
Indicator Selection	Author's selection as representative Data quality/availability	Review of environmental literature, expert advice, and peer review; final selection through evaluation by 4 criteria Data quality/availability
Missing Data	Case deletion	Imputation - regression and correlation analysis Case deletion
Scale-Effect Adjustments	Per capita basis Per unit land area (various types)	Per capita basis Per unit GDP Per unit land area (various types) Total electricity consumption Total population
Normalisation Method	Conversion to common unit	Winsorisation[c] Proximity to target/Re-scaling
Weighting Method	Equal weights	Equal weights with refinements based on expert advice
Aggregation Method	Living Planet Index: Geometric mean Ecological Footprint: Linear	Simple mean
Sensitivity Analysis	None	Input-output Monte Carlo simulation

c = This two-tailed winsorisation involves lowering values that exceed the 97.5 percentile to the 97.5 percentile and raising values smaller than the 2.5 percentile to the 2.5 percentile in the belief that data points in these regions reflect data quality problems. Winsorisation avoids having a few extreme values dominate the analysis.

Canada vs. the OECD selects its 25 environmental indicators to represent the major areas of environmental concern. Most of the statistical data in this study comes from the OECD's *1999 Environmental Data Compendium*, which the OECD publishes every two years with the goal of providing "the best internationally available data on the environment and related areas" (OECD 2005b: 6). Although the OECD relies largely on information provided by member governments, it attempts to ensure quality by verifying this information before publication.

Canada vs. the OECD uses several standard techniques for constructing the composite index used to rank performance. Boyd (2001) applies various scale-effect adjustments to the indicators (see table 2.1 for complete list) to ensure comparability among countries of different sizes, but tends to use per capita adjustments. Per capita adjustments prevent countries with large populations from undue relegation to worst performers status. For example, the United States, with the largest population among OECD nations, would almost invariably be at the bottom of every category in absolute terms. The study ranks OECD countries from best to worst on each indicator, which is the normalisation ranking method. Calculation of an overall rank for each country uses the simple mean of the country's rank on each of the indicators for the most recent years. Each indicator receives equal weight. Calculation of a country's final rank excludes indicators that are missing data, thus, the study averages the overall rank over a reduced number of indicators.

PERFORMANCE AND POTENTIAL 2004-2005

Conference Board of Canada (CBC) is a not-for-profit organisation, rather than a government department, funded exclusively through fees charged for services to the private and public sectors (CBC 2004). In 1999, CBC began publishing an annual report that evaluates Canada's economic, social, and environmental performance relative to other OECD countries. The 2004-05 evaluation reports on 24 of 30 OECD countries with a focus on environmental management. *Performance and Potential 2004-2005* excludes five OECD countries from the analysis (Czech Republic, Hungary, Poland, Slovak Republic, and Turkey) because of a lack of reliable data, and excludes Luxembourg due to its economic union with Belgium (CBC 2004).

The CBC study uses 110 indicators organised into six categories: economy, innovation, environment, education and skills, health, and society. The environmental category has 24 indicators (see appendix A). CBC uses the following three criteria, in combination with the OECD pressure-state-response (PSR) model, to determine which indicators to include (CBC 2004: 16).

1. Is there a general agreement that a movement in the indicator in one direction is better than in the other?
2. Are the data available for most of the countries?
3. Are the data comparable across countries?

Performance and Potential 2004-2005 ranks countries using an overall index calculated from standardised scores (z-scores) for each of the individual indicators (CBC 2004: 25). The standardisation normalisation procedure calculates the difference between a country's indicator value and the average value divided by the standard deviation for each indicator, multiplied by 100.[5] The indicators use a variety of scale-effect adjustments (see table 2.1 for complete list), but the CBC study tends to adjust indicators using a per unit land area with population density greater than five people (e.g., units of metric tonnes of nitrogen oxides emissions per square kilometre of area with population density greater than five people). Countries need data to cover a minimum of four out of five indicators, or 80% data coverage across the indicators, for inclusion in the composite index calculation. *Performance and Potential 2004-2005* applies equal weights to each indicator when calculating the overall composite index, which is the simple mean of the standardised scores. Subsequently, each country is ranked from highest to lowest on the index.

A further comparison designates the top 12 performing countries on each indicator as a gold, silver, or bronze performer. The study awards gold to the countries that score in the top third, silver to the middle third, and bronze to the bottom third. In previous years, *Performance and Potential 2004-2005* ranked countries as 'top,' 'average,' or 'poor' performers based on the same categorisation. However, the current method replaces this approach to reflect the

[5] $I_{i,j} = \frac{x_{i,j} - \bar{x}_i}{\mathrm{Std}(x_i)} * 100$, where $x_{i,j}$ is the i^{th} raw indicator value for the j^{th} country and x_i is the i^{th} raw indicator value.

fact that these countries are already the best in the world for each category (CBC 2004).

Changes to CBC methodology in the 2004-05 report produced large changes to the final ranks. The list of indicators increased from 16 to 24, expanding to include three indicators of air quality in urban centres and several for water quality, including freshwater phosphorus concentrations, freshwater suspended particulate matter, and industrial organic pollutant concentrations. The methodology selected a different mix of indicators as well, and scale-effect adjustments changed from GDP to per unit land area with population density greater than five people for several air emission indicators. As mentioned, previous editions of the CBC report placed Canada 12th and 16th, while this edition incorporating these changes places Canada 9th.

CANADA'S ENVIRONMENTAL PERFORMANCE

At the request of the David Suzuki Foundation, the Sustainable Planning Research Group with the School of Resource and Environmental Management at Simon Fraser University conducted a study to assess Canada's environmental performance relative to other countries in the OECD (Gunton et al. 2005). *Canada's Environmental Performance* develops and applies an environmental sustainability reporting system, consisting of 29 indicators[6] (see appendix A) and two ranking systems, to assess Canada's progress. This system produces information designed to assist policy makers and the public with identifying strengths and weaknesses in Canada's environmental performance. It also helps identify both key issues and successes in environmental sustainability both within Canada and in other nations that can help develop better environmental management strategies.

The first step Gunton et al. (2005) take in assessing Canada's progress is the development of an environmental sustainability reporting system. *Canada's Environmental Performance* reviews the following 10 environmental reporting

[6] The current research uses the same basic indicator set, but with three alterations that reduce the number to 26 (see table 1.4) to accommodate the specific research goals. These changes are detailed in the Environmental Sustainability Performance Indicator section in chapter1.

methodologies to compile a list of environmental indicators.[7]

1. *OECD Environmental Performance Reviews for Canada* (OECD 1995; 2004)
2. *Canada vs. the OECD: an Environmental Comparison* (Boyd 2001)
3. *Alberta Genuine Progress Indicator Accounting (GPI) Project* (Anielski 2001)
4. *GPI Atlantic Natural Resource and Environmental Accounts* (Colman 2001)
5. *Environmental Trends in British Columbia* (B.C. 2002)
6. National Round Table on the Environment and the Economy (NRTEE) Sustainability Indicators Project (NRTEE 2003)
7. David Suzuki Foundation *Sustainability within a Generation* Framework (Boyd 2004)
8. Fraser Basin Council (FBC) *State of the Fraser Basin Report* (FBC 2004)
9. CBC *Potential and Performance Review* (CBC 2004)
10. Yale Environmental Sustainability Index (Esty et al. 2005)

The 10 selected studies include one done by an international agency focusing on multiple country assessments because it is most likely to include best practices of member countries. Also included are a number of evaluative frameworks from independent research organisations, as well as several included to reflect the Canadian context of the study.

Next, *Canada's Environmental Performance* evaluates the compiled list of environmental indicators using the following four criteria

- The indicator must provide a meaningful measure of environmental sustainability.
- The indicator must be generally understandable for a non-technical audience.
- The data required for the indicator must be reliable and available in a timely fashion, as well as produced on a regular basis using consistent definitions for OECD countries.
- The indicator should not directly replicate other indicators.

These evaluative criteria mirror those in the *Handbook on Constructing Composite Indicators* (Nardo et al. 2005: 10).

[7] The current research updates this list of indicator frameworks by replacing the Yale ESI (Esty et al. 2005) with the most recent Yale Environmental Performance Index (Esty et al. 2008), as well as adding the Gunton et al. (2005) study and a recent WWF *Living Planet Report* (WWF 2006).

> *Indicators should be selected on the basis of their analytical soundness, measurability, country coverage, relevance to the phenomenon being measured, and relationship to each other.*

The evaluation selects 37 indicators that the researchers judge to express environmental sustainability, 29 of which have OECD data available for international comparisons.

Canada's Environmental Performance groups the indicators under one of nine thematic categories used in the David Suzuki Foundation report *Sustainability within a Generation* (Boyd 2004). While Gunton et al. (2005) use a variety of scale-effect adjustments (see table 2.1 for complete list), the study tends to use per capita adjustments more frequently. Similar to Boyd's (2001) study, *Canada's Environmental Performance* ignores indicators with missing data. Thus, a country's overall rank is obtained over a reduced number of indicators, with indicators equally weighted during aggregation of the final composite index.

Gunton et al. (2005) employ two normalisation methods to assess a country's environmental sustainability performance. The Environmental Performance Rank (EPR) normalises the indicator data using the ranking method, while the Environmental Performance Grade (EPG) normalises the data using a distance-to-reference-country method. EPR for a country is the rank of the simple mean of all indicator ranks. EPG for a country is the value on each indicator relative to the best performer multiplied by 100.[8] Since the best performer has an EPG of 100%, it also quantifies the magnitude of differences observed among environmental performances, which an ordinal ranking method can not. *Canada's Environmental Performance* assigns countries an overall ordinal rank based on the simple mean aggregation of all indicator EPGs.[9]

[8] EPG equation: $I_{i,j} = \frac{x_{i,j}}{x_{rc}} * 100$, where $x_{i,j}$ is the i^{th} raw indicator value for the j^{th} country and x_{rc} is the raw indicator value for the reference country.

[9] Although the current research uses the same indicator set as Gunton et al. (2005), the composite indices each study develops are different. The composite index for the current research is the environmental sustainability performance composite index.

LIVING PLANET REPORT

WWF began its Living Planet Reports in 1998 to show the state of the natural world and the impact of human activity upon it. The *Living Planet Report* describes the changing state of global biodiversity and the pressure human consumption of natural resources exerts on the earth's ecosystems. It relies on five indicators (see appendix A) selected for ecological reasons. The Living Planet Index, formed from three subindices, reflects the health of the planet's ecosystems, while the Ecological Footprint demonstrates the extent of human demand on these ecosystems. The Ecological Footprint does not include freshwater because consumption is not expressible in terms of the footprint's global hectares, hence the report addresses freshwater consumption as a separate indicator. The *Living Planet Report* tracks these measures over several decades, revealing past trends, before exploring three scenarios that depict how society may develop. The scenarios illustrate how different choices may lead to a sustainable society living within robust ecosystems, or a collapsing society living within degraded ecosystems, resulting in a permanent loss of biodiversity and erosion of the planet's ability to support life.

The Living Planet Index tracks trends in the earth's biological diversity. It tracks global populations of 1,313 vertebrate species of fish, amphibians, reptiles, birds, and mammals as a composite index created from three separate subindices. These three subindices track trends in populations of 695 terrestrial species, 274 marine species, and 344 freshwater species respectively. Each subindex represents the average change of all species populations within that group. For example, the terrestrial subindex is the average of the change in each of the 695 terrestrial species tracked. The overall composite index, the Living Planet Index, is an equally weighted geometric mean of the three subindices. Although vertebrates represent only a fraction of known species, WWF assumes that trends in their populations are typical of biodiversity overall. By tracking wild species, the Living Planet Index is also monitoring the health of ecosystems.

Biodiversity suffers when the biosphere's productivity can not keep pace with human consumption and waste generation (WWF 2006). The Ecological Footprint tracks these pressures as the summand of the area of biologically productive land and water needed to provide ecological resources and services such as food, fibre, timber, land on which to build. The footprint also includes the land needed to absorb carbon dioxide released by burning fossil fuels. The Ecological Footprint is expressed as an area in global hectares with world-average biological productivity. For example, Canada's ecological footprint of 7.6 global hectares per person is the summand of the following types of areas required to support the consumption of an average citizen: cropland (1.14), grazing (0.40), forests (1.16), fishing (0.15), carbon dioxide from fossil fuels (4.08), nuclear energy (0.50), and built-up land (0.18) (WWF 2006). Footprint calculations use yield factors to account for national differences in biological productivity (i.e., tonnes of wheat per United Kingdom or Argentinean hectare versus world-average global hectare), and equivalence factors to account for differences in world-average productivity among land types (i.e., world-average forest versus world-average cropland). The calculations to derive the Ecological Footprint use various land type areas to adjust for scale effects, while, to compare among countries, the Ecological Footprint itself is adjusted on a per capita basis (see table 2.1 for complete list). The comparison encompasses 147 countries, including 28 OECD-member countries. Countries without sufficient data coverage are excluded from the footprint analysis.

YALE 2008 ENVIRONMENTAL PERFORMANCE INDEX

The Yale Centre for Environmental Law and Policy and the Centre for International Earth Science Information Network at Columbia University in collaboration with the World Economic Forum's Global Leaders for Tomorrow Environment Task Force developed the Yale Environmental Performance Index (EPI). The Yale EPI, incorporating 149 countries (including 29 OECD-member countries), centres on two broad environmental protection objectives: (1) reducing environmental stresses on human health, and (2) promoting ecosystem vitality (Esty et al. 2008). EPI gauges environmental health and ecosystem vitality by tracking 25 indicators in six policy categories: environmental health, air pollution, water, biodiversity and habitat, natural resources, and climate change. The selection process for the 25 indicators incorporates a broad-based review of the environmental policy literature, including the Millennium Development Goal dialogue, the Intergovernmental Panel on Climate Change, and the *Global Environmental Outlook-4*. Expert judgment is also included in the process.

The 2008 EPI uses a proximity-to-target methodology focused on a core set of environmental outcomes linked to policy goals. For each indicator, EPI identifies a relevant long-term public health or ecosystem sustainability goal. These targets do not vary by country and are drawn from international agreements, standards set by international organisations, national authorities, or prevailing consensus among environmental scientists (Esty et al. 2008). By identifying specific targets and measuring how close each country comes to them, EPI provides a quantifiable foundation for policy analysis.

A proximity-to-target approach provides a way to assess the effectiveness of environmental policies against relevant performance goals. The design of this approach helps policy makers:

- recognise environmental problems;
- track pollution control and natural resource management trends;
- identify priority environmental issues;
- determine which policies are producing good results;
- provide a baseline for performance comparisons;
- find peer groups on an issue-by-issue basis; and
- identify best practices and successful policy models (Esty et al. 2008).

The Yale EPI expands the list of countries included in the 2006 Pilot EPI by imputing data to fill isolated gaps (Esty et al. 2006; Esty et al. 2008). In the pilot edition of EPI, the selected countries all possess complete data sets across the indicators thus guaranteeing that missing data would not be an issue. The 2008 edition of EPI filled isolated data gaps with regression and correlation analyses as well as averaging, nevertheless, the 2008 EPI still rejected countries missing more than a few data points.[10]

To ensure comparability among countries, the Yale EPI adjusts indicators for scale effects by per unit GDP, per unit of land, and per capita (see table 2.1 for complete list). To avoid extreme values skewing aggregations, the Yale EPI winsorises 'outlier' indicator values by trimming them to the 95th percentile value. In the few cases where a country did better than the target, EPI set the value to that of the target. In other words, a country did not receive a reward for

[10] On the other hand, the Environmental Sustainability Index, a predecessor to EPI, employed a sophisticated statistical technique, Markov chain Monte Carlo simulation, to estimate missing data (Esty et al. 2005). This technique substitutes missing values with ones drawn from a quasi-random distribution that depends on the correlations observed among data sets.

out performing the target. After these adjustments, an arithmetic transformation, known as re-scaling, stretches the individual values onto a zero-to-100 scale where 100 corresponds to the target and zero to the worst observed value.[11]

The 2008 EPI conducts a principal components factor analysis (PCFA) on the indicator set to delineate groups and develop weights. But the results are inconclusive. Thus, policy groupings identified earlier are similar to those used by the pilot EPI, which are a synthesis of PCFA results and expert judgment.[12] Absent PCFA-derived weights, the 2008 EPI aggregates indicators using equal weights refined with expert advice. The overall EPI value is a weighted mean of the six policy category scores.

A sensitivity analysis alters five factors thousands of times as inputs into EPI and evaluates the subsequent outputs in a Monte Carlo simulation, thus capturing all interrelationships among input factors. EPI's sensitivity analysis focuses on these five methodological issues: (1) the measurement error of the raw data, (2) the choice of truncating at target values, (3) the choice to correct for skewed distributions in the indicators values, (4) the indicator weight employed, and (5) the aggregation function at the policy level (Esty et al. 2008). Specifically, the analysis introduces the measurement error by adding to each value in the dataset a random error with a mean equal to zero and standard deviation equal to the observed standard deviation of the corresponding indicator. The analysis generates thousands of alternative datasets that include estimates of measurement error in some of the data values. The two triggers for capping indicators at target values and for correcting skewed data distributions are binary (yes/no). Meanwhile, indicator or subcomponent weights employ four alternatives: factor analysis-derived weights at the indicator level, equal weighting at the indicator level, equal weighting at the subcategory level, and equal weighting at the policy level. Finally, a binary trigger determines the aggregation function used either simple mean or geometric mean.

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11 Proximity-to-target equation: $I_{i,j} = 100 - \left(\frac{x_{i,j} - \min(x_i)}{\text{Target} - \min(x_i)} * 100 \right)$, where $x_{i,j}$ is the i^{th} raw indicator value for the j^{th} country and x_i is the i^{th} raw indicator value. For targets where smaller is better, the equation uses maximum values.

12 PCFA of the pilot EPI identified three variable groups, corresponding to the environmental health, sustainable energy, and biodiversity and habitat categories used in the 2006 study. The other three categories—air quality, water resources, natural resources—emerge from a literature search and expert consultations.

2.2) AREAS OF CONTRAST AMONG POLICY MEASURES

This section discusses the different approaches among the studies for developing an environmental policy measure. When constructing a composite index, researchers must make five decisions, such as selecting a treatment for missing data, as well as methods for normalisation, weighting, and aggregation. Additionally, to compare performances among differently sized countries, researchers need to apply various scale-effect adjustments. Uncertainty and sensitivity analyses of different composite indices indicate that country ranks likely depend upon the methods selected at each of these decision point (Freudenberg 2003; Nardo et al. 2005; Saisana, Nardo, and Saltelli 2005). In fact, to understand the effects of the different decisions, the *Handbook on Constructing Composite Indicators* recommends using uncertainty and sensitivity analyses iteratively while constructing a composite index (Nardo et al. 2005: 23-24). The differences noted in this section form the basis for the uncertainty and sensitivity analyses detailed in chapter 3.

The choices of these studies indicate favoured methods for three decisions: missing data treatment, weighting, and aggregation (table 2.2). The most favoured treatment for missing data is some form of averaging around missing values, either on a country, or an indicator, basis. In fact, only one study, Esty et al. (2008), imputes missing data using mainly regression and correlation analytic methods.[13] These studies also favour equal weights, with only one study, Esty et al. (2008), using weights partially derived from expert judgment, although the pilot EPI did use statistically derived weights (Esty et al. 2006). Most of the studies also choose to aggregate a composite index using some form of simple mean, with only one study, WWF (2006), using the geometric mean method. On the other hand, each study chooses a different normalisation method. Gunton et al. (2005) use two methods, a ranking method that is common with Boyd (2001) and a distance-to-reference country method that is unique among the studies.

[13] As mentioned in an earlier footnote, the Environmental Sustainability Index, a predecessor to EPI, employed a sophisticated statistical technique, Markov chain Monte Carlo simulation, to estimate missing data (Esty et al. 2005). This technique substitutes missing values with ones drawn from a quasi-random distribution that depends on observed data.

Table 2.2: Contrasting missing data treatment, normalisation, weighting, and aggregation methods used among the studies

ASPECT	METHODS	STUDY
Missing Data Treatment	Average around missing value[a]	Boyd (2001)
		CBC (2004)
		Gunton et al. (2005)
		WWF (2006)
		Esty et al. (2008)
	Regression and correlation analysis	Esty et al. (2008)
	Markov chain Monte Carlo[b]	Esty et al. (2005)
Normalisation	Ranking[c]	Boyd (2001)
		Gunton et al. (2005)
	Standardisation[d]	CBC (2004)
	Distance-to-reference country	Gunton et al. (2005)
	Conversion to common unit	WWF (2006)
	Proximity to target/re-scaling[e]	Esty et al. (2008)
Weighting Method	Equal weights	Boyd (2001)
		CBC (2004)
		Esty et al. (2005)
		Gunton et al. (2005)
		WWF (2006)
	Equal weights refined w/ expert judgment	Esty et al. (2008)
	PCA-derived weights	Esty et al. (2006)
Aggregation Method	Simple mean[f]	Boyd (2001)
		CBC (2004)
		Gunton et al. (2005)
		WWF (2006)
		Esty et al. (2008)
	Geometric mean[g]	WWF (2006)

a = Omit missing records from analysis.

b = Markov chain Monte Carlo is a sophisticated statistical technique used to estimate missing data. This technique substitutes missing values with ones drawn from a quasi-random distribution that depends on the correlations observed among data sets.

c = Outliers do not affect this method and it allows tracking the relative position of a country's performance over time.

d = Converts indicators to a common scale with a mean of 0 and standard deviation of 1 (*z*-score).

e = Quantifies the relative position of a given indicator vis-à-vis a target. Normalises indicators to an identical range (0, 1).

f = This method is useful when all indicators have the same measurement unit; weights express trade-offs among indicators.

g = This method best suits non-comparable and positive indicators expressed in different ratio scales; multiply indicators; and weights appear as exponents and still express trade-offs among indicators, but less so than with linear.

These studies apply many different scale-effect adjustments to the various indicators used to assess national environmental performance. Scale-effect adjustments applied by the studies for 11 of the 26 indicators used by the current study demonstrate more variation than the others (table 2.3). These indicators form three groups, according to how the current study adjusted each for scale-effects. Most of the studies agree that the appropriate scale-effect adjustment to apply to agriculture related indicators—fertiliser use, pesticide use, and livestock—is per unit area of arable land. Several of the indicators—energy use, forests, and fisheries—appear to require two different scale-effect adjustments to fully capture their essence. The current study adjusts energy use for scale effects by per capita and per unit GDP denominators, forests by per unit annual growth and per unit forested area, and fisheries by per unit annual growth and world catch. Choices about which method of scale-effect adjustments to use for the third group of indicators—emissions of greenhouse gases, sulphur oxides, nitrogen oxides, and volatile organic compounds, as well as distance travelled—appear to affect strongly how a study ranks Canada (see table 1.3). A finding that suggests these scale-effect adjustments may be responsible for considerable variation in the final output ranks of a composite index. This relationship between final rank and method used for scale-effect adjustments is explored further in the uncertainty and sensitivity analyses conducted in the current study.

Table 2.3: Contrasting scale-effect adjustments used by the studies for selected indicators used by the current study

INDICATOR	SCALE-EFFECT ADJUSTMENT	STUDY
Energy Use	per capita	Boyd (2001)
		Gunton et al. (2005)
	per unit GDP	Boyd (2001)
		Gunton et al. (2005)
Greenhouse Gas Emissions	per capita	Boyd (2001)
		CBC (2004)
		Esty et al. (2008)
		Gunton et al. (2005)
	per unit GDP	CBC (2004)
		Esty et al. (2008)
Sulphur Oxides Emissions	per capita	Boyd (2001)
		Gunton et al. (2005)
	per unit GDP	CBC (2003)
	per unit area land with population density >5	Esty et al. (2008)
		Esty et al. (2005)
		CBC (2004)
Nitrogen Oxides Emissions	per capita	Boyd (2001)
		Gunton et al. (2005)
	per unit GDP	CBC (2003)
	per unit area land with population density >5	Esty et al. (2005)
		CBC (2004)
VOC Emissions	per capita	Boyd (2001)
		Gunton et al. (2005)
	per unit area land with population density >5	Esty et al. (2005)
		CBC (2004)
Pesticide Use	per capita	Boyd (2001)
	per unit area arable land	CBC (2004)
		Gunton et al. (2005)
Fertiliser Use	per capita	Boyd (2001)
	per unit area arable land	CBC (2004)
		Gunton et al. (2005)
Livestock	per capita	Boyd (2001)
	per unit area arable land	Gunton et al. (2005)
Forests	per capita	Boyd (2001)
	per unit annual growth	Gunton et al. (2005)
	per unit area forested land	Gunton et al. (2005)
	Per unit area forested land	Esty et al. (2008)
Fisheries	per capita	Boyd (2001)
		Gunton et al. (2005)
	per unit annual growth	Esty et al. (2008)
	world catch	Gunton et al. (2005)
Distance Travelled	per capita	Boyd (2001)
		Gunton et al. (2005)
	per unit area land with population density >5	Esty et al. (2005)

CHAPTER 3:
ANALYSING THE UNCERTAINTY IN POLICY MEASURES

Generally, uncertainty analysis focuses on how variation in input data affects the whole, while sensitivity analysis apportions the effects. Uncertainty analysis focuses on how uncertainty in the input data propagates uncertainty throughout the structure and final value of a composite index. Sensitivity analysis assesses how the different sources of variation qualitatively and quantitatively affect the final value of a composite index. As detailed in chapter 2, sources of uncertainty centre on the choices made during the construction of a composite index; therefore, these uncertainty and sensitivity analyses focus on methodically evaluating the affects of using different missing data treatments, normalisation methods, scale-effect adjustments, weights, and aggregation techniques.[14] The analyses also gauge the effects of systematically excluding each indicator from the composite index. These six elements provide the basis for the uncertainty and sensitivity analyses using input-output Monte Carlo simulations that examine the variation each element induces in the value of a country's composite index and its corresponding final rank. The output of interest for all scenarios is each country's rank, based on the value of a scenario's composite index.

Performing several Monte Carlo simulations iteratively provides information that helps select from among the alternative techniques when finalising the composite index. The composite index for the current study is the environmental sustainability performance composite index (ESPCI). Moreover, PCFA of the environmental sustainability performance indicators (ESPIs) groups them into subindices, which assess specific policy subcategories of environmental

[14] Recall that only one method is available for an analyst to build a composite index that compares dissimilar entities such as countries, but the method requires several decisions about the individual techniques one employs (Nardo et al. 2005). The method starts with selecting a set of performance indicators with the aid of a guiding conceptual framework and then deciding how to treat missing data. Next, an analyst must decide on the scale-effect adjustments to use to be able to compare indicators across countries of different sizes. Once these steps are completed, an analyst normalises the performance indicators to a common measurement scale so that individual indicators may be compared and aggregated. Finally, an analyst selects the weights and method of aggregation for combining the individual indicators into a composite index.

performance. The reader is cautioned to remember that changes in the value of these sustainability indices do not necessarily constitute a change in sustainability and that they might not adequately appraise sustainability. The current research uses the freely distributed SIMLAB software (Saltelli et al. 2004) with Excel 2003 to perform the Monte Carlo simulations on the construction of the composite index and to analyse the results. The current research also uses the SPSS 17 software for further statistical analyses.

The results of the uncertainty and sensitivity analyses answer the first research question regarding how a policy maker might best measure a country's environmental sustainability performance. These results also provide evidence for evaluating the first hypothesis regarding measurement techniques influencing a country's performance rank. They help clarify why findings differ among studies, as well as provide insight into how analysts should formulate and interpret environmental policy measures. Moreover, these results also clearly demonstrate techniques for using the Gunton et al. (2005) indicator set effectively as policy measures.

This chapter first discusses the various techniques that the uncertainty and sensitivity analyses use to study how uncertain input variables affect the final output. Next, a discussion of the initial Monte Carlo simulation results show the affects and sources of variation, as well as help explain the differences among the studies reviewed in chapter 2. Subsequently, results of several iterative Monte Carlo simulations help to select from among the various composite index construction techniques to finalise ESPCI. Once ESPCI is finalised, the chapter discusses the development of the assorted subindices that track different environmental policy areas. The chapter closes by discussing the limitations of these analyses.

3.1) GENERAL APPROACH

An input-output Monte Carlo simulation is the basis for the uncertainty analysis. Saisana, Saltelli, and Tarantola (2005) and Nardo et al. (2005) provide and recommend using such a framework because it captures all specified sources of uncertainty simultaneously, including synergistic effects arising from the interaction of input factors. With such an approach, one transforms identified sources of uncertainty, such as missing data treatments, normalisation methods, scale-effect adjustments, weights, aggregation techniques, and indicator set selection, into a set of factors that form an input distribution that one draws samples from for Monte Carlo simulations. The analyses estimate the importance of the indicator set by systematically excluding each indicator from the composite index. The uncertainty and sensitivity analyses conducted on Yale's Environmental Performance Index use a similar input-output simulation framework (Saisana and Saltelli 2008).

For the current research, the input factor distributions are discrete. The simulations draw values from these discrete distributions as triggers that apply, to the underlying indicator data, a specific composite index construction method (table 3.1). A sensitivity analysis using Sobol's method (Sobol' 1993) as improved by Saltelli (2002) apportions this range of uncertainty to the input factors: missing data treatments, normalisation methods, scale-effect adjustments, weights, aggregation techniques, and indicator set selection (by systematically excluding each indicator from the composite index). This section first discusses the techniques used for the uncertainty analysis, and then it discusses the techniques used for the sensitivity analysis.

Table 3.1: Input factors and distributions used as triggers to select index construction methods during the Monte Carlo simulations

INPUT FACTOR	TRIGGER	METHOD
X1: Missing Data Treatment	1	Average around missing values
	2	Unconditional mean imputation
	3	Regression imputation
	4	Markov chain Monte Carlo
X2: Scale-Effect Adjustments	1	Scenario #1
	2	Scenario #2
	3	Scenario #3
X3: Normalisation	1	Ranking
	2	Standardisation (*z*-score)
	3	Re-scaling
X4: Indicator Exclusion	0	All indicators
	1	All indicators but energy consumption
	2	All indicators but energy intensity
	3	All indicators but water consumption
	4	All indicators but greenhouse gases
	5	All indicators but renewable electricity including hydro
	6	All indicators but renewable electricity excluding hydro
	7	All indicators but sulphur oxide emissions
	8	All indicators but nitrogen oxide emissions
	9	All indicators but VOC emissions
	10	All indicators but carbon monoxide emissions
	11	All indicators but ozone depleting substances
	12	All indicators but municipal waste
	13	All indicators but recycling municipal waste
	14	All indicators but nuclear waste
	15	All indicators but municipal sewage treatment
	16	All indicators but pesticide use
	17	All indicators but fertiliser use
	18	All indicators but livestock
	19	All indicators but number of species at risk
	20	All indicators but percent of species at risk
	21	All indicators but protected areas
	22	All indicators but timber harvest
	23	All indicators but timber harvest to growth ratio
	24	All indicators but fisheries harvest to production ratio
	25	All indicators but fisheries harvest to world catch
	26	All indicators but distance travelled
X5: Weights	1	Equal weights
	2	Statistically based weights
X6: Aggregation Method	1	Simple mean aggregation
	2	Geometric mean aggregation

Note: This table displays the input factors and their associated discrete distributions for the Monte Carlo simulations. Selection of a particular value from a discrete distribution triggers a specific technique to be used during the construction of the composite index.

UNCERTAINTY ANALYSIS TECHNIQUES

Both Saisana, Saltelli, and Tarantola (2005) and Nardo et al. (2005) recommend using a quasi-random sampling scheme to obtain values from the input distribution. This sampling scheme, based on Sobol's method (1993), as modified by Saltelli (2002), produces quasi-random sequences that generate sample points to best represent the entire distribution of possible combinations among the input factors (Saisana, Nardo, and Saltelli 2005). Sampling the input distribution thousands of times and generating numerous values of the composite index and associated rank, allows an empirical estimation of the probability distribution function of each country's final rank. These rank distributions reflect the uncertainty of the output due to the underlying uncertainty in the input data. The gauge of central tendency for this output is the most likely rank, in conjunction with a reasonable estimate of the range over which the rank might change depending on choices made during composite index construction.

The first of these choices is deciding how to handle missing data. The current analysis uses four missing data treatments: average around missing values, unconditional mean imputation, regression imputation, and Markov chain Monte Carlo[15] (table 3.1). The reviewed studies use three of these methods (refer to table 2.2), while the Organisation for Economic Co-operation and Development *(OECD) Handbook on Constructing Composite Indicators* presents the fourth (Nardo et al. 2005). Both unconditional mean imputation and regression imputation are examples of single imputation whereas Markov chain Monte Carlo is an example of multiple imputation, which captures more of the inherent uncertainty of predicting missing values. In the current research, the regression imputation method uses parsimonious regression models to replace missing indicator data. Missing data are calculated using a series of multiple regression models of the significantly correlated relationships among indicators. In other words, regression equations developed from indicators that are correlated significantly with the indicator missing data are used to estimate the absent values. For most cases, the regression model with the highest adjusted R^2 value

[15] Markov chain Monte Carlo is a sophisticated statistical technique used to estimate missing data. This technique substitutes missing values with ones drawn from a quasi-random distribution that depends on the correlations observed among data sets.

became the model of choice for the regression imputation; however, in a few situations the analysis trades slightly lower adjusted R^2 values for substantially smaller standard errors. The Markov chain Monte Carlo missing data treatment uses these regression imputation models as well.

The next decision a composite-index builder faces is the choice of scale-effect adjustments. The current analysis develops three scale-effect adjustments scenarios from the information in chapter 2 (refer to table 2.3). The first scenario uses per capita adjustments exclusively, the second scenario uses primarily GDP adjustments with a per capita adjustment for the distance travelled indicator, and the third scenario uses primarily per unit land area with >5 people per square kilometre, with greenhouse gases adjusted for per capita effects (table 3.2). None of the reviewed studies adjusts volatile organic compound (VOC) emissions by GDP (refer to table 2.3). Rather than exclude this indicator and imbalance the number of indicators for each scenario, the current analysis applies the GDP adjustment to VOC emissions for the second scenario.

Table 3.2: Scale-effect adjustments for the three scenarios considered by the Monte Carlo simulations

INDICATOR	#1	#2	#3
Greenhouse Gas Emissions	per capita	per unit GDP	per unit GDP
Sulphur Oxides Emissions	per capita	per unit GDP	per unit area land with population density >5
Nitrogen Oxides Emissions	per capita	per unit GDP	per unit area land with population density >5
VOC Emissions	per capita	per unit GDP	per unit area land with population density >5
Distance Travelled	per capita	per capita	per unit area land with population density >5

After adjusting for scale effects, a composite-index builder selects a normalisation method. From table 2.2, these simulations include the ranking, standardisation, and re-scaling methods, while excluding the other three, conversion to common unit, proximity to target, and distance-to-reference country. Converting these indicators to a common scale is not appropriate given the disparate nature of the items, while targets for all indicators are not available rendering the proximity-to-target approach unusable. The distance-to-reference country can produce division-by-zero errors if the reference country's value happens to be zero.[16] Each of the normalisation methods used by the Monte Carlo simulations has a distinct equation (table 3.3). The normalisation ranking method ranks countries from best to worst. The standardisation normalisation procedure calculates the difference between a country's indicator value and the average value divided by the indicator's standard deviation. The re-scaling method is a simple arithmetic transformation that stretches an indicator value onto a zero-to-one scale where one corresponds to the best performing country and zero to the worst performing one.

The next input factor, while not explicitly modelling a choice in the composite index construction process, gauges the impact of indicator selection. It is not possible to represent the choice of indicator set as an input factor for the Monte Carlo simulations, but it is possible to exclude systematically each indicator from the aggregation process to observe the variation induced in the output (table 3.1). Obviously, this approach will not capture all the variance introduced from the selection of different indicator sets, but it will provide an indication of its significance to the overall process.

Table 3.3: Equations for the three normalisation methods used by the Monte Carlo simulations

METHOD	EQUATION
Ranking	$I_{i,j} = \text{Rank}\left(x_{i,j}\right)$
Standardisation	$I_{i,j} = \dfrac{x_{i,j} - \bar{x}_i}{\text{Std}\left(x_i\right)}$
Re-scaling	$I_{i,j} = \dfrac{\left\lvert x_{i,j} - \text{Worst}\left(x_i\right)\right\rvert}{\text{Range}\left(x_i\right)}$

$I_{i,j}$ = the i^{th} normalised indicator value for the j^{th} country
$x_{i,j}$ = the i^{th} raw indicator value for the j^{th} country

16 Distance-to-reference country: $I_{i,j} = \dfrac{x_{i,j}}{x_{rc}}$, or $= \dfrac{x_{i,j} - x_{rc}}{x_{rc}}$, where $x_{i,j}$ is the i^{th} raw indicator value for the j^{th} country and x_{rc} is the raw indicator value for the reference country.

After selecting and normalising the indicators, a composite-index builder decides upon appropriate weights and a method of aggregation. Most of the reviewed studies use equal weights and the simple mean aggregation method, but one uses statistically based weights, while another uses the geometric mean aggregation method (table 2.3). The current analysis uses equal and statistically based weights, re-scaled to one when the analysis excludes an indicator. Statistically based weights are developed by squaring, to eliminate negative values, and then scaling to one the results of a principal components analysis (PCA) of the raw indicator values. After selecting weights, a composite-index builder decides which aggregation method to use to combine all indicators into a single value. The current analysis uses both the simple mean and geometric mean aggregation methods (table 3.4). The simple mean uses addition to combine indicators, summed according to a set of weights, whereas the geometric mean combines indicators using multiplication. Indicators are raised to the power of each indicator's weight, which are then multiplied together to form a composite index.

Table 3.4: Equations for the two aggregation methods used by the Monte Carlo simulations

METHOD	EQUATION
Simple Mean	$\mathrm{CI}_j = \sum_{i=1}^{n} w_i I_{i,j}$
Geometric Mean	$\mathrm{CI}_j = \prod_{i=1}^{n} I_{i,j}^{w_i}$

CI_j = the composite index value for the j^{th} country
$I_{i,j}$ = the i^{th} normalised indicator value for the j^{th} country
w_i = the i^{th} weight value for the i^{th} indicator

SENSITIVITY ANALYSIS TECHNIQUES

Quantities, termed sensitivity indices, assess the importance of a given input factor by estimating its fractional contribution to the output variance. When several layers of uncertainty are present, the models that the composite indices represent may become non-linear and possibly non-additive. Thus, a variance-based sensitivity analysis is most appropriate because it is able to account for synergistic effects that develop among input factors (Saltelli et al. 2000). Sobol′ sensitivity indices (Sobol′ 1993), as modified by Saltelli (2002), provide a computationally efficient method for determining not only first-order effects, but total effects as well (Saisana, Saltelli, and Tarantola 2005). Interested readers should consult these references for further details of the mathematical theory underlying the construction of Sobol′ sensitivity indices.

The method proposed by Sobol′ decomposes the variance of an underlying function into summands of increasing dimensions according to

$$V = \sum_{j=1}^{k} V_j + \sum_{1 \le i < j \le k}^{k} V_{ij} + \cdots + V_{12\ldots k}, \tag{3.1}$$

where V is total variance, k is the number of inputs, V_j is the variance associated with the j^{th} input, V_{ij} is the variance associated with the interactions between the i^{th} and j^{th} inputs, and $V_{12\ldots k}$ is the variance associated with the interactions among all k inputs. A straightforward Monte Carlo integration computes each generic term in this decomposition. A first-order sensitivity index for the j^{th} input factor is

$$S_j = V_j / V, \tag{3.2}$$

where S_j is the first-order sensitivity index, V_j is the variance associated with the j^{th} input, and V is total variance. Second-order sensitivity indices estimating interaction effects between two inputs are provided by

$$S_{ij} = V_{ij} / V, \tag{3.3}$$

and k^{th}-order sensitivity indices estimating interaction effects among k inputs are provided by

$$S_{12\ldots k} = V_{12\ldots k} / V. \tag{3.4}$$

Other higher-order sensitivity indices estimating different interaction effects are calculated according to this pattern.

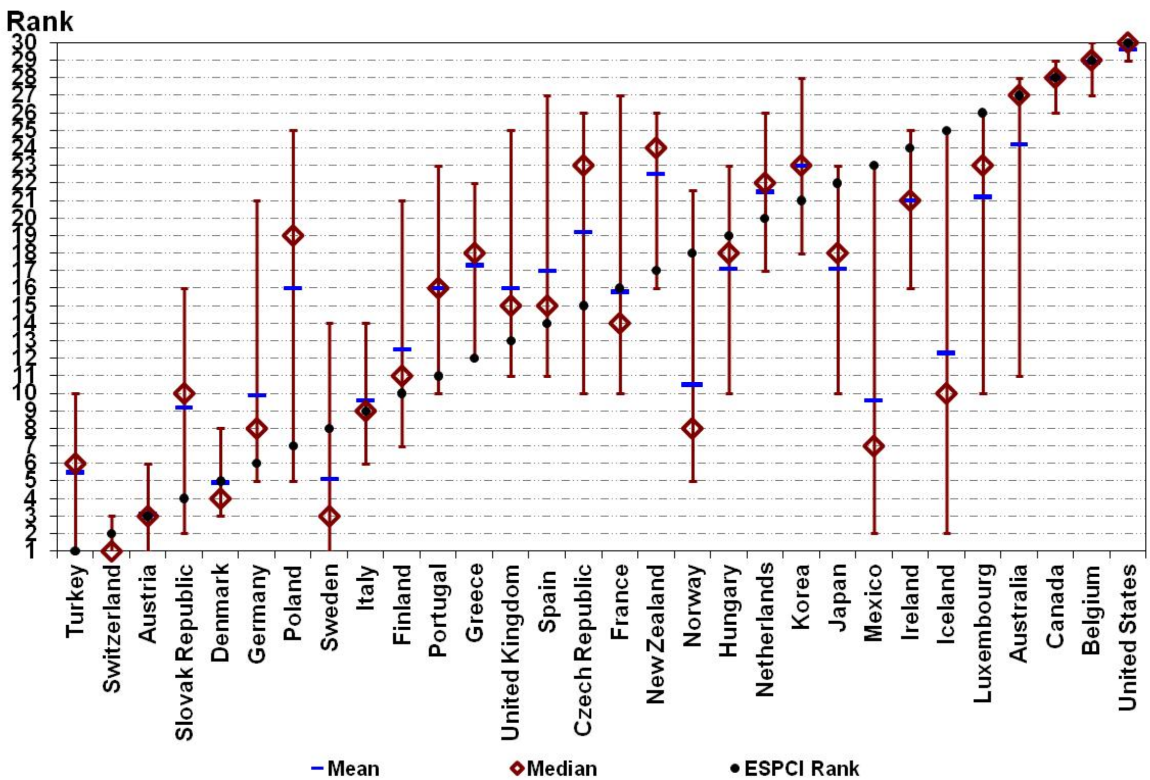
A model without interactions among input factors is additive, and the sum of the S_j′s equals one. An analyst may easily identify the output variance attributable to each input factor because the indices represent the fraction of the total variance induced by each input factor. For non-additive models, an analyst must compute higher-order sensitivity indices to gauge interaction effects; however, due to computational costs, one does not usually estimate higher-order indices. A model with k input factors requires the calculation of 2^k-1 indices, each requiring a sample of size N to compute, and computational costs may become prohibitively large (Saisana, Saltelli, and Tarantola 2005; Campolongo et al. 2000). Consequently, Homma and Saltelli (1996) use the Sobol' method to calculate the total-effect sensitivity index, which combines in one term all the interactions involving a given input factor. This approach reduces the number of model evaluations to $2N(k+1)$ and still provides an estimate of higher-order effects (Saisana, Saltelli, and Tarantola 2005; Campolongo et al. 2000). The number of model evaluations for the current research is 7,168.

3.2) VARIATION OF ENVIRONMENTAL PERFORMANCE RANKS

This section discusses the uncertainty analysis results of the overall composite index of the current study, environmental sustainability performance composite index (ESPCI). Uncertainty analysis examines how variation inherent in the input factors propagates through the structure and final value of the composite index. In this context, the variation induced by the various decisions made during composite index construction produces different ranks for OECD-member countries. Recall that only one method is available for an analyst to build a composite index that compares dissimilar entities, but the method requires several decisions about the individual techniques one employs (Nardo et al. 2005). Rather than the means, the current analysis uses medians for primary comparisons because most countries' distributions of ranks are not symmetrical. Moreover, the current analysis uses the 5th and 95th percentiles of each country's rank distribution as its best and worst rank to avoid infrequent outputs overly influencing the interpretation of results.

AFFECTS OF VARIATION

Figure 3.1 summarises the results of the uncertainty analysis and is ordered by each country's rank on ESPCI, finalised later in this chapter through the iterative use of sensitivity analysis. Countries with good environmental performances rank highly on ESPCI (i.e., 1st, 2nd, 3rd), while countries with poor environmental performances rank lowly (28th, 29th, 30th). Figure 3.1 also presents both the Monte Carlo-based median performance rank for each OECD-member country with associated 5th and 95th percentile whiskers and the Monte Carlo-based mean performance rank. Using 5th and 95th percentile whiskers prevents infrequent outlying values from overly influencing the results. While leaders generally are separable from laggards under all scenarios, results indicate much variance among the country ranks. In fact, more than half (17) the countries of this study exhibit 5th - 95th percentile ranges greater than 10 ranks, meaning the range of final ranks for these countries spans more than a third of the entire scale. Moreover, 10 countries possess a range of final ranks greater than half the entire scale, and two countries display ranges that are at least two-thirds of the scale. Iceland possesses the most volatile rank with a 5th - 95th percentile range of 23 ranks, followed closely by Mexico, with a range of 21 ranks, and Poland, with a range of 20 ranks.



Notes: The graph is ordered according to rank on ESPCI. Countries with good environmental performances rank highly on ESPCI (i.e., 1st, 2nd, 3rd), while countries with poor environmental performances rank lowly (28th, 29th, 30th). As one moves up the Rank axis, a country's environmental sustainability performance decreases. Whiskers represent the 5th and 95th percentile of a country's performance ranks, which prevent infrequent outlying values from overly influencing the results.

Figure 3.1: Uncertainty analysis of ESPCI ranks for OECD-member countries

While some ranges are larger than others, all rank distributions display some amount of variation. As mentioned, the variation for most countries produces distributions of ranks that tend to be non-symmetrical, typically exhibiting long tails. Countries with skewed distributions will have different Monte Carlo-based mean and median performance ranks; the further apart these two values the longer the tail (fig. 3.1). The Czech Republic and Poland possess the greatest difference between means and medians, about four and three ranks respectively; both countries' distributions are skewed towards better performance by longer tails of high ranks. In addition to these typical distributions, two countries exhibited different types. Mexico is the only country that displays a bimodal distribution that likely possesses two means and medians, while Iceland's large distribution of ranks tends to be uniform throughout with fewer values isolated in the tails.

Developed later in this chapter, the ESPCI-based ranks differ from the Monte Carlo-based median ranks by an average of four ranks. However, several countries display much larger differences: Mexico (16 ranks), Iceland (15 ranks), Poland (12 ranks), and Norway (10 ranks). Mexico's large difference is likely attributable to its bimodal distribution of ranks because the Monte Carlo-based median performance rank incorporates all ranks, while the ESPCI-based rank clearly comes from one of the modes. Iceland's difference is explainable in a similar fashion: its ESPCI-based rank occurs at one end of its uniform distribution. Moreover, the differences for Poland and Norway likely arise because the ESPCI-based ranks come from the tails of their respective distributions where less frequent ranks appear. All this variation clearly demonstrates the underlying uncertainty contained in the final composite index. Consequently, a country's specific rank depends very much on the decisions made during the construction of the composite index.

SOURCES OF VARIATION

Next, the discussion shifts to the sources of variation that produce these uncertain outputs. The sensitivity analysis explores the main drivers behind the observed deviations and reveals the bases of these much larger ranges and differences.

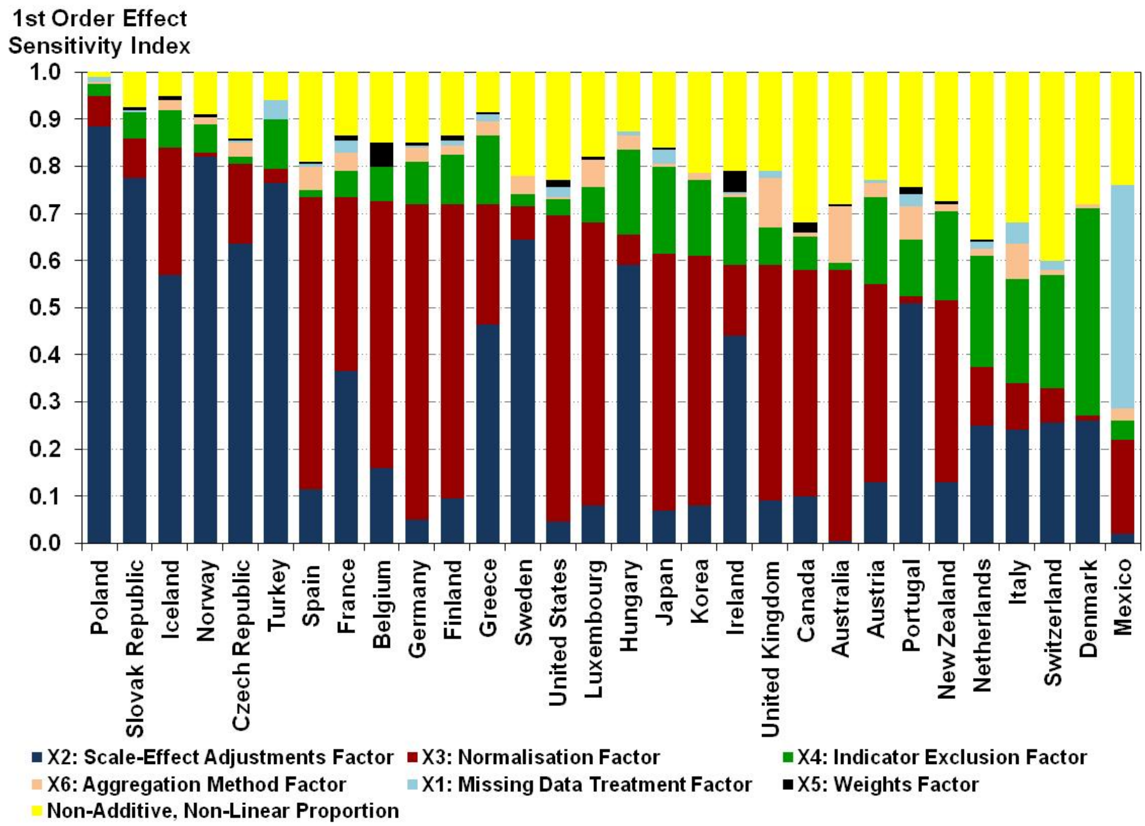
The sensitivity analysis centres on the first-order-effect and total-effect indices calculated according to Sobol' (1993) and improved by Saltelli (2002). Averaged across all countries, the scale-effect adjustments and normalisation factors affect the final output ranks the most and are statistically significant at the 95% level of confidence (table 3.5). Together, these factors account for about 68% (including interaction effects) of the observed variation in the final ranks of ESPCI. These two factors, either singly or in combination, are key drivers for most of the variation observed for each country's rank distribution (refer to bottom two segments for each bar in fig. 3.2). Because the first-order-effect Sobol' indices do not sum to one, the composite index structure is non-additive and non-linear (1-0.814 = 0.186), thus, input factors interact with each other. Indeed, the interaction effect for the normalisation factor is itself an important influence, being statistically significant at the 95% level of confidence. When one combines first-order effects with interaction effects (total-effect Sobol' indices, table 3.5), the indicator exclusion factor emerges, at the 95% level of confidence, as a statistically significant driver of the observed variation in performance ranks (refer to third segment for each bar in fig. 3.2). In fact, according to the total-effect indices the indicator exclusion factor is the largest source of variation for Denmark's rank distribution, accounting for 43%. Predictably, excluding Denmark's worst indicator, fisheries-harvest-to-primary-production ratio, generates its best rank position.

Table 3.5: Average Sobol' indices allocating variation among input factors, with significant values highlighted

INPUT FACTORS	1ST-ORDER-EFFECT SOBOL' INDICES (SI_1)	TOTAL-EFFECT SOBOL' INDICES (SI_T)	INTERACTION EFFECT (SI_T-SI_1)
Scale-Effect Adjustments	**0.316**	0.416	0.100
Normalisation	**0.316**	0.482	**0.166**
Indicator Exclusion	0.118	**0.207**	0.090
Aggregation Method	0.032	0.120	0.088
Missing Data Treatment	0.027	0.066	0.039
Weights	0.005	0.023	0.018
Sum	0.814	1.315	0.501

Note: Highlighted values are significant at the 95% level of confidence according to the Tchebycheff significance test.

Most countries' rank-distribution variances are very linear, containing only minor non-linear portions due to interaction effects (top-most segment of each bar in fig. 3.2). The non-additive, non-linear portion not explained by the first-order-effect Sobol' indices range from less than 1% for Poland to 41% for Switzerland, while Canada's variance is about 32% non-linear. On average, the variance induced in a country's rank distribution due to interaction effects is about 19%. The non-linear portion, while minimal for many cases in comparison with other factors, is still large enough to emphasise the need for considering total-effect indices that capture interactions among input factors.



Note: Graph is ordered according to the combined proportions of the two most influential inputs, scale-effect adjustments and normalisation.

Figure 3.2: First-order Sobol' indices illustrating the sources and proportions of variation in each OECD-member country's rank distribution

While not significant when averaged across all countries (table 3.5), the total-effect indices indicate that the choices of aggregation method and missing data treatment do affect a few countries' rank distributions. Notably, 30% of Australia's total variance is attributable to the aggregation method used because the geometric mean method tends to favour Australia by producing higher rank positions, while the simple mean method tends to produce lower rank positions. Similarly, the choice of missing data treatment most affects Mexico's rank distribution, with 54% of its variation attributable to this factor. Averaging around missing values and unconditional mean imputation tend to produce lower rank positions for Mexico's relative standing, while regression imputation and Markov chain Monte Carlo imputation tend to produce higher ranks. As before, countries with good environmental performances rank highly on ESPCI (i.e., 1st, 2nd, 3rd), while countries with poor environmental performances rank lowly (28th, 29th, 30th).

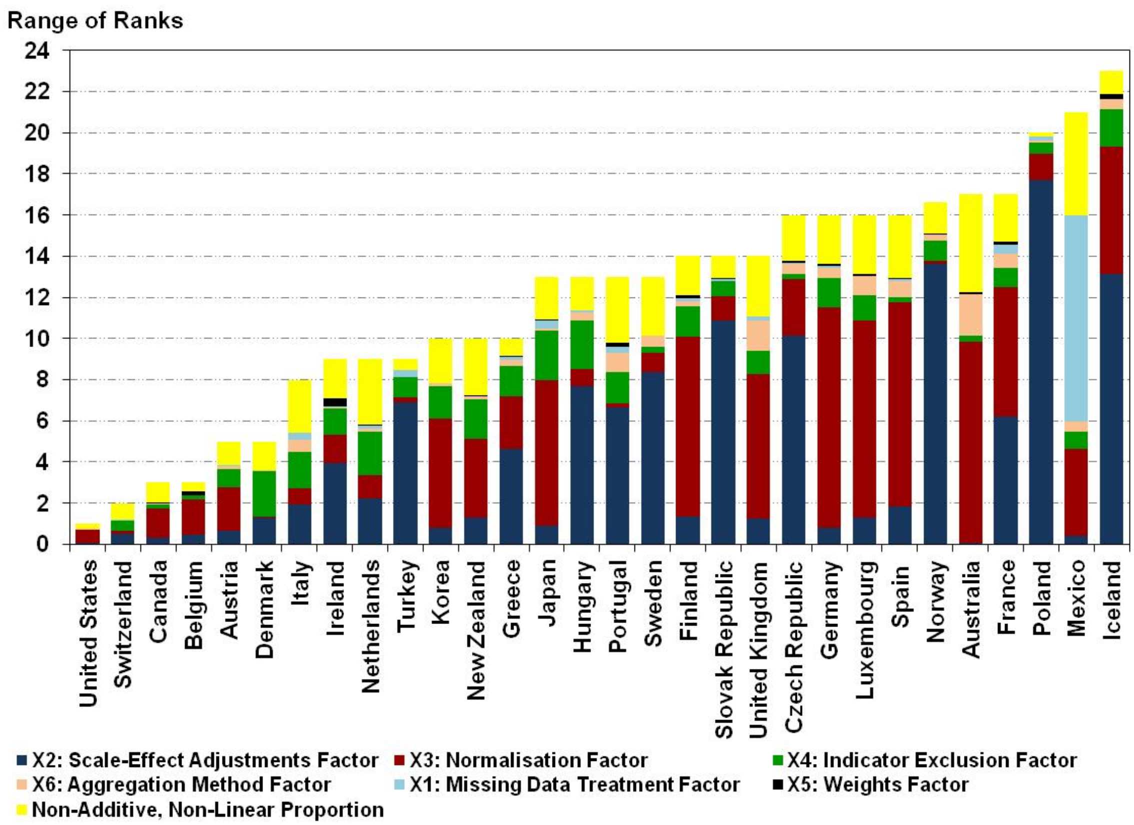
Reviewing the total-effect indices also helps explain the above average country variances previously observed. The country with the largest range of ranks, Iceland, attributes 50% of its variance to the scale-effect adjustments method whereby per capita adjustments produce much lower ranks than either GDP or populated land area adjustments. The normalisation method used accounts for a further 30% of Iceland's variance because the ranking method generates higher performance ranks than either standardisation or re-scaling. The country with the next largest range of performance ranks, Poland, has a primary driver of variation, scale-effect adjustments, large enough (greater than 80%) that no other input factor emerges as influential. The per capita adjustment generally favours Poland with higher ranks, while GDP and populated land area adjustments generally produce lower ranks. The discussion above already notes Mexico's key driver. In addition to the missing data treatment method, the normalisation method also generates 24% of Mexico's variance with the ranking method tending to produce higher ranks then either standardisation or re-scaling.

For comparison, Canada's rank-distribution variation is 48% attributable to the normalisation method, and 16% each to the scale-effect adjustments and indicator exclusion input factors. Canada's situation is similar to Poland's with regard to the scale-effect adjustments: the per capita adjustment tends towards higher ranks and the other methods towards lower ranks. Note that Canada's range of ranks (3) is much smaller than either Poland's (20) thus it possesses a much smaller variation to distribute across the six input factors. For Canada, the ranking normalisation method tends to produce higher ranks and the other normalisation methods produce lower ranks. Similar to Denmark, excluding Canada's worst indicator, nuclear waste per capita, leads to an improvement in its performance rank.

EXPLANATION OF DIFFERENCES AMONG STUDIES

After delineating the sources of variation, a question naturally arises. How do these results explain the different findings from various benchmarking studies? Combining the first-order-effects Sobol' indices (from fig. 3.2) with 5^{th} - 95^{th} percentile ranges (from fig. 3.1) distributes the sources of variation across each country's range of performance rank (fig. 3.3). One must view these results within a certain context, that being that each study uses different indicators, sometimes using alternate formulations, as well as different data sources. Incorporating these types of variations into the analysis simply is not possible, thus limiting the capacity of the sensitivity analysis results to explain completely the variation observed among studies. Of particular difficulty to incorporate into the sensitivity analysis is the variation among performance indicator sets. In an attempt to assess, at the very least qualitatively, the impact that indicator selection may have upon the results, the analysis employed the indicator exclusion factor. Nevertheless, these results do provide some insight into the reasons for the differences; any unexplained variation may be a residual attributable to the different indicator frameworks each study uses. One should note that table 1.3 only depicts a comparison of the results for one country, while this section presents results for all OECD countries.

Many countries demonstrate volatile ranges highly influenced by one or two input factors. As noted, the most influential inputs are the scale-effect adjustments and normalisation methods, each produce large shifts in many countries' rank (fig. 3.3). On average, these factors each account for over four ranks of variation, or put another away over 14% of the possible range. Indeed, the scale-effect adjustments induce over 16 ranks of variation in Poland's rank distribution, or 54% of the possible range, while the normalisation method induces almost 11 ranks of variation in Germany's rank distribution, or 38% of the possible range. The indicator exclusion factor also induces an important amount of variation for some countries: over a full rank on average, or 5% of the possible range. The indicator exclusion factor may influence Denmark's rank distribution the most producing over two ranks of variation (7% of range), but Japan's rank distribution, due to its larger range of ranks, experiences a larger impact with almost three ranks of variation, or 10% of the possible range. For Canada, the normalisation method produces almost a rank-and-a-half of variation, or about 5% of the range, while the scale-effect adjustments and indicator exclusion factor each account for about a half a rank of variation, or about 1.5% of the range.



Note: Graph is ordered according to each country's range of performance ranks on ESPCI.

Figure 3.3: The sources of variation in each OECD-member country's range of performance ranks

While these sensitivity analysis results explain much variation for many countries, they account for a smaller portion of the variation observed for Canada's environmental sustainability performance. When comparing the amount of variation explained by these results for Canada with the range of results from the reviewed studies (see table 1.3), an obvious discrepancy arises: the performance range observed for Canada by these various studies is much greater than the amount of variation uncovered by this analysis. For Canada, all input factors produce a total effect of 3 ranks of variation, about 10% of the possible range, as compared to the 14-rank differential witnessed across the benchmarking studies, which is about 60% of the possible range of ranks used for comparing results across studies. One should not conclude from this finding that the sensitivity analysis was too narrow to be worthwhile. Indeed, about half of OECD-member countries have about half or more of their respective variation explained by the total effect of all included input factors (fig. 3.3).

The remaining portion of Canada's environmental performance range not captured by the current sensitivity analysis likely depends on the indicator set used by each study. Recall that only one method is available for an analyst to build a composite index that compares dissimilar entities, but the method requires several decisions about the individual techniques one employs (Nardo et al. 2005). In addition to selecting appropriate performance indicators, other decisions are missing data treatments, normalisation methods, scale-effect adjustments, weights, and aggregation techniques. Because the current analysis includes all other decision points, any unexplained variation is a residual attributable to the different sets of performance indicators the various studies employ. However, the variation the current study attributes to the other decision points may change if the sensitivity analysis included other techniques, such as the non-compensatory multi-criteria method of aggregation or the proximity-to-target method of normalisation. If the variation induced by each decision point changed, the residual variation attributed to the selection of the indicator framework would change as well.

Due to logistical challenges from incorporating several disparate indicator frameworks into the computer code, the current sensitivity analysis does not model the indicator-selection decision point. If this decision point were included, the analysis would start by selecting from among indicator frameworks before proceeding to the next decision point for constructing a composite index, missing data treatment. Rather the current analysis uses a single indicator framework (refer to table 1.4). Moreover, the indicator exclusion factor, which systematically excludes each indicator from the set used for the composite index, is a significant input factor for explaining variation, at the 95% level of confidence. The sensitivity analysis includes this input factor for the express purpose of estimating the impact of indicator selection on measurement efforts. While not concrete evidence, this result supports the assertion that choice of indicator sets is a decision point that may induce a considerable amount of variation.

The results suggest that several included input factors—normalisation method, scale-effect adjustments, indicator exclusion—account for much of the variation observed among studies. Additionally, the results imply that the set of indicators selected by each benchmarking effort produces much variation as well. However, a direct decomposition of each country's rank from each study according to these findings is simply not possible given the different indicator frameworks each study uses. Therefore, to be defensible, studies require an effective conceptual framework to guide indicator selection. This conclusion is supported by the fact that the indicator exclusion factor is significant, at the 95% level of confidence. Refer to figure 1.2 for the current study's guiding conceptual framework, which helps determine an indicators relevancy (evaluated in appendix B). Another conclusion these results reinforce is that an analyst should build composite indices through the iterative use of sensitivity analysis to document the effects of the selections made when constructing the index. Refer to section 7.1 for conclusions and recommendations concerning selection of indicators and conceptual frameworks.

3.3) FINALISATION OF COMPOSITE INDEX

This section provides the justification for the final form of the current research's overall composite index by explaining why the various methods were selected for its construction. One may use sensitivity analysis iteratively, using the results from previous analyses to inform subsequent simulations. Non-influential factors identified by the first Monte Carlo simulation may assume any value from their distributions without significantly affecting the final country ranks. Fixing these factors at specific values isolates the variation caused by the significant factors thus simplifying further assessment. The missing data treatment factor uses the average around missing values method, the weights factor uses equal weights, and the aggregation method factor uses the simple mean for all subsequent analyses. While these factors are non-influential and may be set at any value, several reasons provide support for these specific selections. First, unlike the other three methods incorporated into this input factor, the average around missing values method for handling missing data does not alter the original data set in any way. Second, other studies frequently use equal weights, which may be the simplest option, particularly since a clearly superior option does not exist. Third, several conditions limit the application of the geometric mean method of aggregation and most other studies use the simple mean approach for aggregating composite indices.

With these three input factors fixed, the analysis shifts to the remaining factors. While the indicator exclusion factor is set to the original list of 26 indicators for the final calculation of the composite index, for this further analysis it remains unfixed and allowed to induce variation in the output country ranks. This portion of the analysis focuses on the scale-effect adjustments and normalisation input factors that drive much of the variation observed in the output ranks. The results help determine the most appropriate settings at which to fix these factors for the final calculation of the composite index.

Several iterative Monte Carlo simulations provide information for the final construction of the composite index. The first simulation was discussed earlier; this section focuses on simulations 2 through 7 in which each sensitivity analysis systematically eliminates one method from either the scale-effect adjustments or normalisation factors while holding the other inputs constant as discussed above (table 3.6). For example, during the second simulation, the sensitivity analysis holds the missing data treatment, weights, and aggregation factors constant while allowing the scale-effect adjustments, indicator exclusion, and normalisation factors to vary. However, the ranking method was removed from the normalisation factor, leaving just the standardisation and re-scaling methods.

Table 3.6: Parameters used for Monte Carlo simulations that finalised the construction of the composite index

MONTE CARLO SIMULATION	DESCRIPTION OF PARAMETER CHANGES
2	Removed ranking method from normalisation factor; Missing data treatment factor set to average around missing values method; Weights factor set to equal weights method; Aggregation factor set to simple mean method.
3	Removed standardisation method from normalisation factor; Missing data treatment factor set to average around missing values method; Weights factor set to equal weights method; Aggregation factor set to simple mean method.
4	Removed re-scaling method from normalisation factor; Missing data treatment factor set to average around missing values method; Weights factor set to equal weights method; Aggregation factor set to simple mean method
5	Removed per capita method from scale-effect adjustments factor; Missing data treatment factor set to average around missing values method; Weights factor set to equal weights method; Aggregation factor set to simple mean method
6	Removed GDP method from scale-effect adjustments factor; Missing data treatment factor set to average around missing values method; Weights factor set to equal weights method; Aggregation factor set to simple mean method
7	Removed area w/ >5 people method from scale-effect adjustments factor; Missing data treatment factor set to average around missing values method; Weights factor set to equal weights method; Aggregation factor set to simple mean method

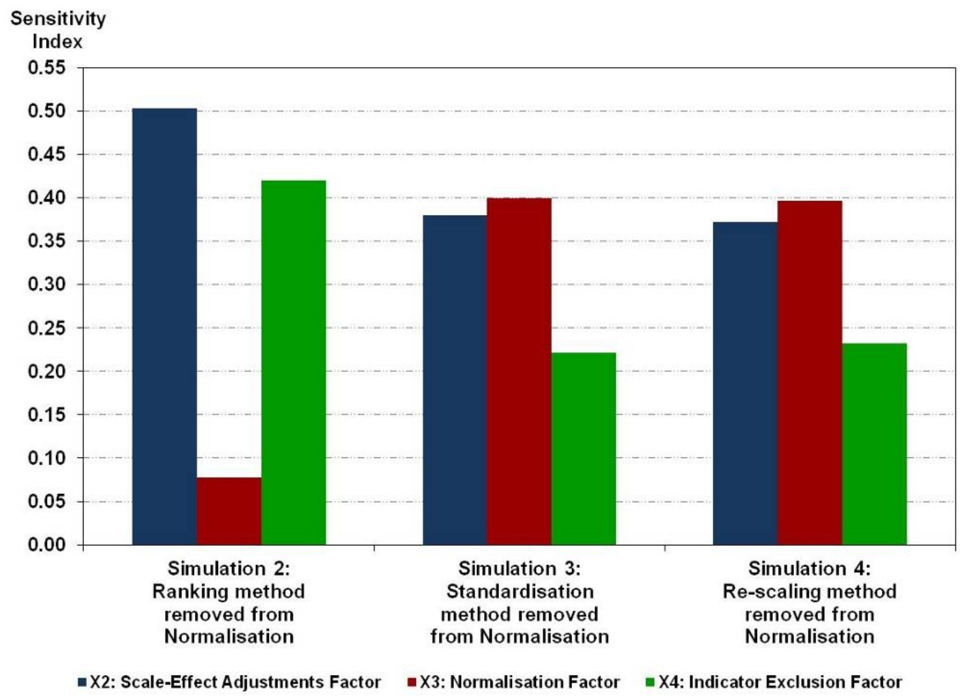
Note: Simulation 1, in which all factors varied, is the original Monte Carlo analysis discussed in previous sections.

The average variation attributable to each input factor changes with the exclusion of each method (fig. 3.4). The upper graph depicts the results of excluding one normalisation method from a series of sensitivity analyses, while the lower graph shows the results of excluding one scale-effect adjustments method from another series of analyses. In both graphs, sensitivity indices illustrate the variation each factor induces in the final performance ranks. A comparison of the level of induced variation for each altered input factor provides an analyst with information about how each excluded method affects the variation of final ranks. This information aids with selecting an appropriate normalisation and scale-effect adjustments method for the final composite index.

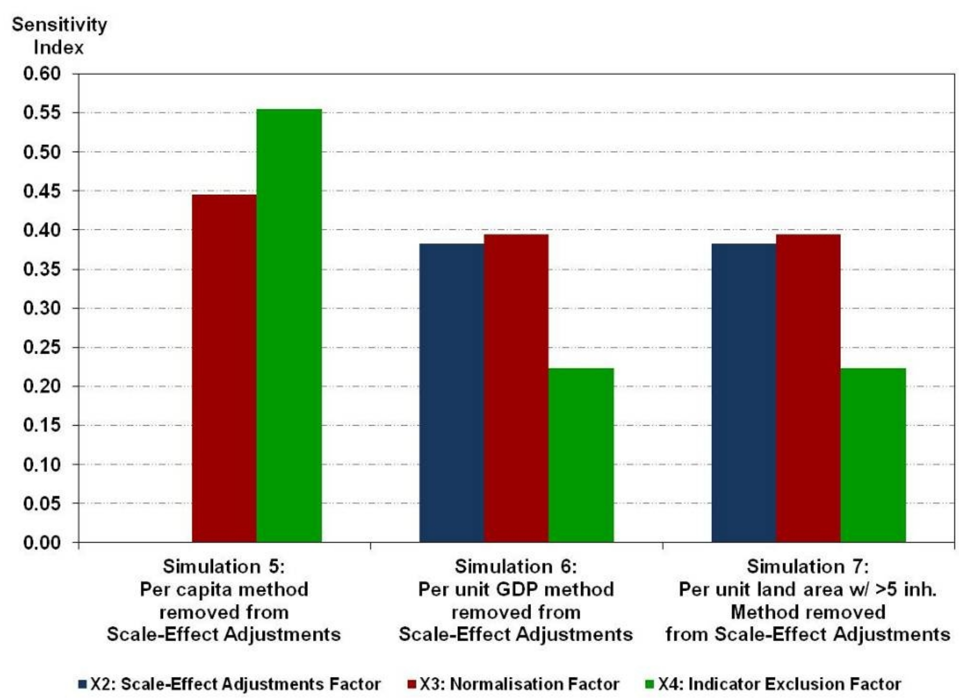
Of the three normalisation methods, excluding the ranking method reduces the variation attributable to the normalisation factor the most. Excluding either the standardisation or re-scaling method (but still retaining the ranking method) produces very similar patterns of variation (fig. 3.4). The standardisation and re-scaling methods retain more information from the underlying indicator values than does the ranking method. Indeed, a major critique of the ranking method reflects the fact that once converted to ordinal ranks one loses the information of how close (or far apart) indicator values for different countries might be. Both the standardisation and re-scaling methods retain this type of information. Additionally, the re-scaling method produces easily interpretable results; hence, the final construction of the composite index fixes the normalisation factor at the re-scaling method.

A similar pattern emerges for the scale-effect adjustments input factor. Excluding the per capita method reduces the average variation attributable to the scale-effect adjustments factor to zero. Excluding either the GDP or area with >5 people method (but still retaining the per capita method) produces very similar levels of variation, as noted above for normalisation method. Thus, the GDP and area with >5 people adjustments are producing very similar outputs of country ranks. An insight as to why this pattern exists, similar to the one discussed for the normalisation factor, did not emerge from the analysis. Another criterion, the ease of communicating results to stakeholders, helps choose which scale-effect adjustments to apply to the composite index. Per capita scale-effect adjustments distribute environmental effects across a country's population, and are likely the most easily understood by the general public, particularly when compared to the area with >5 people adjustment. Hence, the final construction of the composite indicator (table 3.7) fixes the scale-effect adjustments factor at the per capita method. Refer to section 7.1 for conclusions and recommendations involving the choices an analyst should consider when constructing a composite index.

(A)



(B)



Notes: Simulation 1, in which all factors vary, is the original Monte Carlo analysis discussed in previous sections. The upper graph depicts the results of excluding one normalisation method from a series of sensitivity analyses, while the lower graph shows the results of excluding one scale-effect adjustments method from another series of analyses. In both graphs, sensitivity indices illustrate the variation each factor induces in the final performance ranks.

Figure 3.4: The sensitivity indices of the Monte Carlo simulations 2 thru 7 (described in table 3.6) investigating the affects on performance ranks of methods used by the normalisation and the scale-effect adjustments factors

Table 3.7: The final structure of the environmental sustainability performance composite index

INPUT FACTOR	SELECTED METHOD
Missing Data Treatment	Average around Missing Values
Scale-Effect Adjustments	Per Capita
Normalisation	Re-scaling
Indicator Exclusion	All Indicators
Weights	Equal Weights
Aggregation Method	Simple mean

Finalising the structure of the composite index allows the discussion to return to the large discrepancies between the ESPCI-based ranks and the median-based ranks for Mexico, Poland, Iceland, Czech Republic, and Norway (fig. 3.1). As discussed previously, using the average around missing values as the missing data treatment shifts Mexico's rank away from its Monte Carlo-based median towards lower performances. Interestingly, finalising the choice of scale-effect adjustments affects the other four countries in different ways. Selecting the per capita adjustment favours both Poland and Czech Republic with higher rank positions than the median-based ranks would lead an analyst to expect. On the other hand, Norway and Iceland each get lower rank positions under this arrangement. Choosing either of the other scale-effect adjustments reverses this situation. As before, countries with good environmental performances rank highly on the environmental sustainability performance composite index (ESPCI) (i.e., 1st, 2nd, 3rd), while countries with poor environmental performances rank lowly (28th, 29th, 30th).

3.4) DEVELOPMENT OF POLICY SUBINDICES

This section provides the justification for the final form of the current research's policy subindices by explaining the methodology used for developing them.

During the development of a composite index, an analyst should review the associations among the underlying indicators that combine to form the index. This review should consider the correlation matrix of the indicators from two opposing perspectives. Strongly correlated indicators render a composite index less sensitive to missing values, the selection of weights, the normalisation method, and other steps involved in the analysis because the correlations imply that the indicators contain overlapping information (Freudenberg 2003; Nardo et al. 2005). Therefore, one of the correlated indicators could be missing or excluded without losing all the information it contained. On the other hand, large correlations may imply that indicators are double counting the same phenomenon, developing a less than parsimonious index (Freudenberg 2003). If the index uses equal weighting, then having strongly correlated indicators might also overweight one aspect of sustainability and make the overall score misleading. The correlation structure of the indicators helps group ESPIs when constructing policy subcategories measuring various aspects of environmental sustainability. Principal components factor analysis (PCFA), described in appendix C, balances these opposing perspectives by grouping highly correlated variables onto the same component.

PCFA of the 26 performance indicators reveals five principal components that cumulatively explain over 93% of the observed variation (table 3.8). Appendix C discusses pertinent details about PCFA including the stopping criteria used to determine the number of retained components and the rotation techniques used to enhance interpretation of results. The first component accounts for the most variation (over 26%), followed closely by the second component; together these components explain over half of the variation. The last three components describe roughly equal portions, ranging from about 11% to 17% of the variation.

Rotating these components according to the varimax method helps to interpret the fundamental nature of the dimension that each component quantifies. The loading coefficients indicate the strength of the association between an indicator and a specific component (table 3.9). To help interpret these loadings, an analyst should use a method that incorporates the effects of sample size for determining significant values (Stevens 2002; Spicer 2005). For this sample size, values that exceed the critical value of 0.82 (refer to appendix C) are statistically significant at a 99% level of confidence. While important, these significant loadings are only guides to interpreting the fundamental nature of a dimension. An indicator's highest loading (if not significant) as well as important secondary loadings provide further information that aides with interpreting the nature of a dimension. Significant loadings provide the best evidence regarding the nature of the components, followed by the highest, non-significant values, and, lastly other important secondary loadings. Table 3.9 highlights all these noteworthy values.

Table 3.8: The cumulative and individual variances explained by extracted and rotated ESPI components

COMPONENT	ROTATION SUMS OF SQUARED LOADINGS		
	TOTAL VARIANCE EXPLAINED BY COMPONENT	% OF VARIANCE	CUMULATIVE %
1	6.84	26.29	26.29
2	6.20	23.85	50.14
3	4.42	17.00	67.14
4	3.85	14.82	81.95
5	2.91	11.18	93.13

Applying this significance test determines 13 statistically significant loading coefficients across the five components. The first and second components contain four significant loadings each, while the third component possesses three. The fourth and fifth components have one significant loading each. Although only guides, these loadings provide the highest quality information about the nature of a dimension; therefore, an analyst may interpret components with several significant loadings more easily and with more certainty. A component's interpretation is refined by using information gleaned from the other highest, but non-significant, loadings as well as secondary loadings. Use of the information content of these other loadings is particularly important for describing the fourth and fifth components.

Table 3.9: Loading coefficients from a principal components factor analysis of ESPIs, rotated with the varimax technique

ENVIRONMENTAL SUSTAINABILITY PERFORMANCE INDICATOR	COMPONENT 1	2	3	4	5
Energy Consumption	0.41	**0.86**	0.04	0.04	0.28
Energy Intensity	0.24	**0.88**	-0.34	0.03	-0.08
Water Consumption	**0.78**	0.10	0.07	**0.53**	0.19
Greenhouse Gas Emissions	**0.95**	0.25	0.05	-0.16	-0.11
Electricity From Renewable Resources (w/ hydro)	-0.17	**-0.73**	0.11	-0.15	-0.61
Electricity From Renewable Resources (w/out hydro)	0.14	**-0.97**	-0.06	-0.10	-0.17
Sulphur Oxides	**0.73**	0.19	-0.49	0.33	-0.17
Nitrogen Oxides	**0.52**	**0.83**	-0.17	0.10	0.08
Volatile Organic Compounds	**0.94**	0.20	-0.14	0.12	0.19
Carbon Monoxide	**0.92**	0.08	-0.27	0.20	0.12
Ozone-Depleting Substances	**0.41**	**0.46**	**0.39**	**0.66**	0.03
Municipal Waste	0.11	0.37	0.03	-0.04	**0.82**
Recycling	-0.44	-0.01	-0.34	0.31	**-0.75**
Nuclear Waste	**0.94**	-0.11	-0.007	0.09	0.22
Municipal Sewage Treatment	**-0.42**	0.23	-0.38	**0.63**	**-0.41**
Pesticide Use	-0.06	-0.21	**0.96**	0.11	-0.02
Fertiliser Use	-0.24	0.17	**0.88**	-0.16	0.29
Livestock	-0.21	-0.45	**0.69**	-0.21	0.45
Number Species at Risk	**0.57**	-0.37	**0.52**	-0.16	-0.03
% Species at Risk	-0.24	0.38	0.02	**-0.79**	0.23
Protected Areas	0.12	0.31	-0.26	**0.59**	-0.28
Forest Harvested	-0.18	-0.42	-0.21	**-0.84**	-0.19
Forest Harvest to Growth Ratio	0.049	**-0.76**	-0.25	**-0.51**	-0.28
Fisheries Harvest to Primary Production Ratio	-0.32	**0.58**	0.11	**0.45**	-0.14
Fisheries Harvest to World Harvest	0.06	0.31	**0.86**	0.39	-0.07
Distance Travelled	**0.65**	0.36	0.34	-0.16	**0.53**

= significant loading at the 99% level of confidence
= indicator's highest but non-significant level of loading
= important secondary loadings

From a policy analysis perspective, these loading coefficients provide good support for formulating subindices measuring various environmental policy areas (table 3.10). Greenhouse gas emissions, volatile organic compounds, carbon monoxide, and nuclear waste load significantly onto the first component. Other key values that help decipher this component include the sulphur oxides indicator's largest coefficient as well as the secondary loading coefficients for the nitrogen oxides and the ozone-depleting substances indicator. Hence, the first policy subindex assesses waste and pollution because five indicators of this type load highly onto this component, including four that load significantly at a 99%

level of confidence. The nitrogen oxides indicator loads highly onto the first component with the other air pollution indicators, but, reflecting its association with energy use, it also significantly loads onto the second component. The current study groups the nitrogen oxides indicator with the other related indicators in the waste and pollution policy subindex (WPPS), a grouping other studies support (Boyd 2001; Conference Board of Canada (CBC) 2004; Boyd 2004; Esty et al. 2005; Gunton et al. 2005). While the ozone-depleting substances indicator loads most highly on the fourth component, it also loads highly and approximately equally onto three other components, including the first one. Thus, due to this indicator's status as a pollutant, the current analysis includes it in WPPS, a placement supported by Boyd (2004) and Gunton et al. (2005). As discussed below, water consumption, number of species at risk, and distance travelled are indicators that, while loading highly on WPPS, also load almost as highly on other, conceptually more appropriate, policy subindices.

The second component represents the sustainable energy policy subindex (SEPS). Energy consumption, energy intensity, and electricity from renewable resources (without hydro) load significantly onto this component. The other key value is the highest loading coefficient for the electricity from renewable resources (with hydro) indicator. Indeed, four energy related indicators load highly onto the sustainable energy component, with three that load significantly at a 99% level of confidence. Interestingly, both renewable energy indicators load negatively, while energy consumption and energy intensity load positively, as one would expect given the divergent nature of these two groups of indicators. This aspect provides further evidence that the component determines the policy subindex of sustainable energy. Note, that as constructed for the current research, the renewable energy indicators define improvements inversely to the consumption indicators. The renewable energy indicators define improving conditions as an increase in levels of production, while the consumption indicators define improving conditions as a decrease in consumption. The forest-harvest-to-growth ratio and fisheries-harvest-to-primary-production ratio indicators load highly onto this component as well, but as noted, load almost as highly on another, conceptually more appropriate, policy subindex, discussed below.

Table 3.10: ESPI policy measures created from component loading coefficients and informed by literature sources

COMPONENT	POLICY MEASURE	ENVIRONMENTAL SUSTAINABILITY PERFORMANCE INDICATOR	LOADING COEFFICIENTS	RANK OF COEFFICIENT ON COMPONENT
1	Waste and Pollution	Greenhouse Gas Emissions	0.94	**1st**
		Volatile Organic Compounds	0.94	**1st**
		Nuclear Waste	0.94	**1st**
		Carbon Monoxide	0.92	**1st**
		Sulphur Oxides	0.73	1st
		Nitrogen Oxides	0.52	2nd
		Ozone-Depleting Substances	0.42	3rd
2	Sustainable Energy	Electricity From Renewable Resources (w/out hydro)	-0.97	**1st**
		Energy Intensity	0.88	**1st**
		Energy Consumption	0.86	**1st**
		Electricity From Renewable Resources (w/ hydro)	-0.73	1st
3	Sustainable Food	Pesticide Use	0.96	**1st**
		Fertiliser Use	0.88	**1st**
		Fisheries Harvest to World Harvest	0.86	**1st**
		Livestock	0.69	1st
4	Nature Conservation	Forest Harvested	-0.84	**1st**
		% Species at Risk	-0.79	1st
		Protected Areas	0.58	1st
		Water Consumption	0.53	2nd
		Forest-Harvest-to-Growth Ratio	-0.51	2nd
		Fisheries-Harvest-to-Primary-Production Ratio	0.45	2nd
		Number Species at Risk	-0.15	4th
5	Sustainable Cities	Municipal Waste	0.82	**1st**
		Recycling	-0.75	1st
		Distance Travelled	0.53	2nd
		Municipal Sewage Treatment	-0.41	2nd

The third component determines the sustainable food policy subindex (SFPS). The three significant indicators for the third component are pesticide use, fertiliser use, and fisheries harvest to world harvest. Another important value is supplied by the livestock indicator's highest loading. Thus, four food related indicators load highly onto the SFPS component, with three that load significantly at a 99% level of confidence.

Although somewhat less clear, the fourth component appears to determine nature conservation. Only one indicator loads significantly on the fourth component, that being the forest harvested indicator. Several indicators have their highest, albeit non-significant, loading coefficients on the fourth component, but two are of particular interest: percent of species at risk and protected area. Secondary loadings for water consumption, forest-harvest-to-growth ratio, and fisheries-harvest-to-primary-production ratio are also important for this component. In fact, three indicators related to conserving various elements of nature load highly onto this component, with one that loads significantly at a 99% level of confidence, while another three indicators have high secondary loadings. Clearly, the forest-harvest-to-growth ratio and the fisheries-harvest-to-primary-production ratio track some aspect of nature conservation (i.e., trees and fish). Including water consumption in the nature conservation policy subindex (NCPS) receives support from Esty et al. (2005) and Esty et al. (2006). Perhaps the most controversial assignment, because of its weak loading on this component, is the inclusion of the number of species at risk. This indicator loads most highly on the first component related to waste and pollution and has an important secondary loading on the third component related to sustainable food, both of which are much greater than the loading on the fourth component. The number of species at risk indicator loads highly on these components because pollution levels and habitat change likely adversely affect animal populations. However, this component already includes the highly loaded percent of species at risk indicator, and the number of species at risk indicator does not load significantly on any component. Moreover, several studies provide additional support for inclusion of this indicator in NCPS (Boyd 2001; Gunton et al. 2005; Boyd 2004).

Similar to the fourth policy measure, the fifth component is also somewhat difficult to interpret, but it appears to capture the concept of building sustainable cities. The lone significant indicator loading onto the fifth component is municipal waste. A single indicator, recycling, loads its highest, but non-significant, coefficient onto this component as well. Further information is supplied by two other secondary loadings for municipal sewage treatment and distance travelled. Thus, two indicators related to solid waste management load highly onto this component, with one that loads significantly at a 99% level of confidence. Moreover, the municipal sewage treatment and distance travelled indicators possess high secondary loadings on this policy measure. As one might expect, the two indicators related to solid waste management display juxtaposed loading coefficients: municipal waste loads positively and recycling loads negatively, providing further evidence that this component determines the policy subindex of sustainable cities. Note, that as constructed for the current research, the municipal waste indicator defines improvements inversely to the recycling indicator. The recycling indicator defines improving conditions as an increase in levels of materials recovered, while the municipal waste indicator defines improving conditions as a decrease in waste. A sustainable city minimises the adverse environmental impacts arising from its citizen's daily activities, such as managing liquid and solid waste, perhaps with various recycling efforts, as well as providing various transportation options that discourage the use of individual automobiles. Moreover, Boyd (2004) and Gunton et al. (2005) provide support for including the distance travelled indicator in the sustainable cities policy subindex (SCPS).

With the composition of the policy measures formulated, one may calculate subindex scores and country performance ranks (table 3.11). Notably, country ranks display much variability across the results for the policy measures. Ranked 28th overall on ESPCI, Canada actually performs among the top 10 countries for producing sustainable food (6th), while 1st overall Turkey performs rather poorly at building sustainable cities placing 25th. Almost all countries exhibit variable performance across the policy measures similar to these examples (table 3.11). A notable exception is the United States, a country that performs poorly across all policy measures. Such variability indicates that different policies and factors are influencing a country's overall environmental sustainability performance. Decomposing the overall results into various policy subcategories allows the various pressures underlying these environmental policy areas to emerge for further analysis.

Table 3.11: Policy measure scores and performance ranks for OECD-member countries

COUNTRY	ESPCI		WPPS		SEPS		SFPS		NCPS		SCPS	
	SCORE	RANK	SCORE	RANK	SCORE	RANK	SCORE	RANK	SCORE	RANK	SCORE	RANK
Turkey	0.728	1	0.915	2	0.529	9	0.938	4	0.677	5	0.479	25
Switzerland	0.722	2	0.916	1	0.575	5	0.767	20	0.641	13	0.641	6
Austria	0.716	3	0.850	9	0.600	3	0.858	14	0.664	7	0.616	7
Slovak Republic	0.713	4	0.869	5	0.393	24	0.909	10	0.735	2	0.573	11
Denmark	0.709	5	0.808	13	0.717	1	0.778	19	0.664	8	0.563	12
Germany	0.708	6	0.869	6	0.465	16	0.848	15	0.644	11	0.678	3
Poland	0.704	7	0.858	8	0.411	20	0.944	3	0.671	6	0.547	15
Sweden	0.696	8	0.739	21	0.490	12	0.924	7	0.630	17	0.725	2
Italy	0.678	9	0.869	7	0.535	8	0.779	18	0.634	15	0.510	23
Finland	0.677	10	0.688	23	0.482	14	0.947	2	0.634	14	0.661	5
Portugal	0.670	11	0.837	11	0.669	2	0.829	16	0.545	27	0.482	24
Greece	0.663	12	0.770	18	0.472	15	0.917	8	0.619	21	0.516	21
United Kingdom	0.657	13	0.785	16	0.442	19	0.751	21	0.656	9	0.584	9
Spain	0.652	14	0.788	15	0.525	10	0.874	13	0.548	26	0.537	19
Czech Republic	0.650	15	0.835	12	0.379	25	0.915	9	0.492	29	0.675	4
France	0.649	16	0.776	17	0.450	18	0.820	17	0.632	16	0.516	20
New Zealand	0.649	17	0.665	24	0.589	4	0.538	27	0.772	1	0.549	13
Norway	0.645	18	0.660	26	0.559	6	0.723	23	0.694	4	0.547	16
Hungary	0.642	19	0.873	4	0.410	21	0.936	5	0.561	25	0.392	27
Netherlands	0.635	20	0.876	3	0.406	22	0.552	25	0.621	19	0.611	8
Korea	0.633	21	0.754	20	0.327	28	0.472	28	0.716	3	0.834	1
Japan	0.628	22	0.846	10	0.483	13	0.403	29	0.652	10	0.579	10
Mexico	0.625	23	0.558	27	0.554	7	0.884	12	0.586	22	0.540	18
Ireland	0.619	24	0.791	14	0.464	17	0.735	22	0.582	23	0.465	26
Iceland	0.590	25	0.660	25	0.495	11	0.886	11	0.521	28	0.353	28
Luxembourg	0.551	26	0.712	22	0.188	30	0.550	26	0.643	12	0.511	22
Australia	0.540	27	0.358	28	0.397	23	0.971	1	0.628	18	0.296	29
Canada	**0.497**	**28**	**0.183**	**30**	**0.355**	**26**	**0.929**	**6**	**0.620**	**20**	**0.543**	**17**
Belgium	0.496	29	0.762	19	0.339	27	0.357	30	0.387	30	0.547	14
United States	0.443	30	0.345	29	0.315	29	0.714	24	0.577	24	0.170	30
OECD Median	**0.650**		**0.787**		**0.468**		**0.838**		**0.633**		**0.547**	

ESPCI = environmental sustainability performance composite index, WPPS = waste and pollution policy subindex, SEPS = sustainable energy policy subindex, SFPS = sustainable food policy subindex, NCPS = nature conservation policy subindex, and SCPS = sustainable city policy subindex.

Note: For all policy measures, the closer a country's score is to one the better is its environmental performance. Good environmental performances rank highly (i.e., 1st, 2nd, 3rd), poor environmental performances rank lowly (28th, 29th, 30th).

3.5) LIMITATIONS OF THE UNCERTAINTY AND SENSITIVITY ANALYSES

With the data analyses complete, the discussion turns to several factors constraining the results and interpretations of this section. Results of ranking exercises, such as this one, depend on the choice of issues covered and the indicators used to represent them. Indeed, the benchmarking studies exhibit country ranks that vary with different issue coverage and indicator usage. Incorporating a process that reviews many different approaches and perspectives, with particular attention given to contextually relevant ones, mitigates these selection biases by increasing the probability of detecting relevant issues and indicators. However, some issues and indicators may remain undetected.

At the same time, data availability and quality limit selecting appropriate indicators to those with data that are comparable among countries (refer to table 2.1). Thus, the current study, like others before it, can not track relevant aspects of environmental sustainability (table 3.12). Including in the analysis these other aspects of environmental sustainability would likely alter results because these aspects appear to capture important elements of sustainability. For example, countries that are encouraging urban sprawl receive no penalty, while countries that are building more sustainable cities by increasing public transit and protecting agricultural land receive no credit for worthy efforts towards sustainability. Conducting a benchmarking exercise under these conditions is useful because it focuses attention on measurement and data challenges, which may, in turn, motivate decision makers to seek solutions that fill these data gaps. Moreover, recommendations pertaining to included environmental policy areas are nevertheless relevant.

Furthermore, reliance on national averages overlooks local problems. Localised environmental issues may be a problem, even where national averages are fair to good. For example, poor water quality may exist at local beaches in populated areas versus good water quality throughout the rest of the country. In such situations, recommendations would not encompass locally deteriorated conditions.

In addition to indicator selection issues, one must consider several caveats when interpreting the sensitivity analysis results. First, the current research did not consider uncertainty in the underlying indicator values because estimates of measurement error are unavailable. Large measurement errors have the potential to affect considerably a country's performance ranks because actual indicator values may be substantially different from those used in the analysis. Next, one must be aware that the statistically based weights derived from PCA results (discussed in section 3.1) are similar in value to equal weights. Thus, each set of weights induce similar variation in the output distributions such that the finding of non-significance for the weights input factor is not very surprising. Finally, because none of the reviewed studies used it, the aggregation method input factor does not include the non-compensatory multi-criteria method, which possesses the capacity to alter appreciably a country's performance ranks.

Table 3.12: Indicators of environmental sustainability performance for which data are not available

CHALLENGE	INDICATOR	MEASUREMENT VARIABLE
Genuine Wealth	Genuine Wealth Index	Reporting of Genuine Wealth Index on regular basis
Waste and Pollution	Particulates	Kilograms of particulates emitted per capita
	Hazardous and Toxic Waste	Kilograms of hazardous waste generated per capita
Healthy Food	Organic Agriculture	Proportion of organic agricultural area to total agricultural area
Nature Conservation	Ecosystem-Based Management	The proportion of terrestrial and marine ecosystem in which ecosystem-based management has been implemented
Sustainable Cities	Green Infrastructure Funding	Per capita public transit funding
	Public Transit	Number of urban and suburban transit passengers per capita
	Loss of Agricultural Land	Thousands of square kilometres of agricultural area lost to urbanisation per capita change in population

Source: Gunton et al. 2005: 7-8

CHAPTER 4:
INFLUENCING ENVIRONMENTAL SUSTAINABILITY

With the performance measures formulated, focus switches to another question. What factors affect a country's trajectory on the path towards an environmentally sustainable future? Undoubtedly, more than a few factors are important to a country's environmental sustainability performance. This chapter identifies various influential factors emerging from the literature, and discusses their association with various aspects of environmental sustainability performance. One should note that the literature tends to demonstrate associations only between influential factors and individual performance indicators or policy subcategories, rather than overall environmental sustainability. This finding and the results of the uncertainty and sensitivity analyses from the last chapter seem to indicate that much policy analysis should happen at the individual indicator or subcategory level. The discussion also develops the metric used to represent each influential factor in the subsequent regression and cluster analyses (chapter 5). These analyses use the factor metrics as independent variables to help explain environmental performance on the policy measures. Unless otherwise specified, this research uses 2002 data for calculating factor metrics. After first discussing the retained factors, this chapter then discusses the factors considered but ultimately rejected by applying the criteria of importance and measurability.

4.1) SELECTED INFLUENTIAL FACTORS

The current research considers two points when selecting the potentially influential factors for inclusion in the quantitative analyses that follow (chapter 5). An influential factor is suitable for inclusion if it is demonstrably important to environmental sustainability and an appropriate measurement methodology is available. The discussion of importance develops a plausible theory of association that connects a factor to some aspect of environmental sustainability. Usually, evidence from the literature is at a performance-indicator or policy-subcategory level; hence, individual factors usually relate only to a subset of indicators or policy subcategories. A factor is easily interpretable and its affects are unambiguous; hence, differing values have clear implications for environmental sustainability performance. Lastly, an effective measurement methodology requires the availability of high-quality data to calculate metrics.

Applying these criteria produces the following potentially influential factors (table 4.1).

- Climate
- Population pressure (computed as growth and density)
- Economic output
- Technological development
- Industrial structure
- Energy prices
- Environmental governance
- Pollution abatement and control (PAC) expenditures
- Environmental pricing

Climate is an ungovernable factor, while population growth and density, economic output, technological development, and industrial structure are semi-governable factors. Finally, energy prices, environmental governance, PAC expenditures, and environmental pricing are governable factors. The distinction regarding a factor's governability is only important for the policy implications of the findings (see chapter 6). Refer to the Conceptual Framework section and figure 1.2 in chapter 1 for further discussion. While this section discusses retained factors, the next section focuses on excluded factors—distance (with geographic size and spatial distribution of population as proxies), natural resources endowments, international environmental agreements, and trade.

Table 4.1: Influential factor descriptions, literature support, data sources, and metrics

FACTOR	DESCRIPTION	SUPPORT	DATA SOURCES	METRIC
Climate	Extreme temperatures increase energy consumption for space heating and cooling. Energy consumption in turn produces several adverse environmental impacts. Temperature regimes may also affect sustainable production of food, conservation of natural resources, and biodiversity.	Canada 2001, Tso and Yau 2003, Sailor 2001, Segal et al. 1992, Scott et al. 1994, Lusk et al. 2007, Karlsson and Milberg 2007, Agren and Wetterstedt 2007, Garcia-Ispierto et al. 2007, Haith and Duffany 2007, Pichler and Oberhuber 2007, Buntgen et al. 2007, Wu et al. 2007, Biro et al. 2007, Rees et al. 2007, Dolenec 2007, Houghton et al. 2007, MEA 2005	World Resources Institute Climate Analysis Indicators Tool Excel v. 3.0	Total heating and cooling degree days
Population Pressure	Large populations increase consumption of ecosystems and their corresponding services, as well as strain ecosystem assimilative capacity.	Ehrlich and Holdren 1972, MEA 2005, Canada 2001, Kates 2000, Carr et al. 2005, Curran and de Sherbinin 2005, Esty et al. 2005, CBC 2004	OECD *Environmental Data Compendium* 2004	Population Growth: Annual percentage increase Population Density: Inhabitants per square kilometre of land area with >5 residents
Economic Output	Environmental performance decreases as level of affluence increases due to increased consumption of resources.	Ehrlich and Holdren 1972, MEA 2005, Arrow et al. 1995 Rosa et al. 2004, Dietz et al. 2007, Esty et al. 2005, CBC 2004, Canada 2001, Esty and Porter 2005	OECD *Environmental Data Compendium* 2004	GDP per capita
Technological Development	New technologies use resources more efficiently or allow substitution with less damaging processes or materials.	MEA 2005, Kwon 2005, Bruvoll and Medin 2003, Esty et al. 2005, Loschel 2002	*UN Human Development Report*	Index value from 0 to 1

Continued on next page

Table 4.1—*Continued*

FACTOR	DESCRIPTION	SUPPORT	DATA SOURCES	METRIC
Industrial Structure	Environmental performance decreases as an economy becomes more industrialised, and, thus more energy intensive with a heavier pollution load.	Canada 2001, Auty 1997 Lin et al. 2006, Bengochea-Morancho et al. 2001, Han and Chatterjee 1997, Esty et al. 2005	*Energy Balances of OECD Countries 2001 – 2002* *Energy Statistics of OECD Countries 2002 - 2003* *National Accounts of OECD Countries Detailed Tables Volume II 1993-2004*	Energy-intensive sectors as proportion of GDP
Energy Prices	Higher energy prices promote conservation, efficiency, and innovation.	Taheri 1994, Pindyck 1979 Fuss 1977, Taheri and Stevenson 2002, Popp 2002, Christiansen 2002, Canada 2001, Esty et al. 2005, MEA 2005	*International Fuel Prices* 2003, German Technical Co-operation, German Federal Ministry for Economic Co-operation and Development International Energy Agency's *Energy Prices and Taxes Quarterly Statistics 2005* *Energy Statistics of OECD Countries 2002 - 2003*	Consumption-based weighted average price per toe
Environmental Governance	Effective governance of a variety of pollutants and environmental issues increases environmental sustainability.	MEA 2005, Esty 1999, Esty and Porter 2005, Esty et al. 2005, CBC 2004, Boyd 2003	World Economic Forum's *The Global Competitiveness Report* Executive Opinion Survey 2003 -2004	Sum of survey question scores
PAC Expenditures	Mitigative environmental expenditures that prevent, reduce, or eliminate pollution from production processes or the consumption of goods and services.	OECD 2001a, MEA 2005, Liddle 2001, Brunnermeier and Cohen 2003	OECD *Environmental Data Compendium* 2004	Proportion of GDP or U.S. $ per capita
Environmental Pricing	Imposition of taxes or user fees that charge for pollution and other activities that have external environmental costs not accounted for in the market.	MEA 2005, Cremer and Gahvari 2005, OECD 2004, NRTEE 2002, Bernow et al. 1998, Bailey 2002	OECD *Environmental Data Compendium* 2004	Proportion of GDP or U.S. $ per capita

By presenting support for all but one of the retained influential factors, one report requires a brief introduction. The Millennium Ecosystem Assessment (MEA) provides a scientific basis that supports sustainability efforts, such as the current research (MEA 2005: v). Carried out from 2001 to 2005 and co-ordinated by the United Nations Environment Programme, MEA (2005) assesses how ecosystem changes may affect human well-being. MEA synthesises existing information from the literature, relevant datasets and models, and indigenous knowledge to identify a set of five indirect drivers of ecosystem change (MEA 2005: 65-67) and a series of options for managing ecosystems sustainably (92-100). As such, this report provides a solid foundation for selecting all but one of the influential factors. MEA (2005) supplies only marginally relevant support for including the industrial structure factor, support that is superseded by studies that are more pertinent. Chapter 5 estimates how the retained explanatory factors account for different environmental sustainability performances among the Organisation for Economic Co-operation and Development (OECD) countries, a unique contribution of the current research.

CLIMATE

Climate affects an array of attributes related to a country's environmental sustainability, such as energy consumption and pollution emissions. Energy consumption produces adverse environmental effects during the extraction, transportation, and combustion of energy resources. Extracting energy resources from buried deposits damages local ecosystems by changing water flow, disrupting wildlife, polluting air and water, and eroding soil. Transporting energy resources from point of extraction to point of use generates exhaust emissions, provides opportunities for spills (in the case of oil), and disrupts ecosystems with transmission lines and pipelines. Combusting fossil fuels emit a variety of atmospheric pollutants: carbon dioxide, carbon monoxide, sulphur oxides, and nitrogen oxides. Meanwhile, renewable energy resources also have adverse impacts arising from several aspects. Equipment manufacturing, such as solar collectors, uses polluting materials, while biomass energy derived from trees or crops uses soil nutrients and harvesting may disrupt ecosystems. Wind and solar farms require large amounts of land, and hydro dams flood land for reservoirs, block animal migrations, disrupt aquatic life by altering river flows, and release greenhouse gases (GHGs) from flooded lands.

Indeed, the Government of Canada (GOC) refers to climate as a 'national circumstance' that significantly influences a country's production, consumption, energy use, and pollution-emission patterns (Canada 2001). Tso and Yau (2003), who studied domestic energy-use patterns in Hong Kong, find that low temperatures increase usage of space heaters, while high temperatures increase air-conditioner use; both results expand society's energy consumption and subsequent pollution-emission patterns. In a study of regional electricity consumption across eight states, Sailor (2001) demonstrates that annual per capita residential and commercial electricity consumption varies with temperature, while a study of Israeli summer electric loads, finds a high correlation between temperature and peak electric loads (Segal et al. 1992). Moreover, temperature affects energy-use patterns of commercial buildings to such an extent that building designs are beginning to change, thus influencing a country's performance on the sustainable cities policy subindex (Scott et al. 1994).

Climate also affects such important aspects of a country's environmental sustainability performance as food production, renewable natural resources, and biodiversity. Lusk et al. (2007) determine that seed production varies with temperature, while Karlsson and Milberg (2007) find that temperature, in part, also controls germination, both indicating that temperature influences agricultural productivity. Temperature also mediates decomposition of soil organic matter (Agren and Wetterstedt 2007) and conception rates of dairy herds (Garcia-Ispierto et al. 2007), thus, soil and herd replenishment rates necessary for sustainable agricultural practices depend, in part, on ambient temperature regimes. Furthermore, temperature also shapes pesticide run-off loads arising from agricultural management practices (Haith and Duffany 2007). Temperature influences timber growth rates (Pichler and Oberhuber 2007; Buntgen et al. 2007), forest ranges (Wu et al. 2007), and fish mortality (Biro et al. 2007), all of which affects a country's effectiveness at conserving nature. At the same time, climate may also affect wildlife distribution (Rees et al. 2007), breeding habits (Dolenec 2007), and even gender of some animals (Houghton et al. 2007), ultimately influencing a country's biodiversity. Furthermore, MEA (2005) details similar effects when it concludes that climate change is a primary driver of environmental sustainability. Clearly, climatic temperature possesses the potential to influence many aspects of a country's environmental sustainability, with evidence suggesting this factor affects more than a handful of performance indicators as well as one or two policy subcategories.

Measuring climate as average temperature could produce conflicting signals about environmental sustainability performance. The extremes of hot and cold send a similar message regarding level of energy consumption and related pollution emissions, thereby clouding interpretability of the factor because different values do not produce unique outcomes. Consequently, this study uses degree days as the basis for the climate metric. A 'degree day' is a appraisement of the average temperature's departure from a human comfort level of 18 °C (65 °F).[17] The methodology for calculating degree days produces national averages that represent the temperature faced by an 'average' person in the particular country. Energy analysts use the concept of degree days for heating and cooling services to evaluate energy demand. To capture the effects of both, the climate metric sums heating and cooling degree days to find total degree days for use in further analyses.

Data for the metric comes from the World Resources Institute's Climate Analysis Indicators Tool Excel version 3.0[18]. Founded in 1982 as a not-for-profit organisation, the World Resources Institute is an environmental think tank promoting sustainable interactions between society and the environment. The Indicators Tool provides comprehensive and comparable databases of GHG inventories and other climate-relevant data, such as heating and cooling degree days. A weakness of the climate metric is its lack of information regarding other aspects of a country's climate, such as precipitation and wind regimes. Including

[17] Using a base temperature of 18 °C, one calculates a heating degree day as 18 minus the average temperature of a given day, while a cooling degree day is the reverse: average temperature of a given day minus 18, and a day with an average temperature of 25 °C will have 7 degree cooling days. For both heating and cooling degree days, one calculates the average temperature of a particular day as the mean of the daily high and low temperatures. Thus, if the daily high temperature is 20° and the daily low temperature is 10°, then the average temperature is 15 (resulting in 3 heating degree days). Heating and cooling degree days are cumulative, thus to calculate the annual degree days, one sums the degree day calculations of all 365 days. Naturally, heating degree days accumulate primarily during the winter, whereas cooling degree days tend to accrue during the warmer summer months.

[18] Available for download from http://cait.wri.org/; accessed 24 July 2007.

such information would have required additional variables entering the analysis; to be parsimonious the current study strives to keep the variable set as small as practical. Excluding these aspects could limit the explanatory power of the climate factor such that it is found to be less important than it is in reality.

POPULATION PRESSURE

The next factors represent population pressures. For various reasons, two metrics, rather than one, best represent this factor, these being population growth and population density. Given the metric's dynamic nature, population growth can only account for changes in environmental sustainability performance; thus, a main issue with using this metric is its inability to explain absolute performance. While population density can explain absolute performance, its measurement suffers from a drawback similar to the proxies for the excluded factor distance, discussed in section 4.2. Calculated densities depend on an arbitrary placement of boundaries to define the area of interest. Using national political boundaries includes large amounts of unoccupied land in the calculation, most notably for North America and Australia, which underestimates population densities for occupied land. To mitigate this effect, density calculations use the area of occupied land. Together, these metrics provide a robust representation of population pressures suitable for inclusion in the subsequent regression and cluster analyses.

Through the identity I = P*A*T, Ehrlich and Holdren (1972) assert the importance of growth of population (P), affluence (A), and technology (T) as primary forces driving destructive environmental impacts (I). According to Ehrlich and Holdren (1972), population pressures are the most influential of the three. Moreover, MEA (2005) identifies population growth as one of five factors indirectly influencing sustainability by increasing demand for food, fresh water, timber, fibre, and fuel, thereby expanding material consumption of ecosystems and their corresponding services. When he updates the IPAT identity, Kates (2000) considers population growth in conjunction with the consumption that affluence can engender as primary drivers of environmental problems. At the same time, Carr et al. (2005) document the role, occurring over several scales, of population growth at inducing consumption patterns that produce deforestation and other land cover changes. Moreover, Curran and de Sherbinin (2005) formulate a conceptual framework that combines population, consumption, and environmental degradation using population growth rates as a foundational metric upon which the rest of the framework depends. Finally, GOC considers high population growth a key determinant of GHG emissions (Canada 2001). Consequently, population growth displays a capacity to increase consumption and potentially adversely affect a country's environmental sustainability, apparently influencing several performance indicators and policy subcategories.

In addition to growth as a gauge of population pressures, one may also consider using density. A cluster analysis that Esty et al. (2005) conducts on the Environmental Sustainability Index (ESI) provides evidence of a relationship between cluster membership and population density. Moreover, the Conference Board of Canada (CBC) (2004) finds a high negative correlation between population density and environmental performance such that lower population densities tend to correspond with better environmental performance. Therefore, similar to population growth, population density demonstrates a potential capacity to affect environmental sustainability performance. This evidence suggests that population density may influence several performance indicators and policy subcategories.

Given this support, the present research uses both growth and density to represent population pressures. The subsequent regression analysis determines the effects of each metric, as well as the potential importance of each metric. This study formulates population growth as the annual percentage increase in a country's population from 2001 to 2002 and population density as the number of people per square kilometre of land area with more than five residents. The selected annual population growth rate reflects the longer-term average each country has experienced over the last 10 to 20 years. Growth calculations use data from the OECD's *2004 Environmental Data Compendium* (OECD 2005b), while the density calculation also uses data from the Center for International Earth Science Information Network's Gridded Population of the World version 3[19].

[19] Available for download from http://sedac.ciesin.columbia.edu/gpw/index.jsp; accessed 18 December 2007.

ECONOMIC OUTPUT

As mentioned, the A in the IPAT identity represents affluence, assessed in terms of economic output. Thus, according to Ehrlich and Holdren (1972) affluence is a major driver of environmental degradation. As per capita incomes increase, the structure and rate of consumption changes, resulting in a growing demand for, and pressure on, ecosystems and their corresponding services (MEA 2005; Arrow et al. 1995). This circumstance arises because people tend to consume more goods and services with higher levels of income, thus accelerating the degradation of ecosystems through converting land uses and increasing pollution loads. In an analysis that includes over 140 countries, Rosa et al. (2004) estimate the effects of population and affluence on GHG emissions, ozone-depleting substances emissions, and the ecological footprint. These researchers find that affluence typically increases impacts, but the specific effect depends on the type of impact. In a follow-up study, Dietz et al. (2007) conclude that affluence is a primary driver increasing many countries' ecological footprints. Moreover, through the combined results of cluster analysis, principal components factor analysis (PCFA), and step-wise regression analysis on ESI, Esty et al. (2005) determine that economic output possesses a significant capacity for influencing environmental sustainability performance. CBC (2004) also find a relationship between environmental performance and economic output, while GOC includes economic growth as a variable that helps determine GHG emissions (Canada 2001).

Adverse environmental impacts that do not increase with level of affluence may instead follow an environmental Kuznets curve (EKC) relationship. Stated simply, this hypothesis suggests that societies can advance past an initial environmentally degrading phase by increasing their level of economic activity. This theory proposes that resource use, as well as associated environmental stresses, at first increase with increasing levels of per capita income before plateauing. After this turning point, adverse environmental impacts begin to decrease while per capita income continues to increase. Empirical support for this hypothesis is rather thin, with an EKC-type relationship observed between affluence and relatively few adverse environmental impacts, mainly local air and water pollution emissions (Grossman and Krueger 1995; Ekins 1997; Bruvoll and Medin 2003; Gergel et al. 2004; Dinda 2004).

For several reasons, results regarding pollution emissions related to adverse environmental impacts can not be generalized to wider environmental degradation (Arrow et al. 1995). Research does not establish an EKC-style relationship for the accumulation of stocks of waste (e.g., municipal solid waste) or for widely dispersed pollutants (e.g., carbon dioxide); nor does the existent research identify such a relationship for resource stocks, such as timber and fish. Finally, according to Arrow et al. (1995: 520), most cases of declining emissions with increasing per capita income are due to institutional changes such as environmental legislation. Esty and Porter (2005) also find a similar effect in their study of environmental performance as quantified by urban particulates, sulphur dioxide, and energy use per unit GDP. Consequently, the current study surmises that economic output may considerably influence various aspects of a country's environmental sustainability. Evidence from the literature suggests that economic output affects many performance indicators and policy subcategories, as well as possibly overall environmental sustainability.

The metric the current study uses for economic output is GDP per capita. This calculation uses economic and population data from the OECD's *2004 Environmental Data Compendium* (OECD 2005b). Because of a lack of data, this metric does not include unpaid labour. If unpaid labour were able to be included in the metric calculation, GDP per capita values would increase.

TECHNOLOGICAL DEVELOPMENT

Similar to population growth and economic output, the IPAT identity also contains technological development as a main driver of adverse environmental impacts. MEA (2005) identifies technological development as a relevant factor that indirectly affects ecosystem integrity. The *Assessment* concludes that new technologies increase the efficiency with which society uses ecosystem resources, as well as providing substitutes for some ecosystem services, thus improving environmental sustainability performance. Based on an analysis of three decades of carbon dioxide automobile emission data for Great Britain, Kwon (2005) determines that fuel efficiency and fuel substitution resulting from technological development reduce carbon dioxide emissions. Overall, Kwon (2005) concludes that technological development reduced the carbon intensity of automobile driving over the period studied, substantially lowering the growth rate of carbon dioxide emissions. Bruvoll and Medin (2003) obtain similar results from their analysis of 16 years of Norwegian emission data for 10 air pollutants. Through the combined results of cluster analysis, PCFA, and step-wise regression analysis on ESI, Esty et al. (2005) determine that technological development positively influences environmental sustainability performance. Moreover, many economic-environment models used for policy analysis contain sophisticated representations of technology creation and diffusion (Loschel 2002). Thus, technological developments appear to increase a society's capacity to decouple its economic growth and consumption from adverse environmental impacts. Evidence indicates that technological development affects several performance indicators and policy subcategories, as well as possibly overall environmental sustainability.

Technological development enters this analysis as the dimensionless Technology Achievement Index (TAI). Created by the *UN Human Development Report* (UN Development Programme (UN DP) 2001), this metric models the creation and diffusion of technology in a country's economy, as well as in developing human skills (table 4.2). One re-scales (refer to table 3.3 for re-scaling equation) each indicator before calculating the index for each component as the average of the included re-scaled indicators. In turn, the overall TAI is the average of these four component indices. This analysis updates the original TAI from the 2001 development report, using data from several subsequent reports (UN DP 2001; 2004; 2005) reflecting data availability for specific years.

This metric possesses two weaknesses. First, because the index re-scales several values over the range of those observed, the best and worst values that define that range may change, thus yielding data that can not be compared over time. This weakness does not affect the current study because such a comparison does not occur. Second, as constructed, this metric is incomplete because it is not possible to reflect a country's full range of technologies; many aspects of technology creation and diffusion are hard to quantify. Even if quantifiable, such aspects lack reliable data sources, thus incorporating them into the metric is impossible. With that said, the aspects included in the metric provide a more than adequate gauge of a country's technological development for the purposes of the current study.

Table 4.2: Components and indicators of the Technology Achievement Index used as the technological development metric

COMPONENT	INDICATOR	UNITS
Technology Creation Index	Patents granted to residents Royalties and license fees received	Per million people U.S.$ per 1,000 people
Diffusion of Recent Innovations Index	Internet hosts High-technology exports[a]	per 1,000 people % of manufactured goods
Diffusion of Old Innovations Index	Telephones – mainline and cellular Electricity consumption	per 1,000 people kWh per capita
Human Skills Index	Mean years of schooling Gross tertiary science, math, and engineering enrolment ratio[b]	Age 15 and above % of total enrolment

Source: UN DP 2001

[a] The original TAI uses high- and medium-technology exports as a percent of total exports for this indicator, but this analysis adjusts it to reflect current data availability when updating the index.

[b] The original TAI uses gross tertiary science enrolment for this indicator, but this analysis adjusts it to reflect current data availability when updating the index.

INDUSTRIAL STRUCTURE

Similar to climate, GOC refers to industrial structure as a national circumstance that appreciably influences a country's environmental sustainability trajectory (Canada 2001). As a country becomes more industrialised, its economy becomes more energy intensive, increasingly dominated by larger energy-intensive sectors with heavier pollution loads that degrade the environment. Auty (1997) synthesises evidence from the literature concerning pollution patterns of economies transitioning from traditional to developed status. He finds that as an economy's industrial structure develops, its focus shifts from agriculture to manufacturing, thus altering the pollution pattern of the economy to become more environmentally degrading. The pattern shifts from predominantly water-borne organic pollutants to air pollution and solid waste in urban areas, and through to increases in generation rates of hazardous materials. Several recent studies provide additional support for including this factor because they find that shifts in industrial structure significantly account for increases in carbon dioxide emission levels (Lin et al. 2006; Bengochea-Morancho et al. 2001; Han and Chatterjee 1997). Moreover, through the combined results of cluster analysis, PCFA, and step-wise regression analysis on ESI, Esty et al. (2005) determine that industrial structure possesses a significant capacity for affecting environmental sustainability performance. Evidently, industrial structure degrades a country's environmental sustainability by increasing energy consumption and various pollution emissions. The findings indicate this factor may affect many performance indicators and several policy subcategories.

Delineated relative to the overall OECD industrial structure, the metric for industrial structure incorporates 14 economic sectors grouped by International Standard Industrial Classification (ISIC) Revision 3 divisions (table 4.3). The data coverage and overlap between energy and economic data limit the disaggregation of the economic sectors to that detailed in table 4.3; further disaggregation efforts result in substantial missing data points across the OECD-member countries that are the unit of analysis. The first step in calculating this metric involves determining the most energy-intensive economic sectors, on average, across the OECD, assessed in tonnes of oil equivalent (toe) per unit of total gross value added (GVA) by the respective sector to the economy. A sector's relative position in the rank order of the OECD's industrial sectors defines its energy intensity level, with the most energy-intensive sector positioned at the top and descending to the least energy-intensive sector at the bottom. A clear distinction between energy-intensive and non-energy-intensive sectors emerges from the ordering process. For this analysis, the most energy-intensive industries are the transport sector, non-metallic minerals, and refined petroleum products, chemicals, and rubber.

With the most energy-intensive sectors identified, the next step in calculating the industrial structure metric involves determining the importance of these three sectors to each country's economy. Summing GVAs for a country's three most energy-intensive sectors and dividing by GDP determines the importance of these sectors to a country's economy (fig. 4.1). Formulating the industrial structure metric in this manner allows it to be presented as one value while retaining much information from the original structure. Thus, the metric attains a balance between parsimony and important information content. However, one must recognise that a single value may not adequately represent reality.

Table 4.3: The economic sectors incorporated into the industrial structure metric

ECONOMIC SECTOR	ISIC REV. 3 DIVISIONS	ENERGY INTENSITY (TOE/U.S. $10,000 GVA)
Transport Sector	60, 61, 62, 63, 64	6.93
Non-Metallic Minerals	26	5.99
Refined Petroleum Products, Chemicals, and Rubber	23, 24, 25	5.44
Basic Metals, Fabricated Metal Products, Machinery,	27, 28, 29, 30, 31, 32, 33	3.43
Paper, Pulp, and Printing	21, 22	3.40
Mining and Quarrying	10, 11, 12, 13, 14	3.37
Wood and Wood Products	20	2.38
Agriculture, Hunting, Forestry, and Fishing	01, 02, 05	2.05
Food and Tobacco	15, 16	1.66
Electricity, Gas, and Water Supply	40, 41	1.38
Textile and Leather	17, 18, 19	1.27
Transport Equipment	34, 35	0.60
Public Services	50-55, 65-75, 80, 85, 90-	0.38
Construction	45	0.30

Economic data source: *National Accounts of OECD Countries Detailed Tables Volume II 1993-2004*
Energy data source: *Energy Balances of OECD Countries 2001 - 2002*
Energy Statistics of OECD Countries 2002 - 2003

While this factor uses similar data and concepts as one of the environmental performance indicators, that being energy intensity, the industrial structure metric contains different information because of its relationship to the OECD's industrial structure. *National Accounts of OECD Countries* supplies the GVA data for the economic sectors, while energy consumed by each sector appears in *Energy Balances of OECD Countries* and *Energy Statistics of OECD Countries*. These publications provide detailed statistics on production, trade, and consumption for each source of energy in the OECD using a common definition and methodological format for all member countries.

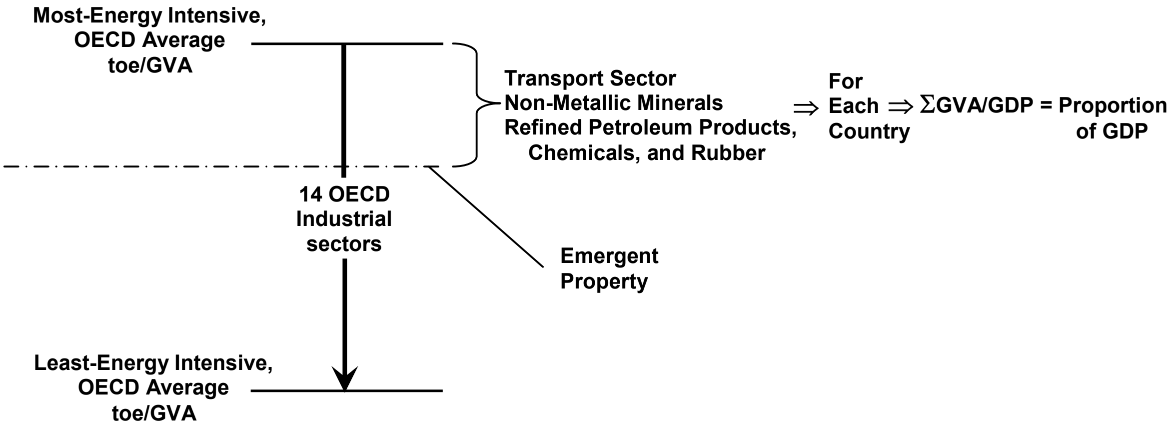


Figure 4.1: A schematic of the organisation and calculation of the industrial structure metric

ENERGY PRICES

Energy prices also shape a country's environmental sustainability trajectory. Because consumers reduce fuel usage to save money, higher energy prices tend to lower energy consumption, as well as associated emissions of many air pollutants (Taheri 1994; Pindyck 1979; Fuss 1977). Moreover, higher energy prices induce, in part, environmental compliance across several manufacturing industries either by pollution abatement techniques or by fuel switching strategies (Taheri and Stevenson 2002). Higher energy prices also promote innovative energy-efficient technologies that conserve energy resources (Popp 2002; Taheri and Stevenson 2002), and increase adoption of new renewable energy sources (Christiansen 2002). A more detailed discussion of each follows.

Taheri and Stevenson (2002) study the interplay of technological development, environmental compliance, and changing energy prices using data for 10 U.S. manufacturing industries from 1974 to 1991. Their measurement of industrial efforts to meet environmental regulations includes compliance and pollution abatement costs as well as reduced emissions of air pollution. They find that higher energy prices increase the cost share of polluting energy sources, prompting cost-conscious manufacturers seeking environmental compliance to spend either on external pollution abatement (i.e., scrubbers) or on internal fuel switching to cleaner energy sources, whichever produces the greater economic benefit. As well, spending on abatement technology supports technological development in pollution control, while spending on fuel switching may prompt development of technologies that allow the use of energy sources in different, novel situations. Popp (2002) reviews U.S. patents from 1970 to 1994 to determine that higher energy prices induce significant amounts of energy-efficient innovations, while Christiansen (2002) finds that the proportion of renewable energy sources in Norway stagnated for over two decades despite favourable government policies, mainly due to low electricity prices.

MEA (2005) stresses that market price signals should reflect all costs including ecosystem damage. Adding a cost for the environmental damage caused by consuming energy, mainly fossil fuels, onto the prices for various forms of energy, effectively increases the price signal for energy, which, in turn, reduces consumption of polluting energy sources. Carbon taxes or cap-and-trade systems are policy actions that have the effect of setting a price for emitting a unit of carbon to the atmosphere (Sterner 2003; Hussen 2000; Tietenberg 2000; Boyd 2003). A carbon tax sets this price directly as a fee for each emitted unit of carbon, while a cap-and-trade system does so indirectly through an artificial market for the emission of carbon. Essentially, governments create and allocate permits to emit a unit of carbon among polluters who may trade them with other parties for a fee negotiated between buyer and seller. The myriad negotiated fees of the market establish the price to emit a unit of carbon to the atmosphere. Government revenues result from collecting the carbon tax or permits fees.

Meanwhile, the Government of Canada (GOC) incorporates energy prices as a major component of its predictive framework for estimating GHG emissions (Canada 2001), while ESI contains a variable for gasoline prices (Esty et al. 2005). Clearly, higher energy prices promote environmental sustainability through conservation activities, fuel efficiency efforts, and use of higher cost renewable energy sources. Evidence suggests that energy prices may affect many performance indicators and policy subcategories, as well as overall environmental sustainability.

Energy prices enter the analysis as a consumption-based weighted average of gasoline, diesel, natural gas, and electricity prices per toe. The calculation of this metric converts all prices to U.S. dollars using purchasing power parities[20] to

[20] Purchasing power parities are currency conversion rates that both convert to a common currency and equalise the purchasing power of different currencies. In other words, they eliminate the differences in price levels among countries. The simplest way to calculate purchasing power parity compares the price of an identical 'standard' good across countries.

maximize comparability of price levels among countries. This factor uses natural gas and electricity consumption data from the International Energy Agency's *Energy Statistics for OECD Countries*, which uses a common definition and methodological format to provide detailed statistics on production, trade, and consumption for all member countries for each source of energy in the OECD. *International Fuel Prices* (Metschies 2003), published by the German Technical Co-operation and financed by the German Federal Ministry for Economic Co-operation and Development, contains diesel and gasoline prices of 165 countries from December 2002, as well as time series of prices from 1991 to 2002. The International Energy Agency's *Energy Prices and Taxes* supplies the natural gas and electricity prices the current research uses. This publication provides end-use price and tax data for all energy sources used in the OECD by member countries and select non-OECD countries. A weakness with this metric is the lack of data concerning other fuel types such as coal and propane. The effect of these missing data is impossible to gauge because both consumption and price data are lacking.

ENVIRONMENTAL GOVERNANCE

Effectively governing pollutants, as well as society's interactions with the environment, promote a country's environmental sustainability by mitigating, or removing, adverse environmental impacts. Hence, environmental governance revolves around the stringency of a country's laws for managing various types of waste (air, water, chemical, toxic), as well as its regulatory context (clarity, stability, flexibility, consistency, stringency) and wider policy-making arena (timing, leadership, compliance effects). MEA (2005) specifically discusses the continuing importance for countries to strengthen environmental governance as they set and enforce legislation regulating their economy's adverse impacts on ecosystems, as they develop innovative institutional frameworks for integrating resource management, and as they improve accountability of environmental decision-making processes. Additionally, Esty (1999) argues that optimal environmental governance maximises social welfare, which suggests that society should improve institutions for controlling pollution and managing resources.

Several recent studies provide additional support for including this factor. Esty and Porter (2005) statistically analyse the relationships between environmental outcomes and several explanatory variables for between 42 and 71 countries. Environmental outcomes were urban levels of particulate matter and sulphur dioxide, and energy use per unit of GDP. They find that the stringency and structure of environmental regulations, level of enforcement, and broader environmental institutions explain significant amounts of variation in environmental performance observed across countries. The ESI analyses indicate that environmental governance is an influential factor determining environmental sustainability (Esty et al. 2005), and CBC (2004) finds that environmental governance associates highly with a country's sustainability performance. Moreover, after analysing Canada's environmental performance, Boyd (2003: 211-212) concludes that performance improved, in part, due to the implementation of more effective laws and regulations. But, to improve further, Canada must address several weaknesses centred on missing or inadequate laws and ineffective enforcement. Clearly, theory and empirical results suggest environmental governance is an influential factor worthy of further assessment, with the evidence demonstrating a possible effect for several performance indicators as well as overall environmental sustainability.

This factor uses data from the *Global Competitiveness Report* Executive Opinion Survey that obtains data from 102 economies representing 97.8% of global GDP (World Economic Forum (WEF) 2004: 168-169). Scientifically constructed, this questionnaire gathers expert opinion from CEOs and senior managers with an international perspective regarding their respective economies. In developed economies, staff members administer the survey via mail, with follow-up phone calls to encourage laggards to respond. In less-developed economies, staff members travel to individual firms to administer the survey. Where evidence supports such a conclusion, a quality assurance process removes surveys completed by other than the intended respondent, as well as surveys that are less than 76% complete (WEF 2004: 169). The quality assurance process retained 7,741 responses (WEF 2004: 169).

Next, the discussion focuses on calculating the metric representing environmental governance in the current study. This dimensionless metric represents principal aspects of environmental governance. It incorporates questions 11.01 to 11.11 from the Executive Opinion Survey, which address

- the laxity of air and water pollution, chemical waste, and toxic waste disposal regulations,
- the clarity and stability of regulations,
- the flexibility of regulations,
- the timing of enacting environmental regulations,
- the leadership demonstrated in environmental policy,
- the consistency of regulation enforcement,
- the stringency of environmental regulations, and
- the effects of compliance on business competitiveness.

Respondents rate their respective economies on these environmental governance areas using a 7-point scale. The average response for each question at the country level represents a country's score. Thus, environmental governance enters the analysis as the total sum of each country's average score across these 11 governance areas.

A potential weakness of this metric is its reliance on an opinion-based survey that may introduce an element of bias. The survey relies solely on the perceptions of business leaders that may not fully capture the differences in regulatory effectiveness. This bias may mean that the survey's results may not reflect reality such that it may not be an accurate appraisement of environmental regulatory quality. However, several aspects of the survey mitigate this weakness:

- respondents were purposely limited to chief executive officers and similar senior management positions to ensure comparability and underlying accuracy of results,
- survey questions were benchmarked to internationally accepted norms so as to ensure comparability and underlying accuracy of results,
- small standard deviation for all questions for developed countries indicates good agreement among respondents instilling confidence that surveyed opinions reflect 'on-the-ground' environmental regulatory regimes, and

- large number of respondents (7,741) ensures law of averages tends to smooth out extreme opinions and ensure the mean response more accurately reflects environmental regulatory quality (WEF 2004: 169).

POLLUTION ABATEMENT AND CONTROL EXPENDITURES

Next, pollution abatement and control (PAC) expenditures prevent, reduce, or eliminate pollution from production processes or from consumption of goods and services. Public sector PAC expenditures mainly concern sewerage, waste water treatment, and the collection and disposal of municipal waste, while private sector (business) expenditures mostly relate to air and water pollution mitigation and hazardous waste disposal (OECD 2001a). Studying how changes in PAC expenditures from 1983 to 1992 affected U.S. manufacturing industries, Brunnermeier and Cohen (2003) conclude that such expenses promote innovative environmental solutions. PAC expenditures directly reduce adverse environmental impacts thereby improving a country's environmental sustainability by affecting several performance indicators (MEA 2005; OECD 2001a; Liddle 2001).

Using data from the OECD *2004 Environmental Data Compendium* (OECD 2005b), the PAC expenditures factor employs two formulations of the metric for inclusion in the current study. The reason for this approach is the uncertainty surrounding which is the most appropriate version for inclusion in the analysis. One metric sums public and private expenditures as a proportion of GDP, while the other sums these expenses as a per capita cost. The subsequent regression analysis uses only one metric at a time, with the analysis repeating after switching the metrics. The data in the compendium pertains to annual investments and expenditures, and, as such, do not present any information regarding in-place or 'sunk' PAC investments. This missing aggregate information is a weakness with this metric. If 'sunk' PAC investments were able to be included in the calculation, metric values would increase.

ENVIRONMENTAL PRICING

Finally, the discussion moves to the last influential factor, environmental pricing. This factor imposes taxes or user fees that charge for pollution and other activities that have external environmental costs not accounted for by the market. Collected funds can provide revenues for protecting and restoring ecosystems and their corresponding services, although, such funds often go into general revenues, becoming available for any expenses rather than being earmarked for environmental expenses. Examples of environmental pricing include energy products, motor vehicles and transport, waste management, and ozone-depleting substances among others. Environmental pricing mechanisms alter consumer behaviour by sending a more appropriate price signal to markets such that environmentally damaging activities become more expensive. This outcome reduces consumption of such activities and thereby improves a country's environmental sustainability (MEA 2005; Cremer and Gahvari 2005; OECD 2004; National Round Table on the Environment and the Economy (NRTEE) 2002; Bernow et al. 1998).

Two recent empirical studies succinctly illustrate the effectiveness of environmental pricing schemes. Modelling the effects of transboundary pollution and competitiveness concerns on environmental policies, Cremer and Gahvari (2005) illustrate that if environmental taxes are large enough, improvements to environmental quality occur through development of cleaner technologies. Bailey (2002), studying the European Union Packaging Waste Directive and its extensive use of economic instruments, concludes that user fees on environmentally damaging activities improve environmental sustainability performance by encouraging investment in pollution abatement, by supporting research activities directed at mitigating adverse environmental impacts, and by developing alternative, cleaner technologies. Thus, environmental pricing alters several types of behaviour to improve a country's environmental sustainability by affecting several performance indicators.

Similar to PAC expenditures, environmental pricing also employs two metrics using data from the OECD *2004 Environmental Data Compendium* (OECD 2005b). As above, uncertainty surrounding which is the most appropriate version for inclusion in the analysis drives this approach. As with PAC expenditures, the current study formulates the metrics for this factor as a proportion of GDP and as a per capita cost. The subsequent regression analysis uses only one metric at a time, with the analysis repeated after switching the metrics.

This metric suffers from a weakness connected to energy prices. The data for environmental pricing encompass taxes and fees for energy products, motor vehicles and transport, waste management, and ozone-depleting substances; however, many countries focus mainly on enacting taxes and fees on energy products, costs that energy prices incorporate (OECD 2005b: table 4b). Hence, this metric experiences a certain amount of information overlap with the energy prices factor. If the environmental pricing factor does not contain unique information, the energy prices factor will overshadow it in the subsequent regression and cluster analyses.

4.2) DISQUALIFIED FACTORS

In addition to the selected influential factors, the current study considers, but ultimately rejects, several other factors. Recall, the current study includes a factor in the analysis if one is able to develop an appropriate measurement methodology and it is unambiguously important to some aspect of environmental sustainability. While one may be able to build an adequate argument for including them, conceptual issues and data problems limit the usefulness of these excluded factors: distance (with geographic size and spatial distribution of population as proxies), natural resources endowments, and international environmental agreements. International trade is another factor that may influence environmental performance, but available evidence suggests that the effects of trade-environment interactions may be either beneficial or adverse. As such, this factor does not provide unmistakable guidance.

DISTANCE

Countries with large internal distances may suffer poor environmental sustainability performances due to more intensive energy consumption arising from transportation demands. Increasing energy consumption increases the emission of many air pollutants. GOC considers geographic size and the spatial distribution of the population as proxies for the internal transportation distances countries encounter when moving people and goods. In theory, the larger the country and the more widely dispersed the population, the more transportation-related adverse environmental impacts it will suffer (Canada 2001). Moreover, a cluster analysis that Esty et al. (2005) conducts on the Environmental Sustainability Index (ESI) provides some evidence for a relationship between cluster membership and a country's geographic size.

Serving as proxies for distance, geographic size of a country and the spatial distribution of its population, both suffer from a similar conceptual issue. Arbitrary political boundaries interfere with the appropriate measurement of these potential factors because such boundaries have nothing to do with transportation demands. For example, if southern Ontario, the highly populated region containing Toronto, were a separate country, its size would be small and the population distribution compact, thus benefiting environmental sustainability. Yet, because it is a part of Canada, the results are completely different. Hence, this conceptual issue of the apt placement of boundaries interferes with the appropriate measurement of either metric such that neither is suitable for inclusion in the present analysis.

A recent study estimates the drivers of GHG emissions for G7 countries using a proxy for a population's spatial distribution. Bataille et al. (2007: 167) use the population-weighted average distance among a country's top 10 metropolitan areas to characterise the environmental influences of a population's distribution. Using this metric to represent a population's distribution, Bataille et al. (2007: 159-162) produce ambiguous support for it as a driver of GHG emissions, depending on whether the analysis focuses on passenger or freight transportation related impacts. Furthermore, the Bataille et al. (2007: 162) analysis provides evidence that mode of transportation, rather than distance travelled, may be a more important influence on GHG emissions as they note that longer distances promote the use of railways, a less carbon-intensive transportation mode. Perhaps the conceptual issue of appropriate boundary placement is confounding the results of the Bataille et al. (2007) study because their metric can not account for international, cross-border traffic.

While this issue of boundary placement negates the use of these metrics, other included factors contain aspects relevant to this excluded factor. Population density presents some facets of population distribution, particularly given the fact that it uses only inhabited land area, as opposed to total geographic land area, for its calculation. At the same time, the industrial structure factor uses the transportation sector, as one of three sectors, when determining national levels of industrial energy intensity.

NATURAL RESOURCES ENDOWMENTS

Esty et al. (2005: 40) conclude that natural resources endowments are important to a country's environmental sustainability. According to ESI, the five highest-ranked countries possess substantial natural resources endowments. Such countries are better able to maintain environmental conditions because they have an existing resource base over which to establish stewardship so as to maintain and enhance ecosystems and habitats.

Measuring a country's natural resources endowments entails aggregating dissimilar resources, like timber, fish, and minerals, into a singular value using a common unit. Money is the typical choice for a common unit, with data usually obtained from national accounts. The process of monetisation presents several conceptual issues that limit its applicability to environmental values (Hussen 2000). First, many researchers think that environmental values should not be reduced to a single value expressed only in monetary terms. However, this objection is often on moral or ethical grounds, which may not be as relevant to a metric for measuring natural resources endowments that would be used to explain performance on a sustainability index. Second, large amounts of uncertainty with the monetary estimate mean the measurement of this concept is almost meaningless. Last, an analyst may overlook important environmental interconnections and ecosystem services if valuing components individually. While likely influential, the measurement of natural resource endowments faces troublesome challenges that negate its inclusion in the present analysis.

INTERNATIONAL ENVIRONMENTAL AGREEMENTS

While the above excluded factors suffer from a conceptual limitation, measuring international environmental agreements must deal with serious data problems. Countries negotiate these agreements to address human impacts on the environment that require collective action. The international community has developed many treaties, protocols, and conventions that attempt to mitigate ozone depletion, climate change, loss of biodiversity, water-born pollution, over-exploitation of numerous species, and the degradation of wetlands and other habitats. Mitchell (2003) determines that international environmental agreements are often equally as responsible as other country characteristics for beneficial environmental outcomes.

The ESI analyses also indicate that international agreements are highly influential (Esty et al. 2005). While these results suggest that this factor is influential, it is difficult to quantify in a form suitable for cross-country statistical comparison. Analysts usually assess participation in international environmental efforts for such purposes by awarding points for signing and ratifying treaties and subsequent conventions, protocols, and amendments as a proportion of the total scoring opportunities to calculate a dimensionless metric.

Such appraisement is too crude to capture the subtleties and nuances that international environmental agreements incorporate. According to Mitchell (2006), the structure of the problem, such as incentive arrangements, institutional capacities, information flows, and cultural norms, addressed by the agreements is crucial to such endeavours. Consequently, while this factor is likely influential for environmental sustainability, participation in international environmental agreements is difficult to quantify adequately for inclusion in the present analysis. Besides, the environmental governance factor partially captures elements of this excluded factor.

TRADE

MEA (2005) identifies the capacity of international trade to mediate environmental performance. The unsustainable management of increasing levels of trade may induce exporting countries to deplete natural resources, to increase local pollution levels, and to degrade ecosystem functions and services. For example, increasing international demand for timber may stimulate some countries to over-harvest, contributing to deforestation and loss of ecosystem services.

Atkinson and Hamilton (2002) quantify the role international trade plays in environmental sustainability as an ecological balance of payments. The ecological balance of payments is a monetised value that quantifies the dependence of a country's consumption on importing resources. Using an input-output framework of international resource flows, Atkinson and Hamilton (2002) derive resource demands in the countries of final use. They find that the adverse environmental effects of trade vary, in part, with level of a country's development, suggesting that economic output is the more useful factor.

Other researchers find similar ambiguous effects of trade on sustainability. Liddle (2001), modelling a trade-environment-development system, determines that the environmental benefits of trade may be either positive or negative, while Alpay (2000), using a Ricardian model, illustrates that trade does not always threaten the environment, and Ekin et al. (1994) describe several situations in which trade benefits the environment, as well as detailing a sustainable trade regime. Again, the importance of included factors partially depends upon them possessing straightforward implications for a country's environmental sustainability performance. Clearly, the effects of international trade on the environment are ambiguous and, in some situations, a better predictor is available such as the included factor economic output. Therefore, the current research excludes trade as an explanatory factor.

CHAPTER 5:
DETERMINING IMPORTANT INFLUENCES

With a list of candidate influential factors in hand, the question now becomes which of these factors, either singly or in conjunction, are most influential in shaping a country's environmental sustainability trajectory. Additionally, the related question of how the composition of these influential factors may change with the different policy subindices that track various environmental aspects also receives attention. The reader is again cautioned to remember that changes in the value of these sustainability indices do not necessarily constitute a change in sustainability and that they might not adequately appraise sustainability.

Estimating how the influential factors account for different environmental sustainability performances among the Organisation for Economic Co-operation and Development (OECD) countries is a unique contribution of the current research. In conjunction, this chapter also answers the second research question and provide information for evaluating the second hypothesis regarding whether these factors consistently influence a country's environmental performance. A general two-pronged evaluation strategy determines how the factors relate to each policy subindex developed in chapter 3. Multiple regression analysis assesses how each factor contributes to the explanation of observed variation for each policy subindex, while cluster analysis investigates how the factors differ across groups of OECD countries formed using the performance indicators. The regression analysis also includes the greenhouse gas indicator separately along side the subindices due to its current importance as an international environmental issue. The current research uses the SPSS 17 and R v. 2.5.1 software to perform these analyses.

Another recent study also attempts to ascertain the drivers of environmental sustainability for its measure of success, the Environmental Performance Index (EPI)[21] (Esty et al. 2008). Compared to the current study, their approach has certain similarities as well as contrasts. Essentially, Esty et al. (2008) test several drivers (table 5.1) for associations with EPI using simple bivariate regression

[21] Refer to chapter 2 and appendix A for a description of EPI.

analysis to explore the amount of variation each explains. Obviously, the studies share the driver/factor of economic activity quantified by per capita GDP, and government effectiveness shares some aspects in common with the environmental governance factor employed by this study: otherwise the set of drivers/factors are different. Esty et al. (2008) do not discuss their selection process; the current study employs a thorough literature review for selecting factors (refer to chapter 4).

Table 5.1: The drivers of the Yale Environmental Performance Index

EPI DRIVER	DESCRIPTION
GDP per capita	Economic activity as quantified by gross domestic product per person
Corruption	The control of corruption measure is aggregated from a number of indicators gauging perceptions of corruption, conventionally defined as the exercise of public power for private gain
Government Effectiveness	Government effectiveness gauges the competence of the bureaucracy, the quality of policymaking, and public service delivery
Voice and Accountability	Voice and Accountability assesses the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media
Competitiveness	Competitiveness is a comprehensive measurement of the comparative strengths and weakness of major and emerging national economies. The Competitiveness rankings of 131 countries are calculated in a Global Competitiveness Report (GCR) from both publicly available data and the Executive Opinion Survey, a comprehensive annual survey conducted by the World Economic Forum together with its network of Partner Institutes

Source: Esty et al. (2008: 34-39)

While both studies attempt to explain individual environmental performance variations, the level of sophistication of the approaches differs. In contrast to the simple bivariate regression analysis that Esty et al. (2008) utilises, the current study uses multiple regression analytical techniques. Because bivariate regression examines only one independent variable at a time, it can not detect interaction or synergistic effects that are the basis for suppression among the tested variables (refer to appendix C for a discussion of suppression in multiple regression analysis). Furthermore, sometimes variables possess similar information content, and so attempt to explain the same variance. With enough overlap, these variables become redundant, but bivariate regression can not detect redundant variables. On the other hand, multiple regression techniques can handle more than one variable at a time. These techniques are able to either mitigate interaction effects by rejecting redundant variables from the final solution or reveal the presence of suppressor variables, which are beneficial to the explanatory power of the analysis. Consequently, the current study expands on the approach to searching for influential factors, and as such, forms a unique contribution in this field of research.

This chapter discusses the analytical results of investigating the factors that determine environmental sustainability performance. It presents the results of the multiple regression analysis between the set of influential factors and the policy subindices, and then it discusses the results of the cluster analysis. Subsequently, the chapter examines several issues that limit the interpretation of these analytical results. Finally, it concludes by synthesising the connections among the regression analysis, cluster analysis, and the examination of limitations.

5.1) MULTIPLE REGRESSION ANALYSIS

This section begins by discussing the selection of a statistically significant subset of factors from the set of 10 in chapter 4 that explain as much of the variation on each policy measure as possible at the 95% level of confidence. Once selected, various statistics characterise the relationships between the significant influential factors and the various policy measures. After characterisation, the discussion gauges the relative importance of each significant influential factor to predicting respective policy measures.

SELECTION OF APPROPRIATE FACTORS

Before conducting a multiple regression analysis, an analyst selects an appropriate subset of predictors from the complete set of independent variables used by a study. The influential factors form the complete set of independent variables from which one withdraws subsets for multiple regression with the dependent variables, the various policy measures. The independent variables are climate, population growth, population density, economic output, technological development, industrial structure, energy prices, environmental governance, pollution abatement and control (PAC) expenditures, and environmental pricing. The dependent variables are environmental sustainability performance composite index (ESPCI), waste and pollution policy subindex (WPPS), sustainable energy policy subindex (SEPS), sustainable food policy subindex (SFPS), nature conservation policy subindex (NCPS), sustainable cities policy subindex (SCPS), and the greenhouse gas (GHG) emissions indicator.

The current analysis uses stepwise and backward regression techniques to form candidate subsets of influential factors for further investigation. In stepwise regression, the equation starts empty and adds predictors according to statistical criteria until no further significant gains to the explained variance occur (Tabachnick and Fidell 2007; Stevens 2002). This technique constantly reassesses the significance of each predictor, thus it may remove from the equation significant predictors previously identified. Backward regression starts with all predictors in the equation and deletes them one at a time if they do not add to the explanatory power of the regression (Tabachnick and Fidell 2007; Stevens 2002). Appendix C discusses these regression techniques in detail, as well as other information pertinent to performing a multiple regression analysis.

According to the *F*-test, various statistically significant candidate subsets of predictors emerge from these analyses at the 95% level of confidence (table 5.2). All policy measures, except NCPS, possess more than one subset of statistically significant predictors. NCPS does not have a statistically significant subset of predictors. For this factor, the analysis forms subsets of predictors by starting with all predictors in the regression, and then removing one predictor at each step until a single predictor remains, repeated for each version of PAC expenditures and environmental taxes. Recall that because of uncertainty about the appropriate formulation, these two factors each use two metrics, one as a proportion of GDP and the other as a per capita cost. The subsequent regression analysis uses only one metric at a time, with the analysis repeated after switching the metrics for these two factors.

With this many predictor subsets, one needs a method for selecting the most apt subset for further evaluation. Akaike's Information Criterion corrected for sample size (AIC_C) balances predictive power of the regression equation with parsimony of independent variables (Burnham and Anderson 2004). The predictor subset with the smallest (most negative) value best achieves this balance, and is the most appropriate subset to carry forward into the next stage of the regression analysis. Appendix C presents further details regarding the calculation and interpretation of AIC_C. Using AIC_C, the predictors are

- for ESPCI, population density, environmental governance, energy prices, and economic output;
- for WPPS, energy prices;
- for SEPS, climate, population growth, population density, economic output, energy prices, and environmental governance;
- for SFPS, population density and economic output;
- for SCPS, climate, population density, economic output, technological development, industrial structure, energy prices, and per capita PAC expenditures;
- for the GHG indicator, economic output, energy prices, and environmental governance; and
- for NCPS, while not statistically significant at the 95% level of confidence, technological development.

Table 5.2: Selecting the appropriate subset of predictors for each policy measure with Akaike's Information Criterion corrected for sample size

POLICY MEASURE	PREDICTORS	AIC_c
ESPCI	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-124.1
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-127.8
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Population Density, Population Growth, Economic Output, Environmental Governance, Technological Development	-131.4
	Constant, Pollution Abatement and Control Expenditures (using per capita), Population Growth, Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Technological Development, Environmental Governance, Economic Output	-135.4
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Population Density, Economic Output, Environmental Governance, Technological Development	-135.3
	Constant, Pollution Abatement and Control Expenditures (using per capita), Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Technological Development, Environmental Governance, Economic Output	-140.6
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Population Density, Economic Output, Environmental Governance	-142.6
	Constant, Pollution Abatement and Control Expenditures (using per capita), Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Economic Output, Environmental Governance	-142.2
	Constant, Environmental Governance, Population Density, Industrial Structure, Energy Prices, Climate (total degree days), Economic Output	-151.2
	Constant, Environmental Governance, Population Density, Industrial Structure, Energy Prices, Economic Output	-152.0
	Constant, Environmental Governance, Population Density, Energy Prices, Economic Output	**-159.2**
	Constant, Environmental Governance, Energy Prices, Economic Output	-157.6
	Constant, Energy Prices	-147.4
Waste and Pollution	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-74.5
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-73.7
	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-82.1
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output	-87.9
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Population Density, Economic Output, Environmental Governance, Technological Development	-88.4

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Table 5.2—*Continued*

POLICY MEASURE	PREDICTORS	AIC_c
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output	-93.8
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Population Density, Economic Output, Environmental Governance	-99.7
	Constant, Environmental Pricing (using per capita), Industrial Structure, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output	-98.1
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Economic Output, Environmental Governance	-104.2
	Constant, Pollution Abatement and Control Expenditures (using per capita), Climate (total degree days), Energy Prices, Industrial Structure, Economic Output, Environmental Governance	-100.9
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Environmental Governance	-104.4
	Constant, Pollution Abatement and Control Expenditures (using per capita), Energy Prices, Industrial Structure, Environmental Governance, Economic Output	-100.7
	Constant, Energy Prices	**-108.1**
Sustainable Energy	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-84.6
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-88.0
	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance	-99.3
	Constant, Environmental Pricing (using per capita), Energy Prices, Population Density, Population Growth, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-95.6
	Constant, Environmental Pricing (using GDP), Economic Output, Pollution Abatement and Control Expenditures (using GDP), Population Density, Population Growth, Climate (total degree days), Energy Prices, Environmental Governance	-105.3
	Constant, Environmental Pricing (using per capita), Energy Prices, Population Density, Population Growth, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output	-108.9
	Constant, Environmental Pricing (using GDP), Economic Output, Population Density, Population Growth, Climate (total degree days), Energy Prices, Environmental Governance	-116.7
	Constant, Environmental Pricing (using per capita), Energy Prices, Population Density, Population Growth, Climate (total degree days), Environmental Governance, Economic Output	-118.6
	Constant, Environmental Governance, Population Density, Population Growth, Energy Prices, Climate (total degree days), Economic Output	**-126.7**
Sustainable Food	Constant, Environmental Governance, Population Density, Environmental Pricing (using GDP), Population Growth, Industrial Structure, Pollution Abatement and Control Expenditures (using GDP), Climate (total degree days), Economic Output, Energy Prices, Technological Development	-61.2

Continued on next page

Table 5.2—*Continued*

POLICY MEASURE	PREDICTORS	AIC$_c$
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-60.2
	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Technological Development	-68.9
	Constant, Pollution Abatement and Control Expenditures (using per capita), Population Growth, Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Technological Development, Environmental Governance, Economic Output	-67.8
	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Technological Development	-75.3
	Constant, Environmental Governance, Population Density, Population Growth, Industrial Structure, Energy Prices, Climate (total degree days), Economic Output, Technological Development	-79.9
	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP)	-86.0
	Constant, Environmental Governance, Population Density, Population Growth, Industrial Structure, Energy Prices, Climate (total degree days), Economic Output	-90.3
	Constant, Pollution Abatement and Control Expenditures (using GDP), Economic Output, Climate (total degree days), Industrial Structure, Population Density, Population Growth	-90.5
	Constant, Environmental Governance, Population Density, Population Growth, Industrial Structure, Climate (total degree days), Economic Output	-114.1
	Constant, Industrial Structure, Climate (total degree days), Population Density, Economic Output, Population Growth	-117.5
	Constant, Economic Output, Population Density, Population Growth, Climate (total degree days)	-124.7
	Constant, Economic Output, Population Density, Climate (total degree days)	-126.7
	Constant, Economic Output, Population Density	**-126.8**
	Constant, Population Density	-121.5
Nature Conservation	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-80.9
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-79.5
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Population Density, Population Growth, Economic Output, Environmental Governance, Technological Development	-88.5
	Constant, Pollution Abatement and Control Expenditures (using per capita), Population Growth, Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Technological Development, Environmental Governance, Economic Output	-87.1
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Population Density, Population Growth, Economic Output, Environmental Governance, Technological Development	-94.7
	Constant, Pollution Abatement and Control Expenditures (using per capita), Population Growth, Climate (total degree days), Energy Prices, Population Density, Technological Development, Environmental Governance, Economic Output	-93.5

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Table 5.2—*Continued*

POLICY MEASURE	PREDICTORS	AIC$_c$
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Population Density, Population Growth, Economic Output, Technological Development	-99.7
	Constant, Environmental Governance, Population Density, Population Growth, Energy Prices, Climate (total degree days), Economic Output, Technological Development	-104.8
	Constant, Pollution Abatement and Control Expenditures (using GDP), Technological Development, Population Growth, Population Density, Climate (total degree days), Economic Output	-103.8
	Constant, Environmental Governance, Population Density, Population Growth, Energy Prices, Economic Output, Technological Development	-109.0
	Constant, Pollution Abatement and Control Expenditures (using GDP), Technological Development, Population Growth, Population Density, Economic Output	-107.4
	Constant, Environmental Governance, Population Density, Population Growth, Economic Output, Technological Development	-124.1
	Constant, Pollution Abatement and Control Expenditures (using GDP), Technological Development, Population Growth, Economic Output	-110.2
	Constant, Environmental Governance, Population Growth, Economic Output, Technological Development	-127.2
	Constant, Technological Development, Population Growth, Economic Output	-129.3
	Constant, Technological Development, Economic Output	-130.5
	Constant, Technological Development	-131.5
Sustainable Cities	Constant, Population Growth, Industrial Structure, Economic Output, Environmental Pricing (using GDP), Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-124.8
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-238.0
	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-129.6
	Constant, Environmental Pricing (using per capita), Industrial Structure, Energy Prices, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-245.6
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Population Density, Economic Output, Environmental Governance, Technological Development	-129.3
	Constant, Environmental Pricing (using per capita), Industrial Structure, Energy Prices, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Economic Output, Technological Development	-252.1
	Constant, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Climate (total degree days), Industrial Structure, Economic Output, Technological Development, Environmental Governance	-128.8
	Constant, Pollution Abatement and Control Expenditures (using per capita), Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Technological Development, Economic Output	**-257.7**
	Constant, Pollution Abatement and Control Expenditures (using per capita), Population Density, Technological Development, Industrial Structure, Energy Prices, Economic Output	-201.7

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Table 5.2—*Continued*

POLICY MEASURE	PREDICTORS	AIC$_c$
	Constant, Pollution Abatement and Control Expenditures (using per capita), Energy Prices, Industrial Structure, Technological Development, Economic Output	-152.3
	Constant, Pollution Abatement and Control Expenditures (using per capita), Energy Prices, Technological Development, Economic Output	-126.7
	Constant, Energy Prices, Technological Development, Economic Output	-125.3
	Constant, Technological Development, Economic Output	-129.9
	Constant, Technological Development	-109.7
GHG Emissions	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-66.8
	Constant, Environmental Pricing (using per capita), Industrial Structure, Population Growth, Population Density, Energy Prices, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-82.3
	Constant, Environmental Pricing (using GDP), Industrial Structure, Economic Output, Population Growth, Population Density, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Technological Development, Environmental Governance	-74.2
	Constant, Environmental Pricing (using per capita), Industrial Structure, Energy Prices, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Environmental Governance, Economic Output, Technological Development	-87.5
	Constant, Environmental Pricing (using GDP), Economic Output, Pollution Abatement and Control Expenditures (using GDP), Population Density, Population Growth, Energy Prices, Environmental Governance, Technological Development	-80.5
	Constant, Environmental Pricing (using per capita), Industrial Structure, Energy Prices, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Economic Output, Technological Development	-90.5
	Constant, Environmental Pricing (using GDP), Economic Output, Pollution Abatement and Control Expenditures (using GDP), Population Growth, Energy Prices, Environmental Governance, Technological Development	-84.6
	Constant, Environmental Pricing (using per capita), Energy Prices, Population Density, Climate (total degree days), Pollution Abatement and Control Expenditures (using per capita), Economic Output, Technological Development	-93.6
	Constant, Environmental Pricing (using GDP), Economic Output, Pollution Abatement and Control Expenditures (using GDP), Energy Prices, Environmental Governance, Technological Development	-87.8
	Constant, Environmental Pricing (using per capita), Energy Prices, Population Density, Pollution Abatement and Control Expenditures (using per capita), Technological Development, Economic Output	-96.4
	Constant, Environmental Pricing (using GDP), Economic Output, Environmental Governance, Energy Prices, Technological Development	-95.8
	Constant, Pollution Abatement and Control Expenditures (using per capita), Population Density, Technological Development, Energy Prices, Economic Output	-98.2
	Constant, Environmental Pricing (using GDP), Economic Output, Environmental Governance, Energy Prices	-101.2
	Constant, Environmental Governance, Energy Prices, Economic Output	**-102.3**
	Constant, Energy Prices	-91.3

Note: Except for NCPS, each subset of predictors is statistically significant at the 95% level of confidence, as determined by stepwise and backward regression analyses. The subset that appears in bold type is analysed further because it has the lowest (most negative) AIC$_C$ value so the subset best balances parsimony with predictive power.

CHARACTERISATION OF SIGNIFICANT INFLUENTIAL FACTORS

With the most appropriate subsets of predictor factors selected, the investigation shifts to how influential these factors are as a group as well as individually. With the exception of NCPS, the very small *p*-values (<0.05) from an *F*-test indicate that the selected subsets for the other policy measures are statistically significant at a 95% level of confidence (table 5.3). Incidentally, because the predictors for SCPS explain 100%[22] of the observed variation, the *p*-value is undefined, essentially equalling zero. The NCPS analysis with the various subsets of predictors, obtained using the multiple regression methods mentioned earlier, does not yield a statistically significant relationship (table 5.2). Thus, the one selected by AIC_C, presented for comparison purposes, is the best explanation of the observed variation for performance on the policy measure for nature conservation. The complete output from SPSS, from which these statistics are drawn, is in appendix D.

In addition to *F*-test statistics, other statistics are also noteworthy. The coefficient of multiple determination, R^2, quantifies the amount of observed variation each subset of factors explains in the dependent variable, in this case one of the policy measures. At the low end, the single predictor factor weakly correlated with NCPS—technological development—accounts for less than 2% of the observed variation (table 5.3). At the high end, the set of seven factors significantly related to SCPS accounts for 100% of its observed variation, while the three predictors—economic output, energy prices, environmental governance—explain just over 80% of the observed variation for the GHG indicator. In the middle, six factors account for about 70% of the observed variation for SEPS, and two—economic output, population density—explain about 60% of the observed variation for SFPS. At the same time, a lone predictor—energy prices—explains just over 55% of the observed variation for WPPS. Overall, the subset of four factors significantly correlated with ESPCI—

[22] While explaining 100% of observed variation is rare, four different subsets of factors explain 100% of the observed variation on SCPS. (Recall that the appropriate subset of factors was selected using AIC_C (table 5.2).) Note that the data for the SCPS analyses were not handled any differently than the analyses for the other policy measures. It appears that the influential factors are particularly suited to explaining performance on the indicators of this policy measure—municipal, waste, recycling, distance travelled, and municipal sewage treatment.

population density, energy prices, economic output, environmental governance—explains about 73% of its observed variation.

After examining the overall relationships, the sign of the standardised partial regression coefficient (β) indicates the nature of the influence of each factor. Essentially, the sign specifies the direction of the relationship between explanatory and dependent variables; a positive value indicates that increases in the factor increase environmental sustainability performance on the policy measures: a negative value indicates that performance on the policy measures decreases as the factor increases. No matter the policy measure with which they are associated, energy prices, environmental governance, technological development, population growth, industrial structure, and PAC expenditures all have positive standardised partial regression coefficients, though the latter three appear in only one subset. Hence, as the value of these factors increases so does the value of the corresponding policy measures and the underlying environmental performance they quantify. For example, rising energy prices tend to induce better environmental performance on the policy measures through reduced energy consumption or improved pollution control technology.

On the other hand, economic output, population density, and climate always have negative values. As the value of these factors increases the value of the associated policy measures declines and environmental performance suffers. Hence, denser, more affluent populations with extreme climatic conditions tend to degrade their environment and suffer poor performance as quantified by the indicators. No factor possesses a coefficient that switches signs.

Table 5.3: Multiple regression statistics from the analyses of each policy measure with the predictor subsets selected by AIC$_C$

POLICY MEASURE	*F*-TEST *P*-VALUE	R^{2a}	PREDICTORS[b]	β[c]	SSCC[d]	VARIANCE EXPLAINED[e]
ESPCI[f]	0.0000094	0.730	Population Density	-0.237	0.053	0.026
			Economic Output	-0.605	0.178	0.208
			Energy Prices	0.717	0.354	0.374
			Environmental Governance	0.726	0.259	0.122
Sum					**0.845**	
Waste and Pollution	0.0000135	0.553	Energy Prices	0.743	0.553	0.553
Sustainable Energy	0.0003225	0.702	Climate (total degree days)	-0.395	0.104	0.100
			Population Growth	0.318	0.079	0.072
			Population Density	-0.477	0.194	0.187
			Economic Output	-0.516	0.125	0.029
			Energy Prices	0.631	0.255	0.201
			Environmental Governance	1.010	0.394	0.114
Sum					**1.150**	
Sustainable Food	0.0000040	0.601	Population Density	-0.678	0.459	0.471
			Economic Output	-0.345	0.119	0.131
Sum					**0.577**	
Nature Conservation[g]	0.513	0.018	Technological Development	0.134	0.018	0.018
Sustainable Cities	.	1.000[h]	Climate (total degree days)	-0.426	0.088	0.242
			Population Density	-0.539	0.108	0.213
			Economic Output	-1.824	0.585	0.152
			Technological Development	1.932	0.737	0.257
			Industrial Structure	0.569	0.196	0.014
			Energy Prices	0.606	0.203	0.049
			PAC Expenditures (per capita)	1.201	0.288	0.073
Sum					**2.205**	
GHG Emissions	0.0000001	0.808	Economic Output	-0.577	0.162	0.190
			Energy Prices	0.738	0.392	0.548
			Environmental Governance	0.487	0.118	0.070
Sum					**0.672**	

a – Coefficient of multiple determination

b – Significance determined at the 95% level of confidence; residual and leverage plots validated regression assumptions and checked for influential values

c – Standardised partial regression coefficient

d – Squared semi-partial correlation coefficient, which sum to R^2 when predictors are uncorrelated

e – Values indicate, on average, how much of the observed variation each individual predictor explains; the values will sum to R^2

f – Environmental sustainability performance composite index

g – Multiple regression analysis did not find a significant relationship between this policy subindex and the factors; this relationship is included for the sake of comparison

h – While explaining 100% of observed variation is rare, four different subsets of factors explain 100% of the observed variation on SCPS. (Recall that the appropriate subset of factors was selected using AIC$_C$ (table 5.2).) Note that the data for the SCPS analyses was not handled any differently than the analyses for the other policy measures. It appears that the influential factors are particularly suited to explaining performance on the indicators of this policy measure—municipal, waste, recycling, distance travelled, and municipal sewage treatment.

RELATIVE IMPORTANCE OF SIGNIFICANT INFLUENTIAL FACTORS

Once characterised, the question of importance of specific factors becomes relevant. Due to suppression and shared contributions, concepts described in appendix C, usual statistics that determine the importance of explanatory variables may be inappropriate. These effects, from associations among the variables, suggest that standardised partial regression coefficients and squared semi-partial correlation coefficients (SSCC) may provide ambiguous information. Such information may lead to faulty conclusions (refer to appendix C for more detail about these two coefficients). The limitations section further explores this phenomenon, known as multicollinearity. Moreover, several regression techniques credit shared contribution to variables entered into the analysis first. At the same time, the effects of suppressor variables depend on the presence of other variables, as well as the correlation between them. Therefore, the order in which a variable enters the regression analysis affects the size of the contribution attributed to it. Averaging the percentage contribution of each explanatory variable from every ordering of the variables produces a useful estimate of the proportion each variable contributes to the prediction of the dependent variable (Gromping 2007; 2006; Soofi et al. 2000; Kruskal 1987a; 1987b; Lindman et al. 1980). Of course, when a relationship possesses only one factor in the predictor set, the contribution from such a factor is simply the coefficient of multiple determination, R^2.

Sequential, or hierarchical, regression analysis in which the analyst specifies the order of variable entry provides a method for quantifying contributions. The current study uses the statistical software package R v. 2.5.1 to estimate the contributions of each factor to explain observed variation. For ESPCI, energy prices (explaining about 37% of observed variation) are about fourteen times as important a predictor as population density (explaining about 3% of observed variation), about three times as important as environmental governance (explaining about 12% of observed variation), and about twice as important as economic output (explaining about 20% of observed variation) (table 5.3). For SEPS, levels of importance for all factors are within an order of magnitude, albeit with energy prices (explaining about 20% of observed variation) about seven times more important than the least important factor, economic output (explaining about 3% of observed variation).

Meanwhile, the factors for SCPS split into two groups. The first group of four factors are relatively equal in importance (explained variation ranging from about 26% to about 15%), with technological development (explaining about 26% of observed variation) marginally the most important. The other group of three factors are less important, with energy prices (explaining about 5% of observed variation) appearing in the middle of this cluster. For producing sustainable food, population density (explaining about 47% of observed variation) is about three times more important than economic output (explaining about 13% of observed variation). Moreover, energy prices (explaining about 55% of observed variation) most influence GHG emissions, being about eight times as important as environmental governance (explaining about 7% of observed variation), and energy prices are the only significant factor for WPPS (explaining about 55% of observed variation). Clearly, the energy prices factor is very important for shaping environmental sustainability performance. This factor appears in almost all selected subsets of significant factors (five out of seven), and it is demonstrably the principal factor of most subsets (four out of five). As mentioned, energy prices also explain about 37% of the observed variation on the overall index, ESPCI.

5.2) CLUSTER ANALYSIS

In addition to multiple regression analysis, the current study also examines the underlying group structure of the performance indicators using cluster analysis. Such an examination yields valuable insights into how the influential factors differ across these groups. It is the second technique of the two-pronged analytical approach the current study uses to gather more information for evaluating research hypotheses. The analysis first proceeds by selecting an appropriate grouping of OECD-member countries based on the environmental sustainability performance indicators (ESPIs). With cluster membership determined for each country, the analysis uses cluster means to interpret the underlying nature of the groups. Lastly, the discussion focuses on how the factor profiles vary across the clusters.

DERIVATION OF CLUSTER MEMBERSHIP

Cluster analysis classifies large groups of items into subgroups of items with similar characteristics using a series of multivariate techniques based on one or on several characteristics. The classification aims to reduce the dimensionality of a data set by exploiting the similarities (or dissimilarities) between subgroups. Cluster analysis techniques are hierarchical if the classification has an increasing number of nested classes, or non-hierarchical, which decides the number of clusters before the analysis begins (Nardo et al. 2005; Hair and Black 2000; Aldenderfer and Blashfield 1984). One non-hierarchical technique is known as *k*-means clustering. The current cluster analysis uses both hierarchical and *k*-means clustering of ESPIs to derive the country groups. It employs a two-stage process whereby a hierarchical technique determines the number of clusters in the data for subsequent use with the *k*-means clustering technique (Milligan 1980). The current research uses Ward's method with the squared Euclidean distance measure. The squared Euclidean distance has the advantage of not taking the square root, which speeds computations, and is the recommended distance measure for Ward's method of clustering. Besides the squared Euclidean distance, the Mahalanobis distance measure, which accounts for correlations among variables, might have been a better choice, but it was not an option included in the software used to conduct the current analysis. When the

Mahalanobis distance measure is unavailable, a researcher typically uses the squared Euclidean distance. Appendix C describes various clustering methods as well as associated distance measures that these methods use as similarity metrics. Determination of the final clustering technique was based on experimentation with various combinations of clustering methods and distance measures described in appendix C. The final clustering technique was selected because it generates the best separation among clusters.

When a country is missing a data point, SPSS excludes that country from a hierarchical cluster analysis, thus limiting the number of countries available for forming groups. Even with the small amount of data missing from the indicator set, this restriction left less than a third of the countries in the analysis (nine out of 30). As a result, the various methods for generating possible clusters discussed in appendix C produce somewhat arguable results. Several interpretations regarding number and cluster membership of countries appear possible. While some variability is typical for cluster analysis (Hair and Black 2000; Aldenderfer and Blashfield 1984), the reduced data set exacerbates the situation. Depending on one's interpretation, the various dendrograms[23] generated with various combinations of clustering algorithms and distance measures indicate that the number of clusters in the indicator data set may range from two through seven. This circumstance may introduce a certain amount of uncertainty into the analysis. Indeed, the dendrogram generated from Ward's method using the squared Euclidean distance measure could also be interpreted as representing two, three, or possibly five clusters, as well as the accepted six (fig. 5.1). The accepted number of clusters was arrived at by gathering more information using *k*-means cluster analysis and by examining changes in distance measures.

[23] A dendrogram is a graph that plots the linkage distance through each step of the fusion process. Clusters fused at each step become increasing dissimilar as the linkage distance increases.

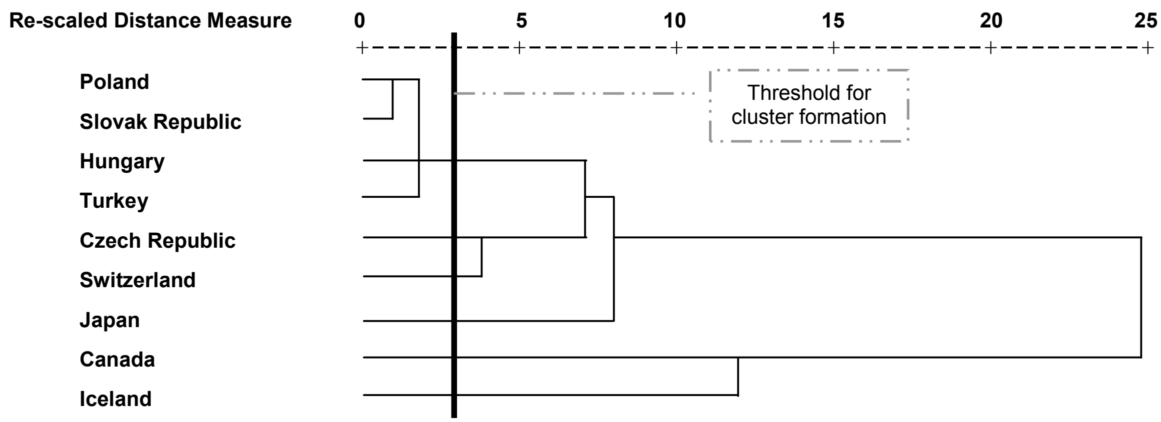


Figure 5.1: Dendrogram of hierarchical cluster analysis of ESPIs using Ward's method with squared Euclidean distance measure indicating threshold for the formation of country clusters

To gather more information, several *k*-means analyses were run using the indicated values for the number of clusters (i.e., 2, 3, 4, 5, 6, 7). Note that for *k*-means clustering, SPSS does not exclude countries due to missing data. Therefore, all OECD-member countries are available for forming groups, increasing the included countries from nine to 30 as compared to hierarchical clustering. The results for values two through five yield one large group with one or more smaller groups containing only a few elements, while the results for a value of seven produces several groups containing only one or two elements. Both outcomes should be avoided because disparate cluster sizes imply that clusters remain unresolved and too many small groups imply that the data have been divided too often (Hair and Black 2000; Aldenderfer and Blashfield 1984). Consequently, the best results of these *k*-means clustering analyses indicate that there are six groups (table 5.4). Six clusters provide an adequate balance between overly large or small group-membership levels, with the obvious exception of cluster 5 containing a single country, Iceland, discussed further below. Moreover, the threshold of cluster formation in the dendogram showing the choice of six clusters is likely the most appropriate placement because it crosses the linkages at the point of the first large increase in the distance measure (fig. 5.1), indicating the first agglomeration of dissimilar clusters (Hair and Black 2000; Aldenderfer and Blashfield 1984). Members of dissimilar clusters are much more heterogeneous than homogenous; therefore, the characteristics of cluster members display much more variability and the clustering solution becomes suspect. Consequently, results strongly indicate that the indicator data set forms six clusters of countries.

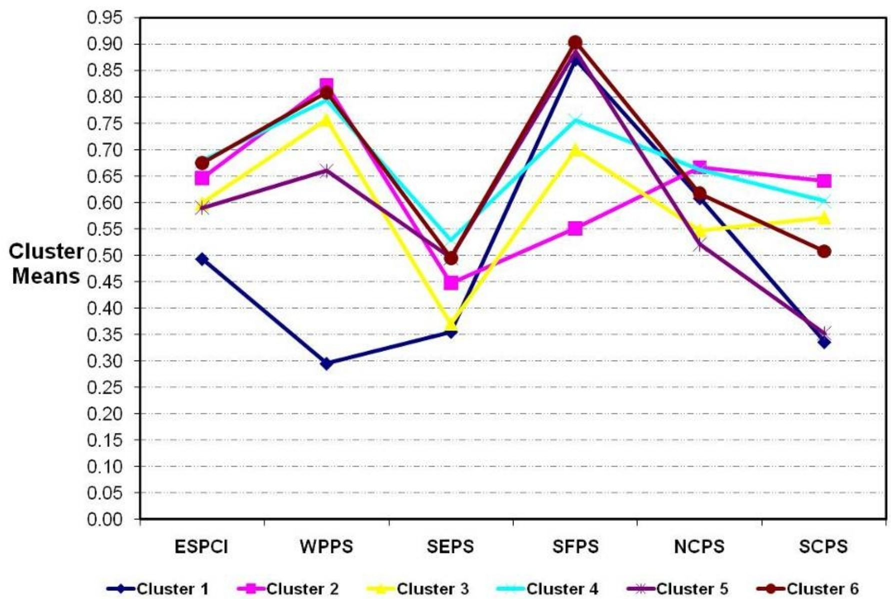
Table 5.4: Cluster membership of OECD countries grouped with the *k*-means clustering technique

LOW PERFORMERS	MIDDLING PERFORMERS			HIGH PERFORMERS	
1	**3**	**2**	**5**	**6**	**4**
United States	Belgium	Korea	**Iceland**	Mexico	Netherlands
Canada	**Luxembourg**	Japan		Spain	**New Zealand**
Australia	Ireland	**Italy**		Portugal	**Norway**
	Czech Republic			Greece	France
	Finland			Hungary	United Kingdom
				Poland	**Sweden**
				Slovak Republic	Germany
				Turkey	**Denmark**
					Austria
					Switzerland

Note: Subsequent comparison of factor means across the clusters excludes countries in bold type because data are missing from factor metrics for these countries.

INTERPRETATION OF CLUSTERS

With the finalisation of cluster membership, an analyst needs to know the nature of the groups. Other than the first cluster, interpreting these clusters on environmental sustainability performance composite index (ESPCI) alone provides no obvious meaning (fig. 5.2.) Cluster 1 mainly groups the laggards of overall performance on ESPCI, while clusters 2, 3, and 5 group middling performers together, and clusters 4 and 6 group the high performers. Instead, to understand the deeper nature of the clusters, an analyst should also examine the pattern of the cluster centres that develop across the policy measures (fig. 5.2). The poor overall performance of the countries forming cluster 1 mainly arises from poor results at reducing waste and pollution, a result that noticeably separates this group from the others. At the same time, the middling-performing countries of cluster 3 produce food more sustainably than those of cluster 2, while Iceland, the single country of cluster 5, differs from the other two middling-performing clusters by its mediocre ability to reduce waste and pollution and its low performance at developing sustainable cities. Similar to the relationship between middling-performing clusters 2 and 3, high-performing countries of cluster 6 produce food more sustainably than the high-performing countries of cluster 4, but cluster-4 countries develop cities more sustainably than cluster-6 countries, as indicated by the policy measure scores. Appendix E provides cluster profiles, including standard deviations of the cluster means, as well as maxima and minima values.



Note: This graph displays the mean, referred to as a cluster mean, of the countries for each cluster across the policy measures. Appendix E provides cluster profiles, including standard deviations of the cluster means, as well as maxima and minima values.

ESPCI = Environmental sustainability performance composite index
WPPS = Waste and pollution policy subindex
SEPS = Sustainable energy policy subindex
SFPS = Sustainable food policy subindex
NCPS = Nature conservation policy subindex
SCPS = Sustainable cities policy subindex

Figure 5.2: Comparison of cluster means across the policy measures

Although Iceland's individual performances on most of the policy measures nearly mirrors that of other clusters, it possesses a unique pattern across the subindices. In fact, Iceland is very likely a member of the entropy group, an observation that is an outlier and independent of the other clusters (Hair and Black 2000: 157). The country is probably a single outlying observation that forms a single-element cluster. Furthermore, Iceland breaks out as a distinct cluster early in the clustering process, with $k = 3$ and remains as a distinct cluster throughout, thus it appears well designated as a member of the entropy group. This point is somewhat moot because missing data among the factors excludes Iceland (along with other countries) from the following comparison of factor means across the clusters.

COMPARISON OF FACTOR PROFILES ACROSS CLUSTERS

A test statistic, Wilks's lambda, compares the equality of all the factor cluster means simultaneously.[24] Wilks's lambda detects when at least one of the means is significantly different from the rest (refer to appendix E for cluster profiles of each factor). This test statistic is appropriate because the number of clusters is not arbitrary. Several hierarchical cluster analyses provided preliminary estimates about the number of clusters that might be present in the structure of the ESPI data. Subsequent *k*-means cluster analyses used these preliminary estimates to refine groups, with final country clusters selected using the first large increase in the distance measure (fig. 5.1). Such a large increase usually indicates that relatively dissimilar clusters are being joined.

Wilks's lambda is a ratio of within group variance divided by total variance. Small values indicate that the amount of variance among means not explained for a respective factor is small (Stevens 2002; Weinfurt 1995). Thus, Wilks's lambda assumes relatively small values if one of the cluster means is significantly different from the others for a specific factor. In other words, lower values of Wilks's lambda indicate greater differences among the cluster means, which, in turn, signifies stronger group separation. The Wilks's lambda analysis includes 20 countries, removed due to missing data are the United States, Luxembourg, Italy, Iceland, Turkey, New Zealand, Norway, Sweden, Denmark, and Switzerland (bold type in table 5.4). Transforming Wilks's lambda to an F statistic enables determination of statistical significance. Consequently, at a 95% level of confidence, population density (p-value = 0.020), economic output (p-value = 0.002), technological development (p-value = 0.000), energy prices (p-

[24] Including both formulations of PAC expenditures and environmental pricing, because each factor is assessed individually so the inclusion of one factor does not affect the results of another.

value = 0.016), environmental governance (*p*-value = 0.002), per capita pollution abatement and control (PAC) expenditures (*p*-value = 0.010), and environmental pricing (per capita) (*p*-value = 0.002) each possess at least one factor cluster mean significantly different from the rest (table 5.5).

Wilks's lambda detects when at least one factor cluster mean is significantly different from the group, but it can not determine which means differ. To ascertain how the factor cluster means differ with out resorting to individual *t*-tests that would unduly inflate the chances of an experiment-wise Type I error[25], an analyst may use a line graph of these means converted to a common scale, in this case, *z*-scores (fig. 5.3). Converting these means to *z*-scores compensates for differing scales among the factors; it allows one to compare visually the cluster means across the factors (without an increase in the Type I error rate). Thus, an analyst may observe the pattern of variation among the factor means that differentiates one cluster from another.

Table 5.5: Results of Wilks's lambda test for equality of factor cluster means

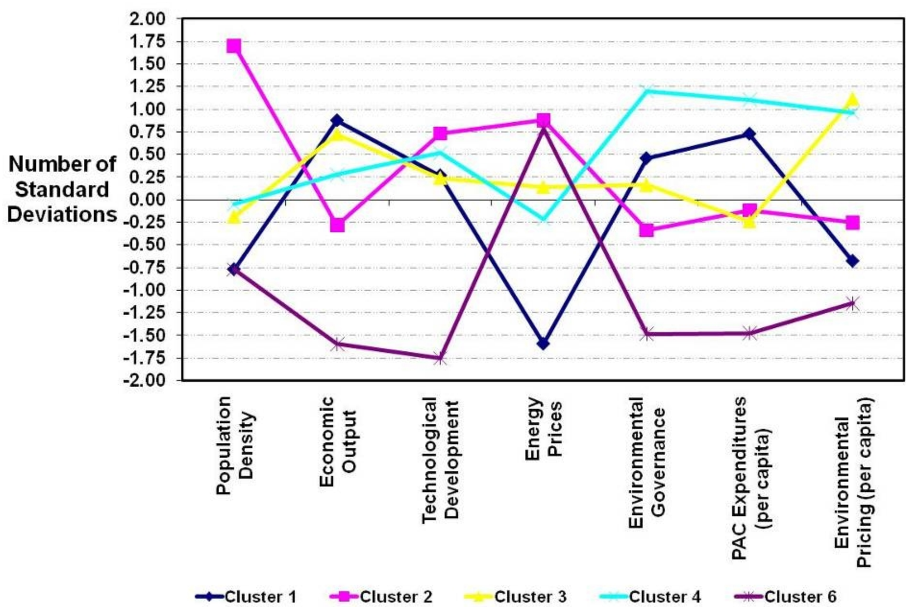
FACTOR	WILKS'S LAMBDA	*F*-VALUE	DF1	DF2	*P*-VALUE
Climate (total degree days)	0.812	0.867	4	15	0.506
Population Growth	0.882	0.500	4	15	0.736
Population Density	**0.481**	**4.046**	**4**	**15**	**0.020**
Economic Output	**0.353**	**6.881**	**4**	**15**	**0.002**
Technological Development	**0.214**	**13.765**	**4**	**15**	**0.000**
Industrial Structure	0.558	2.969	4	15	0.054
Energy Prices	**0.465**	**4.318**	**4**	**15**	**0.016**
Environmental Governance	**0.331**	**7.565**	**4**	**15**	**0.002**
PAC Expenditures (per capita)	**0.436**	**4.846**	**4**	**15**	**0.010**
Environmental Pricing (per capita)	**0.342**	**7.207**	**4**	**15**	**0.002**
PAC Expenditures (GDP)	0.746	1.274	4	15	0.324
Environmental Pricing (GDP)	0.629	2.215	4	15	0.117

Notes: Factors in bold type possess significantly different cluster means, at the 95% level of confidence. Analysis excludes the United States, Luxembourg, Italy, Iceland, Turkey, New Zealand, Norway, Sweden, Denmark, and Switzerland due to missing data.

These factors demonstrate varying capacity to discern among clusters (fig. 5.3). Four of these factors are useful for discerning among all clusters, while one factor appears only to separate the clusters into two groups, and two are likely

[25] A Type I error increases the chances of rejecting the null hypothesis when it is true.

only able to separate one cluster from the pack. Population density and technological development separate cluster 2 and cluster 6, respectively, from the other clusters quite clearly, but may not be able to discern further among clusters. The means for these clusters concentrate near one end of the range, thus indicating that four of the five clusters have similar average population densities and levels of technological development. At the same time, environmental pricing only has the capacity to separate out two groups of clusters, those being clusters 3 and 4 at one end of the range and clusters 1, 2, and 6 at the other. This factor also appears to provide redundant information; an analyst can obtain the separation among clusters it provides from the other factors with more useful discernment abilities. Recall that the comparison of means *z*-scores removes the single-country cluster 5 from further analysis due to missing data.



Notes: This graph displays the mean *z*-scores for factors determined by Wilks's lambda as being significantly different across the clusters, at a 95% level of confidence. Converting these means to *z*-scores compensates for differing scales among the factors, and allows one to compare visually the cluster means across the factors (without an increase in the Type I error rate). The comparison of means removes the single-country cluster 5 from further analysis due to missing data.

Figure 5.3: Comparison of cluster means as *z*-scores for factors with significant differences among their means

The final four factors have a greater ability to differentiate among clusters because their cluster means disperse more evenly over a similar range. Economic output clearly differentiates cluster 6 from the others, and it groups clusters 1 and 3, and clusters 2 and 4 indicating similar means on this factor. Energy prices clearly differentiate cluster 1, as well as appearing to group clusters 2 and 6, and clusters 3 and 4. At the same time, environmental governance clearly separates clusters 4 (at the high end) and 6 (at the low end) from the other clusters as well as from each other; however, clusters 1, 2, and 3 may not be discernable on this factor. The cluster profile for per capita PAC expenditures provides similar separation as environmental governance, but cluster 1 appears to separate from clusters 2 and 3 in the middle of the range. However, cluster 1 may not be discernable from cluster 4 at the top of the range. Consequently, energy prices, economic output, and environmental governance, as a group provide enough information to differentiate these five clusters from each other, with population density and technological development potentially more expedient at discerning clusters 2 and 6, respectively, from the others.

5.3) LIMITATIONS OF ANALYTICAL RESULTS

With the analytical scrutiny of the influential factors complete, one must now consider issues that may be limiting interpretation. Correlations between explanatory variables, termed multicollinearity, may cause problems with multiple regression and cluster analyses. Multicollinearity reduces the ability of multiple regression analysis to discern effects (Stevens 2002; Licht 1995), and as it escalates, three problems become evident (Stevens 2002; Tabachnick and Fidell 2007). Excessive levels of multicollinearity render the multiple correlation coefficient, R, very unstable where slight changes to underlying data may have the capacity to produce wild fluctuations in its value. Escalating multicollinearity also increases the volatility of partial regression coefficients such that the corresponding confidence intervals become larger, reducing the likelihood that such variables are statistically significant. Escalating multicollinearity also confounds the effects of explanatory variables making it difficult to determine the importance of individual explanatory variables.

A simple set of diagnostic statistics allows a researcher to determine the level of multicollinearity a data set may contain. Proposed by Belsley et al. (1980), SPSS produces multicollinearity diagnostics for each variable known as a condition index and associated variance proportions. Each dimension[26] of the regression equation possesses a condition index. The variance proportions indicate the amount of variation a specific dimension induces in each explanatory variable's estimated parameters. A condition index assesses the dependency of one variable on the others, with increasing values associated with larger standard errors in the estimation of variable parameters. As these standard errors become large, estimated parameters become highly uncertain.

Multicollinearity becomes problematic, that is crosses some critical threshold whereby the above issues become apparent, when a large condition index contributes strongly to the variance of two or more explanatory variables. Specifically, Belsley et al. (1980) suggest that the level of multicollinearity crosses this critical threshold when condition index values greater than 30 occur in conjunction with variance proportions greater than 0.5 for two or more explanatory variables. Multicollinearity is not an issue for three (environmental

[26] See appendix C.2 Principal Components Analysis discussion of the true rank or dimensionality of a data set.

sustainability performance composite index (ESPCI), sustainable food policy subindex, greenhouse gas (GHG) emissions) of the five policy measures with two or more explanatory variables because the maximum condition index is not greater than 30 (table 5.6). While the maximum condition indices for ESPCI and GHG emissions are approaching 30, neither possesses more than one variance proportion greater than 0.5, so multicollinearity is not problematic. Similarly, the sustainable energy policy subindex, one of the two policy measures with a maximum condition index greater than 30, also has only one variance proportion greater than 0.5. Thus, indicating that multicollinearity is not problematic for this policy measure as well.

Table 5.6: Statistics for determining level of multicollinearity in the data set

POLICY MEASURE	MAXIMUM CONDITION INDEX	PREDICTORS	VARIANCE PROPORTIONS
ESPCI	29.7	Population Density	0.01
		Energy Prices	0.35
		Environmental Governance	0.82
		Economic Output	0.08
Sustainable Energy	37.5	Climate (total degree days)	0.03
		Population Growth	0.11
		Population Density	0.01
		Economic Output	0.10
		Energy Prices	0.39
		Environmental Governance	0.82
Sustainable Food	6.9	Population Density	0.06
		Economic Output	0.89
Sustainable Cities	34.8	Climate (total degree days)	0.26
		Population Density	0.42
		Economic Output	0.40
		Technological Development	0.57
		Industrial Structure	0.59
		Energy Prices	0.44
		PAC Expenditures (per capita)	0.61
GHG Emissions	27.0	Economic Output	0.08
		Energy Prices	0.34
		Environmental Governance	0.82

Note: Multicollinearity starts to become problematic if the maximum condition index is > 30 in conjunction with variance proportions > 0.5 for at least two predictors (Belsley et al. 1980).

On the other hand, levels of multicollinearity do appear to be crossing the critical threshold for the sustainable cities policy subindex (SCPS). This policy measure has a maximum condition index greater than 30 in conjunction with three variance proportions greater than 0.5 (table 5.6). However, other available evidence suggests the levels of multicollinearity in this data set are only approaching the critical threshold and are, therefore, acceptable. The large coefficient of multiple determination (which depends on the value of the multiple correlation coefficient) for SCPS (refer to table 5.3), combined with the suppression analysis results from appendix C (refer to table C.2) that indicate none of the explanatory variables are redundant, suggests that multicollinearity is not problematic. Consequently, the level of multicollinearity in the data set is just approaching the critical threshold whereby effects would become apparent. In fact, this level of multicollinearity may be inducing the beneficial effects of enhancement and suppression observed among the significant factors (Friedman and Wall 2005).

As mentioned, highly correlated explanatory variables likely explain a portion of the same variance on the dependent variable, making one somewhat redundant. Standard multiple regression techniques do not attribute this redundant variance as an independent contribution to any explanatory variable. The problem arises as to which explanatory variable such variance should be attributed. However, the presence of suppression effects, which depend highly on the order of variable entry into the regression equation, also alters how the analysis allocates this variance. To mitigate these issues when exploring the relative importance of explanatory variables, a researcher may average each explanatory variable's contribution to the regression equation over every ordering of the variables, as the current study does (Gromping 2007; 2006; Soofi et al. 2000; Kruskal 1987a; 1987b; Lindman et al. 1980). This technique pre-empts the use of partial regression coefficients as a gauge for variable importance; therefore, it eliminates from the analysis the uncertainty induced on these coefficients from the level of multicollinearity.

Specification errors may also affect the regression analysis. These errors, which lead to difficulty achieving statistical significance, arise by not including all relevant explanatory variables, or by including irrelevant ones, in the regression analysis. Indeed, including, or excluding, even one explanatory variable may substantially alter regression statistics (Licht 1995). Thoroughly grounding the selection process for explanatory factors in a literature review mitigates the effects of selection error. Using Akaike's Information Criterion corrected for sample size, a technique that balances predictive power with parsimony of independent variables, to select the most appropriate set of variables also mitigates such effects.

In addition to specification errors, weaknesses in the formulation of each metric produce limitations. Broadly, these factor weaknesses induce three types of limitation: information missing, information bias, and information overlap (table 5.7). Analytical results could potentially change with the introduction of new information, such as that represented by the information missing from several of the factor metrics. Moreover, if information bias introduces a gap between a factor metric and the underlying phenomenon it is measuring, large errors could potentially occur in the analytical results. For example, the environmental governance factor relies solely on the perceptions of business leaders that may not fully capture the differences in regulatory effectiveness among jurisdictions surveyed. The analytical results of the current study would probably change if perceptions substantially diverge from the true effectiveness of a jurisdiction's environmental governance. Finally, the information overlap between the environmental pricing factor and the energy prices factor may introduce redundant information into the analysis, but both factors are worthy of inclusion because each contains necessary information that the other does not. The energy prices factor contains information on the cost to consume various energy types, while the environmental pricing factor contains information on taxes and fees associated with other environmentally adverse activities, such as consumption of ozone-depleting substances. As more countries move to tax environmentally adverse activities, this factor should become more relevant.

Multicollinearity affects a cluster analysis by implicitly weighting highly correlated variables more heavily (Hair and Black 2000). The cluster analysis can compensate by using a distance measure that corrects for correlation or by ensuring equal numbers of elements in each cluster (i.e., Ward's method) (Hair and Black 2000). For the current cluster analysis, several ESPIs, specifically the air pollution indicators, are highly correlated ($r > 0.9$) with each other. Thus, these indicators may receive more weight during the clustering process that assigns cluster membership, but to mitigate such effects the cluster analysis uses the mentioned adjustments. On the other hand, the level of multicollinearity detected among the factors has little discernible affect on the statistical test for equality of means across clusters.

Table 5.7: Limitations arising from weaknesses of factor metrics

FACTOR	METRIC WEAKNESS	LIMITATION
Climate	Does not quantify all aspects; excludes precipitation and wind	Information Missing
Population Growth	Annual growth rate unable to account for absolute changes	Information Missing
Population Density	Placement of boundaries	Information Bias
Economic Output	Unpaid labour not included	Information Missing
Technological Development	Is incomplete; many aspects of technological development hard to quantify	Information Missing
Industrial Structure	Data availability limited economic sectors used	Information Missing
Energy Prices	Some energy types not included, notably coal and propane	Information Missing
Environmental Governance	Survey of business leader perceptions may not reflect environmental regulatory effectiveness	Information Bias
PAC Expenditures	Does not quantify in-place or 'sunk' PAC expenditures	Information Missing
Environmental Pricing	Energy prices factor contains much of the same information	Information Overlap

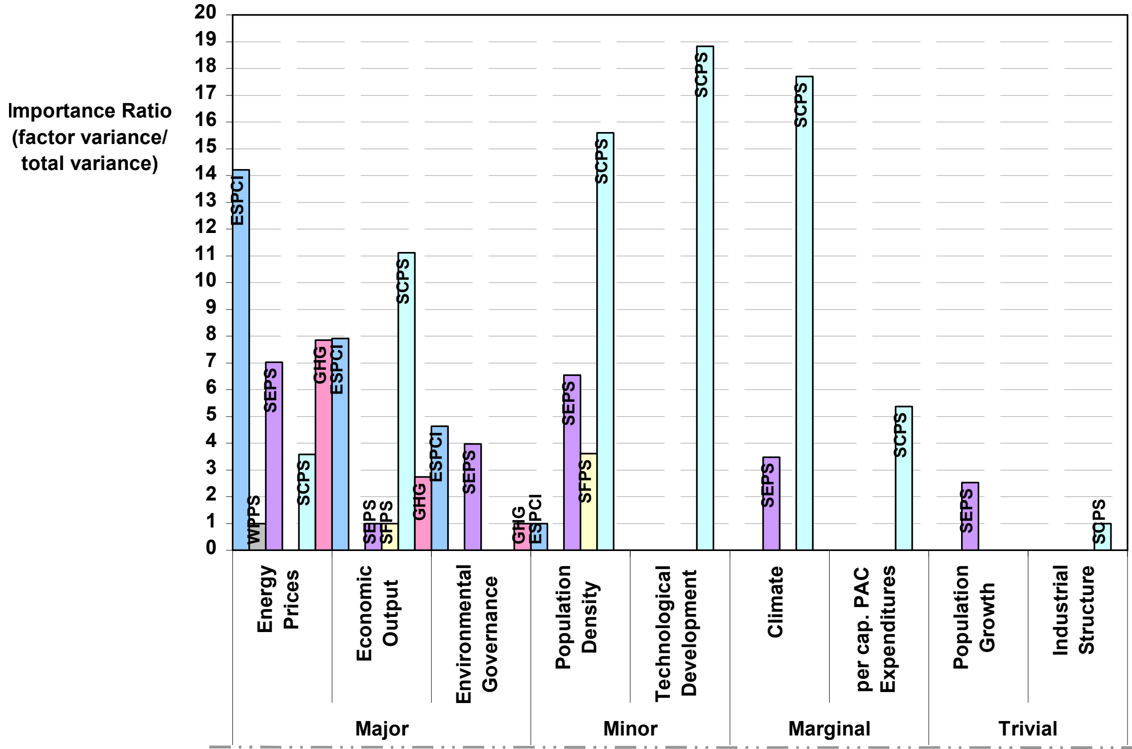
The current research did not consider uncertainty in the underlying indicator values because estimates of measurement error are unavailable. Large measurement errors have the potential to affect extensively final regression statistics because actual indicator and factor values may be substantially different from those used in the analysis.

5.4) SYNTHESIS OF RESULTS

This section combines the results of the analyses in this chapter to refine conclusions. Statistics from the regression analysis are used to calculate importance ratios for the factors. Ratios are calculated by dividing the amount of variance each factor explains on a policy measure by the total variance that all factors as a group explain (statistics from table 5.3). Combining the importance ratios with the cluster analysis results for discerning among country groups categorise factors according to level of significance, major, minor, marginal, and trivial (fig. 5.4). In effect, a triangulation process that combines the findings of two analytical techniques with a literature review identifies the important influential factors for each policy measure.

Energy prices, economic output, and environmental governance are the major influential factors. Multiple regression analysis determines that these three factors are statistically significant, at a 95% level of confidence, to explaining a country's performance on the environmental sustainability performance composite index (ESPCI), the current study's overall index of environmental sustainability (refer to table 5.3). In addition, a variant of sequential regression calculates that energy prices and economic output are about three and one-and-a-half times as important as environmental governance respectively to performance on ESPCI (refer to table 5.3 and fig. 5.4). While somewhat limited by missing data, cluster analysis discovers that energy prices, economic output, and environmental governance provide enough information to very likely discriminate among five[27] different country groups (refer to table 5.5 and fig. 5.3). The Wilks's lambda test for equality of factor cluster means retains 20 countries. Further mitigation of the effects of data limitations occurs by using a line graph to observe the pattern of differences among factor cluster means (fig. 5.3).

[27] The single-country cluster 5 containing Iceland is excluded from this portion of the cluster analysis due to missing data.



Major factors
- are significant to the overall measure of environmental sustainability performance, ESPCI
- are significant to several policy areas
- are strongly capable of discerning among country groups

Minor factors
- possess limited capacity to discern among country groups
- tend to be of lesser importance to policy areas

Marginal factors
- posses no capacity to discern among country groups
- tend to be of lesser importance to policy areas

Trivial factors
- posses no capacity to discern among country groups
- tend to be among the least important to policy areas
- appear in only one policy area

ESPCI = Environmental sustainability performance composite index
WPPS = Waste and pollution policy subindex
SEPS = Sustainable energy policy subindex
SFPS = Sustainable food policy subindex
NCPS = Nature conservation policy subindex
SCPS = Sustainable cities policy subindex
GHG = Greenhouse gas emissions indicator

Note: Importance ratios are calculated by dividing the amount of variance each factor explains on a policy measure by the total variance that all factors as a group explain.

Figure 5.4: Bar graph categorising the factors' level of significance and illustrating the importance of each factor to each policy area

Moreover, the energy prices factor is the only factor influencing performance on the waste and pollution policy subindex (WPPS), as well as being the most important factor for greenhouse gas (GHG) emissions performance (refer to table 5.3 and fig. 5.4). Energy prices explain 55% of the variation for both WPPS and GHG emissions. For predicting performance on the sustainable energy policy subindex (SEPS), the energy prices factor is also marginally the most important one (20% variance explained) out of six. A set that also includes environmental governance (11% variance explained) and economic output (3% variance explained) as well as population density (19% variance explained), population growth (7% variance explained), and climate (10% variance explained) (refer to table 5.3 and fig. 5.4). Conversely, the energy prices factor (5% variance explained) is one of the less important factors for the sustainable cities policy subindex (SCPS). Economic output also significantly influences performance on sustainable food policy subindex (SFPS) (13% variance explained), SCPS (15% variance explained), and GHG emissions (19% variance explained); therefore, like energy prices, economic output also significantly influences performance on four policy measures as well as the overall composite index (table 5.3 and fig. 5.4). In addition to the overall index, environmental governance also exhibits significant influence on two other policy measures, SEPS (11% variance explained) and GHG emissions (7% variance explained) (table 5.3 and fig. 5.4).

In addition to the three major factors, other minor influential factors also bear discussion. According to cluster analysis results, population density and technological development likely each have a limited capacity to separate a few, but not all, of the country groups so are less useful than energy prices, economic output, and environmental governance (refer to table 5.5 and fig. 5.3). The Wilks's lambda test for equality of cluster means indicates that population density and technological development each have at least one cluster mean that is significantly different from the others, at the 95% level of confidence. Population density and technological development separate cluster 2 and cluster 6, respectively, from the other clusters quite clearly, but may not be able to discern further among clusters (refer to fig. 5.3).

At the same time, multiple regression results suggest that population density (47% variance explained) is the most influential factor for performance on SFPS (more than three times economic output – 13% variance explained) (refer to table

5.3). It is also among the group of four of the more influential factors for SCPS (21% variance explained), the other three being climate (24% variance explained), economic output (15% variance explained), and technological development (26% variance explained) (fig. 5.4). Population density (19% variance explained) is also almost as important to performance on SEPS as energy prices (20% variance explained). However, population density is the least important factor (3% variance explained) of the four influential factors for ESPCI, those being the three major factors (fig. 5.4). Along with population density, technological development is among the group of four of the more influential factors for SCPS, the others being climate and economic output. Technological development emerges as SCPS's most important factor, slightly ahead of population density (refer to table 5.3 and fig. 5.4). In total, technological development appears as a significant factor on one policy measure[28], while population density occurs in the set of significant factors for four subindices.

In addition to these groups of major and minor influential factors, is a group of marginally influential factors. While cluster analysis did not identify climate as an important factor, regression results demonstrate its importance to SEPS and SCPS (refer to table 5.3 and fig. 5.4). Climate is about half as important to performance on SEPS (10% variance explained) as energy prices (20% variance explained), the most important factor for this policy measure. Climate is almost as important to performance on SCPS (24% variance explained) as technological development (26% variance explained); being among the group of four more influential factors on this policy measure, a group that also includes population density and economic output. At the same time, per capita pollution abatement and control (PAC) expenditures, according to cluster analysis results, have a limited capacity to differentiate among country groups. This factor clearly separates cluster 6 from the others, with some ability to separate clusters 2 and 3 as a group from the rest, however, cluster 1 may not be discernible from cluster 4 (refer to fig. 5.3). Multiple regression results indicate per capita PAC expenditures are among the lesser important factors (7% variance explained) for predicting performance on SCPS. The other lesser important factors for SCPS are

[28] Recall that multiple regression analysis did not identify a significant explanatory relationship for NCPS; the discussion presents its relationship with technological development for comparison purposes.

energy prices (5% variance explained) and industrial structure (1% variance explained).

After these marginal factors, are several others that appear somewhat trivial. Population growth (7% variance explained) and industrial structure (1% variance explained) are among the least important factors on their respective policy measures, SEPS and SCPS (refer to table 5.3 and fig. 5.4). Moreover, cluster analysis fails to identify either of these two factors as important. Finally, as cluster analysis results indicate, per capita environmental pricing exhibits a limited ability to discern among country groups (refer to fig. 5.3). Environmental pricing only has the capacity to separate out two groups of clusters, those being clusters 3 and 4 at one end of the range and clusters 1, 2, and 6 at the other (refer to fig. 5.3). However, this ability appears redundant when compared to other identified factors, notably environmental governance and energy prices.

These influential factors affect environmental performance in different ways. No matter to which policy measure they correspond, energy prices, environmental governance, technological development, per capita PAC expenditures, population growth, and industrial structure all appear to enhance underlying environmental performance as indicated by positive standardised partial regression coefficients[29] (refer to table 5.3). On the other hand, economic output, population density, and climate have negative coefficient values, thus these factors appear to retard a country's performance on various environmental policy measures.

Five factors are not important for ESPCI, and are only important for two policy subindices, SEPS and SCPS. In addition to energy prices, economic output, environmental governance, and population density, SEPS includes climate and population growth. In addition to energy prices, economic output, and population density, SCPS includes climate, technological development, industrial structure, and per capita PAC expenditures. SEPS and SCPS may quantify complex circumstances that have many shaping factors, some with more subtle effects. The more subtle effects become less important as the performance indicators are more highly aggregated. Reinforcing the idea that singular

[29] Recall that a positive value indicates that increases in the factor increase environmental sustainability performance as measured by a composite index, while a negative one indicates that performance decreases as the factor increases.

composite indices should only be studied along side other, less aggregated indicators, similar to the way the current research uses the policy subindices and GHG emissions indicator. Additionally, SCPS may be missing crucial information because data are not available to include three relevant indicators—green infrastructure funding, public transit, and loss of agricultural land (table 3.12). Inclusion of such information may likely change the set of important influential factors.

Climate is only important for SEPS and SCPS and not on the overall composite index, ESPCI. This finding is in some conflict with the Government of Canada's assertion that climate is a 'national circumstance' that significantly influences a country's environmental performance (see chapter 4) (Canada 2001). Each policy measure may have a different explanation for the divergence. For SCPS, climate shares approximately equal importance with technological development and population density. However, the importance of population density to other policy measures, SEPS and SFPS, provide enough support for this factor to emerge as more important to ESPCI than climate. For SEPS, the policy measure containing energy consumption and intensity indicators, energy prices are twice as important as climate. Additionally, the energy prices factor is the only important factor for WPPS and is the most important factor for GHG emissions, the policy measures containing air pollution related indicators linked to energy use. Consequently, the energy prices factor appears to be more influential than climate at shaping adverse environmental impacts and it emerges as an important factor for ESPCI over climate. As above, singular composite indices should only be studied along side other, less aggregated indicators.

Performing a cluster analysis on ESPIs produces six clusters (refer to table 5.4). These six clusters separate into only three distinct groups on the overall index of performance, ESPCI (fig. 5.2). Cluster 1 obviously contains the laggards, clusters 2, 3, and 5 group various types of middling performers, and clusters 4 and 6 capture different types of high performers. Further characterisation of the clusters requires examining cluster separation on the policy subindices as well (fig. 5.2). Poor performance at reducing waste and pollution contributes greatly to the position of cluster 1 at the bottom of the scale. Distinguishing among clusters 2, 3, and 5 requires a researcher to review how the clusters group on

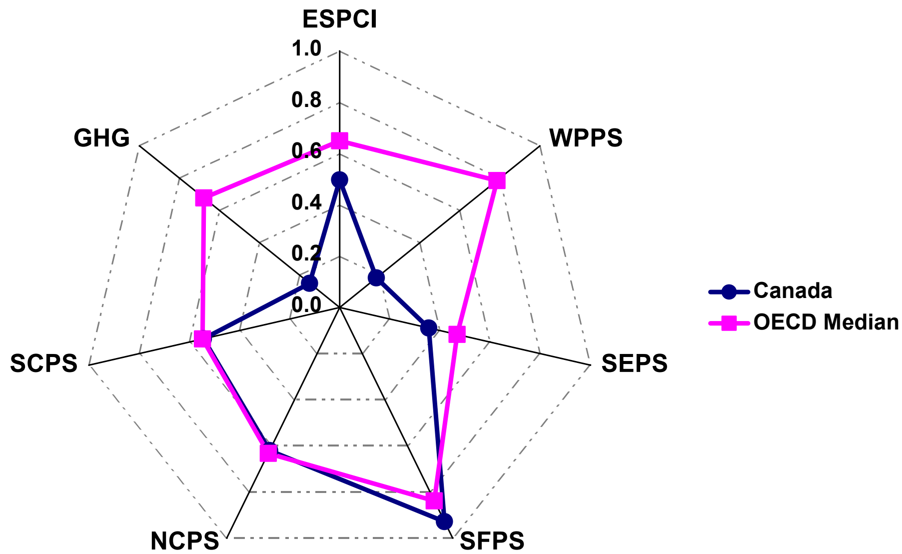
SFPS, WPPS, and SCPS; distinguishing between clusters 4 and 6 requires consideration of SFPS and SCPS. As indicated by policy measure scores, middling-performing countries of cluster 3 produce food more sustainably than those countries of cluster 2, while cluster 5 differs by its mediocre ability to reduce waste and pollution and its low performance at developing sustainable cities. High-performing countries of cluster 4 and 6 differ by opposing performances at producing food and developing cities more sustainably than the other. As noted, a researcher may make these same discernments with the factors energy prices, economic output, and environmental governance, as well as population density and technological development to lesser extents (refer to fig. 5.3). Two crucial insights arise from comparing these two cluster characterisations: (i) cluster 4 and 6 achieved their respective high overall performances in markedly different ways, perhaps indicating two different development pathways; and (ii) cluster 1 may owe its poor overall performance to the double effects of having the highest economic output combined with the lowest energy prices. Refer to section 7.2 for conclusions and recommendations concerning influential factors.

CHAPTER 6:
EXPLORING CANADIAN POLICY IMPLICATIONS

How might these results help improve a country's environmental sustainability performance? Using Canada as an exemplar to derive the policy implications of these findings, the following discussion examines how the main influential factors affect a country's performance on the environmental measures. Included among the policy measures is the greenhouse gas (GHG) emissions indicator because climate change is an important environmental issue that deserves separate treatment. The reader is cautioned to remember that changes in the value of these sustainability indices do not necessarily constitute a change in sustainability and that they might not adequately appraise sustainability. The main influential factors are those categorised as major (energy prices, economic output, and environmental governance), minor (population density and technological development), or marginal (climate and per capita pollution abatement and control expenditures) (fig. 5.4 previous chapter). This chapter determines the key main influential factors for improving Canada's environmental performance, assesses the impacts of these key factors on Canada's performance on important environmental policy measures, compares the main influential factors to drivers of GHG emissions, and describes potential Canadian policy implications.

6.1) CANADA'S KEY FACTORS

Canada's meagre environmental showing (according to the environmental sustainability performance composite index (ESPCI)) is mainly attributable to poor performance on two policy measures. Canada underperforms on the waste and pollution policy subindex (WPPS) and, to a lesser extent, on the sustainable energy policy subindex (SEPS), while it meets or beats the Organisation for Economic Co-operation and Development (OECD) median on the other policy subindices (fig. 6.1). In the radar diagram, policy measures with values that fall below the median exhibit poor performance; the further below the median, the worse the relative environmental performance as quantified by the various policy indices. Canada's performance at reducing waste and pollution, as quantified on the policy subindex, is only about one-quarter that of the OECD median, or about one-fifth of the OECD best performer. Performance on the GHG emissions indicator show similar comparisons as well. On the other hand, Canada's performance at producing sustainable energy, as quantified on the policy subindex, is about 80% of the OECD median and about 40% of the OECD best performer. Appendix F presents radar diagrams comparing policy measures to the OECD median for all member countries, as well as graphs comparing individual performance indicators to the OECD median and data for the important influential factors.



Note: Poor performance is exhibited by policy measures with values that fall below the OECD median, the further below the median, the worse the relative environmental performance as measured by the various policy indices.

ESPCI = Environmental sustainability performance composite index
WPPS = Waste and pollution policy subindex
SEPS = Sustainable energy policy subindex
SFPS = Sustainable food policy subindex
NCPS = Nature conservation policy subindex
SCPS = Sustainable cities policy subindex
GHG = Greenhouse gas emissions indicator

Figure 6.1: Radar diagram comparing across policy measures Canada's performance with OECD median, OECD best (1.0), and OECD worst (0.0)

The analytical results have implications for Canadian environmental policy. The main influential factors associated with ESPCI (energy prices, economic output, environmental governance, and population density), WPPS (energy prices), SEPS (energy prices, economic output, environmental governance, population density, and climate) each possess varying degrees of amenability to policy actions. Recall that these factors are either ungovernable, mainly outside a country's control, semi-governable, large proportions of both ungovernable and governable elements, or governable, primarily acted upon by government fiat (refer to fig. 1.2). Climate is not very amenable to policy actions, while environmental governance and energy prices are clearly very malleable. Environmental governance is malleable by definition and energy prices are malleable by government policies that add the cost of adverse environmental impacts from energy consumption into the commodity price. Arguably, population density and economic output are somewhat unyielding to policy pressures, but not to the extent of climate, and considerably less amenable to policy actions than environmental governance or energy prices. In addition, the preceding summary at the end of chapter 5 determines that climate is a marginal influential factor (refer to fig. 5.4 for the factors categorised by level of importance). Hence, this analysis suggests that Canadian policy makers wishing to improve performance on the environmental measures should consider improving environmental governance and increasing energy prices, either singly or in conjunction.

6.2) PERFORMANCE IMPACTS OF KEY FACTORS

To answer the question of performance improvement, this section examines how two key factors could affect environmental sustainability. Using the unstandardised regression coefficients contained in appendix D and each country's set of factor values, the following analyses estimates the rank Canada might have attained with changes in energy prices and environmental governance. These two factors have demonstrably more impact on policy measures of environmental sustainability than the other factors and both are amenable by public policy. Several sensitivity analyses are conducted that demonstrate how Canada's environmental rank would change with changes in these two key factors.

For these sensitivity analyses, first energy prices are altered, then environmental governance, and, finally, both factors are altered simultaneously (table 6.1). The first sensitivity analysis sets energy prices in Canada to the median for OECD countries, while a second one sets them to the average of the three OECD countries with the highest energy prices (top-three average). The third sensitivity analysis sets environmental governance to the average of the three OECD countries with the highest levels of environmental governance (top-three average), and, the last one sets both energy prices and environmental governance to their respective top-three averages. Note that Canada's present energy prices are among the lowest of OECD countries, well below OECD median prices (refer to table 6.2, section 6.4). However, Canada's overall level of environmental governance is slightly above the OECD median level (refer to table 6.3, section 6.4). Reducing Canada's levels of environmental governance to the OECD median would logically retard its environmental performance, so the analyses only adjust this factor upwards by using the top-three average. In this manner, one may identify general areas for policy actions that may improve Canada's poor environmental sustainability performance.

Results in table 6.1 clearly illustrate the different impacts that energy prices and environmental governance produce on performance across the listed policy measures. Canada's low ranks on the four measures (28th, 30th, 26th, 26th) are mainly attributable to low contributions from the energy prices factor. If energy prices approached the OECD median, Canada's performance on three of the four subindices increases substantially from among the worst performers to the middle of the pack for ESPCI, WPPS, and SEPS, 15th, 16th, and 15th respectively. In fact, Canada's predicted score for each of these policy measures is quite close to the OECD median score, differing by 0.001, -0.001, and 0.004 respectively. However, a 5% range centred on Canada's predicted score for each of these policy measures contains a number of other countries with similar performances. In addition to Canada, this range contains nine other countries for ESPCI, 10 for WPPS, and seven for SEPS. Canada's performance on the greenhouse gas (GHG) indicator with OECD median energy prices improves marginally to 22nd place, with a predicted score somewhat lower than the OECD median (-0.069) and no other similarly performing countries nearby.

Table 6.1: Changes in Canada's environmental rank with changes in energy prices and environmental governance

Policy Measure	Canada's Actual Rank	Canada's Estimated Rank with Energy Prices at		Canada's Estimated Rank with Environmental Governance at	Canada's Estimated Rank with Energy Prices and Environmental Governance at
		OECD Median	Top-Three Average	Top-Three Average	Top-Three Average
ESPCI	28	15	2	24	1
Waste and Pollution	30	16	2	n.a.	n.a.
Sustainable Energy	26	15	3	21	1
GHG Emissions	26	22	2	25	2

n.a. = not applicable; environmental governance is not a significant factor for this subcategory.

Remarkably, if Canadian energy prices rose to the average of the three OECD countries with the highest prices, Canada would leap into top-three status across all four policy measures. Canada's performance scores placed 2nd on ESPCI, WPPS, and the GHG indicator, 0.02, 0.133, and 0.227 behind the respective top performers on each policy measure. Moreover, Canada's performance score placed 3rd on SEPS, 0.03 and 0.014 behind the respective top two performers. In contrast, because Canada's levels of environmental governance are already above average, performance improvements from the environmental governance factor may only occur if it increases to the elite level of the top-three average. Even then, such improvements would produce marginal results since Canada's level of environmental governance does not differ greatly from that of the top three countries. Indeed, setting environmental governance to the level of the top three average, only improves Canada's performance on two policy measures: Canada's predicted score moves from 2nd and 3rd to 1st on ESPCI and on SEPS respectively. Canada's rank on the GHG policy measure does not change with this increase in governance levels. Consequently, the energy prices factor emerges as the most important one for improving Canada's environmental performance across several policy measures for environmental sustainability, including GHG emissions.

6.3) COMPARISON OF FACTORS WITH GHG EMISSIONS DRIVERS

Appendix G details several frameworks or perspectives emerging from the literature that characterise greenhouse gas (GHG) emissions drivers. These drivers provide an interesting comparison to the important factors the current study finds for GHG emissions, those being energy prices, economic output, and environmental governance. Similar to the Kaya identity (Kaya and Yokobori 1993) and the IPAT-based studies (Cole and Neumayer 2004; York et al. 2003; Fan et al. 2006; Schulze 2002), the current study finds that economic output is an important driver of GHG emissions. However, contrary to the Kaya and IPAT identities, the population pressure measures of growth and density are not important drivers. The results of the current study are consistent with the Bataille et al. (2007) decomposition analysis. Relative to other countries, the decomposition analysis demonstrates that climate, industrial structure, and population distribution (a proxy for geography) do not affect appreciably Canada's high levels of GHG emissions. Industrial structure and population distribution have little affect, while the favourable impact of Canada's access to low-polluting electricity sources, largely offset the effects of climate and fossil fuel production. Clearly, the results from the Bataille et al. (2007) analysis indicate other, unaccounted, drivers affecting emission levels, which the current study demonstrates could be the policy factors environmental governance and energy prices.

Higher energy prices would likely spur innovation to decrease the energy intensity of the economy as energy consumers seek to save money and reduce consumption. If the higher prices result from pricing carbon emissions then energy consumers will tend to purchase energy with lower carbon content, thus decreasing the carbon intensity of the energy consumed. According to Esty et al. (2008: 73), three developed and industrialised OECD-member countries—Switzerland, Norway, Sweden—have appreciably lowered per capita GHG emission levels and are close to achieving reduction targets, in part, because of fuel taxes. Consequently, energy prices appear capable of altering the behaviour of a population, as postulated by the I = P*B*A*T model, a version of the IPAT identity detailed in appendix G that incorporates human behaviour (B).

6.4) CANADIAN POLICY IMPLICATIONS

This analysis provides good news and positive guidance for Canadian environmental efforts. The results show that Canada's poor environmental performance is not largely due to factors beyond its control such as climate and geography. Instead, weak public policy causes Canada's poor performance, particularly the decision to allow energy prices to remain among the lowest in the OECD across the energy types used to formulate the factor (table 6.2). Appendix F contains data for the significant influential factors for all OECD-member countries. As these results demonstrate, energy prices are extremely important to overall environmental sustainability performance, as well as waste and pollution mitigation efforts, and GHG emissions reduction actions. This factor is also important to sustainable energy efforts, but to a lesser degree.

Table 6.2: Comparing Canadian energy prices to OECD median and top-three average prices by energy type

ENERGY TYPE	CANADIAN PRICE (2002 U.S.$/TOE)	OECD MEDIAN PRICE (2002 U.S.$/TOE)	OECD TOP-THREE AVERAGE (2002 U.S.$/TOE)
Gasoline[a]	$652.93	$1,184.23	$1,523.49
Diesel[a]	$494.59	$833.91	$1,280.58
Industrial Natural Gas[b]	$160.10	$207.60	$476.63
Household Natural Gas[b]	$301.70	$479.70	$949.30
Industrial Electricity[b]	$581.40	$790.70	$1,980.62
Household Electricity[b]	$802.33	$1,569.77	$2,515.50

Sources:

a = Metschies, Gerhard P. 2003. *International fuel prices, 3rd ed*. Eschborn, Germany: German Technical Co-operation, German Federal Ministry for Economic Co-operation and Development.

b = International Energy Agency (IEA). 2006. *Energy Prices & Taxes, 4th Quarter 2006*. Paris: IEA Head of Publications Services.

Compared to energy prices, environmental governance is a less important factor for guiding Canadian policy formation but may still contribute to improvements. Many components of Canada's environmental governance are near the leading edge, falling somewhere between the OECD median and the average of the OECD top-three highest levels; however, three components equal the OECD median levels, while one is very close (table 6.3). Appendix F contains data for the important influential factors for all OECD-member countries. To increase environmental sustainability performance on the policy measures, efforts can specifically focus on increasing the stringency of these four environmental governance components—air pollution, water pollution, toxic waste disposal, and chemical waste. Policy makers may also strive to develop policies in these areas that are particularly relevant and complementary to those developed for increasing energy prices.

Table 6.3: Comparing Canadian levels of environmental governance to OECD median and top-three average levels by component

Environmental Governance Component	Canadian Level	OECD Median Level	OECD Top-Three Average Level
Environmental Governance	61.2	59.7	68.1
Air Pollution Regulations (11.01)	5.7	5.7	6.6
Water Pollution Regulations (11.02)	5.8	5.8	6.6
Toxic Waste Disposal Regulations (11.03)	5.9	5.9	6.7
Chemical Waste Regulations (11.04)	5.9	5.8	6.7
Stringency of Environmental Regulations (11.05)	5.9	5.7	6.6
Compliance with Environmental Regulations (11.06)	5.6	5.3	6.4
Compliance with International Agreements (11.07)	5.8	5.6	6.5
Clarity and Stability of Regulations (11.08)	5.3	4.9	5.9
Flexibility of Regulations (11.09)	4.8	4.5	5.2
Consistency of Regulation Enforcement (11.10)	5.5	5.2	6.1
Effects of Compliance on Business (11.11)	5.0	4.8	5.5

Source: World Economic Forum. 2004. *The Global Competitiveness Report 2003-2004*. New York: Oxford University Press.

By increasing energy prices, Canada could plainly improve environmental sustainability performance on several fronts. Prices for most energy types are substantially below respective OECD median prices (table 6.2). All prices are about half of the corresponding OECD median, except for industrial and household natural gas and industrial electricity prices, each being roughly two-thirds the OECD median. Adding a cost to reflect the environmental damage caused by consuming energy, particularly fossil fuels, onto the prices for various forms of energy, would effectively increase energy prices within the Canadian economy. In this way, energy consumers would receive a more accurate signal for the actual cost to society of energy consumption. Specifically, Canada could likely greatly improve performance at reducing GHG emissions if it moved to price carbon emissions to the atmosphere, either through a carbon tax or through a cap-and-trade system. Any policy action that increases energy prices in the Canadian economy accrues additional benefits from better performance on other policy measures for which energy prices is also an important factor, specifically ESPCI, waste and pollution, sustainable energy, and sustainable cities.

Increasing energy prices to sustainable levels is likely not an easy task. Moving Canadian energy prices to the OECD median would involve increases ranging from about 30% to almost 100% across the energy types, while moving to the average prices of the top-three OECD countries would involve increases ranging from about 130% to roughly 240% (table 6.2). Research done in 2000 by the Analysis and Modelling Group for Canada's National Climate Change Process provides a few useful comparators for these ranges. Through a macroeconomic analysis of various options for reducing GHG emissions, the Analysis and Modelling Group determine that even if acting alone Canada could meet Kyoto targets with mostly modest price increases. Gasoline prices would rise by 13% to 35%, household natural gas prices would increase by 30% to 75%, and electricity rates would increase by about 2% in Quebec ranging to 84% in Alberta, with variability depending on a province's sources of electricity production (e.g., hydro) (National Round Table on the Environment and the Economy (NRTEE) 2005). B.C.'s electricity rates would likely exhibit a similar increase to Quebec's, given their similarity of hydroelectric production sources. These ranges compare favourably with the respective energy types from the current study (table 6.2); the median-based price increases are very similar and several of the top-three-based price increases are not that much larger.

The adjustments would take time and would involve considerable challenges, which governments can mitigate using several approaches. Governments can:

- provide long lead times to allow polluters to prepare for coming changes,
- phase these changes in over a long period to allow further time for preparation, and
- implement changes in a revenue-neutral manner so that all increases are refunded to consumers through tax cuts in other areas.

Recent studies forecast that Canada's economy would grow even with energy costs increased by a steep carbon price intended to bring Canada's GHG emissions down to levels that international climate change scientists recommend

(NRTEE 2007; Rivers and Sawyer 2008). One analysis demonstrates that a carbon price can be revenue neutral to government coffers so that overall levels of taxation would not increase (Rivers and Sawyer 2008). Indeed, that analysis also predicts that if the carbon price were revenue neutral, Canadian economic growth through 2020 would be reduced by only 0.9% compared to the base scenario without a carbon price (Rivers and Sawyer 2008). Consequently, the negative impacts of pricing carbon should be relatively minor, more than justified by the substantial environmental benefits.

Pricing carbon to increase energy prices to sustainable levels should also invigorate Canada's burgeoning 'green' economy. Sweden provides aid for renewable energy development and public transit through energy taxes that collect roughly U.S.$10 billion per year, with approximately one billion of that from a carbon tax (Barde 2000), while the United Kingdom's Fossil Fuel Levy generates about U.S.$150 million per year to finance similar alternative energy development efforts (U.N. Development Programme 1998). Denmark has also initiated a gradually increasing carbon tax that it uses partly to finance emerging energy technologies (Barde 2000). By adding a carbon price to the cost of energy, alternative, non-carbon-based forms of energy, such as wind and tidal, become more cost competitive with fossil fuels, thereby providing the 'green' economy with an infusion of financial support. In turn, these efforts create an opportunity to increase market share and the corresponding increases in employment from infrastructure construction (e.g., installation of wind turbines and associated power distribution equipment) and from manufacturing (e.g., wind turbines). For example, Germany has 45,000 jobs in the wind sector alone, and the United Kingdom, through development of a 6,000 MW offshore wind facility, created 20,000 jobs (Tampier 2004). Moreover, a recent assessment by the Clean Air Renewable Energy Coalition, determines that Canada's opportunity to develop low-impact, renewable electricity sources could be as high as 31,875 MW. Such capacity could potentially create and sustain through 2020 about 12,700 to 26,900 jobs (depending on assumptions) (NRTEE 2005). The United States presents a similar opportunity, with plans to nearly double energy production from renewable sources from 2000 to 2025 (U.S. Department of Energy 2003). Refer to section 7.2 for conclusions and recommendations concerning Canadian policy implications of these results.

CHAPTER 7:
CONCLUSIONS AND RECOMMENDATIONS

This chapter discusses the conclusions and recommendations arising from the results of this study. It marshals evidence from the findings, specifically chapters 3 and 5, to evaluate the study's hypotheses from chapter 1. Discussion first centres on the hypothesis concerning an environmental performance evaluation system before proceeding to the second hypothesis regarding significant factors influencing a country's environmental sustainability trajectory. Moreover, results from chapter 6 inform conclusions and recommendations pertaining to Canadian policy implications arising from the influential factors. Guided by the research questions, recommendations follow conclusions for each hypothesis, and, finally, areas for future research are explored. Major insights arising from the current study mentioned in the abstract appear in **boldface** type to allow readers to find this information easily. While reviewing the conclusions and recommendations arising from the current study, the reader is cautioned to bear the following caveats in mind: changes in the value of the sustainability indices do not necessarily constitute a change in sustainability and these indices might not adequately appraise sustainability. Readers interested in the justifications for the formulations of the overall index and the policy subindices may refer to sections 3.3 and 3.4 respectively.

7.1) HYPOTHESIS #1: ENVIRONMENTAL PERFORMANCE EVALUATION SYSTEM

The following section details the conclusions and recommendations pertaining to the first hypothesis. First, the discussion centres on the conclusions emerging from the results of the uncertainty and sensitivity analyses in chapter 3, followed by a discussion of the recommendations arising from them, and an examination of areas for future research.

CONCLUSIONS

Repeated, for convenience, is the first hypothesis from chapter 1. Next, specific conclusions provide evidence to evaluate its validity.

H_1: Countries' ranks for environmental sustainability performance will depend, in part, on the measurement techniques selected for evaluation.

1. Countries' ranks depend, in part, on decisions made during construction of a composite index. Seventeen countries exhibit a range of performance ranks greater than 10 (one-third the overall range), while 10 countries experience a range greater than 15 (one-half the overall range). One country possesses a range of 23 performance ranks (about three-quarters of the overall range). Such results do not demonstrate the robustness and reliability that policy makers seek with measurement tools, but the results do illustrate the limitations of composite indices.
2. **Main sources of variation arise from the scale-effect adjustments and normalisation method used**[30], with the indicator exclusion factor an important secondary source. Combined, **the main sources explain about 68% of the variation among the member countries' environmental performance ranks**. The secondary source accounts for about 16% of the variation while being the largest source of variation for Denmark's rank distribution (43%).

[30] Major insights arising from the current study mentioned in the abstract appear in **boldface** type to allow readers to find this information easily.

3. **Choice of indicator set for the environmental reporting system appears to explain much of the observed variability among studies reviewed in chapter 2.** The five studies are:
    - *Canada vs. the OECD* (Organisation for Economic Co-operation and Development) (Boyd 2001)
    - *Performance and Potential 2004-2005: Key Findings, How Can Canada Prosper in Tomorrow's World?* (Conference Board of Canada (CBC) 2004)
    - *Canada's Environmental Performance: an Assessment* (Gunton et al. 2005)
    - *Living Planet Report* (World Wide Fund (WWF) 2006)
    - Yale 2008 Environmental Performance Index (Esty et al. 2008)

   All inputs into the uncertainty and sensitivity analyses produce about three ranks of variation for Canada's performance, about 10% of the possible range. For comparison, the 14-rank differential observed for Canada across the five studies is about 60% of the possible range of 23 ranks. The portion of Canada's performance range not captured by this analysis likely depends on the set of indicators used. Recall that only one method is available for an analyst to build a composite index that compares dissimilar entities such as countries, but the method requires several decisions about the individual techniques one employs (Nardo et al. 2005). In addition to selecting appropriate performance indicators, other decisions are missing data treatments, normalisation methods, scale-effect adjustments, weights, and aggregation techniques. Because the current analysis includes all other decision points, any unexplained variation is a residual attributable to the different sets of performance indicators the various studies employ. However, the variation the current study attributes to the other decision points may change if the sensitivity analysis included other techniques, such as the non-compensatory multi-criteria method of aggregation or the proximity-to-target method of normalisation. If these variations change, the residual variation attributed to the selection of the indicator framework would change as well. The importance of the indicator exclusion factor, which signals, at least qualitatively, that the set of indicators is highly influential further supports this deduction.

4. Variation in rank distributions across countries contains a large non-linear portion. On average, the variance induced in a country's rank distribution due to interaction effects among all the decision points encountered when building a composite index is 19%.
5. Lack of data eliminates several important indicators (refer to table 3.12) from the set, thus, the coverage of the environmental reporting system suffers. All studies suffer from this problem. Including these aspects of environmental sustainability in the analysis would likely alter results because they appear to capture necessary elements of sustainability.

These discussion points provide much evidence to support the first hypothesis. Clearly, measuring a country's environmental progress or performance depends on the techniques employed, starting with selection of the indicator set and supporting data, through to several of the processes used for constructing a composite index, particularly the preference for scale-effect adjustments and normalisation method.

RECOMMENDATIONS

Repeated, for convenience, is the first research question from chapter 1. It provides context and guidance for formulating specific recommendations emerging from the conclusions for the first hypothesis.

Q_1: How can a policy maker best measure a country's environmental sustainability progress and performance? And, what are significant areas of uncertainty in measurement and ranking methods?

1. **Because performance ranks developed from composite indices tend to be unstable, studies should also analyse subcategories of indicators (policy subindices or measures) formed with principal components factor analysis (PCFA) as well as analysing important individual indicators (e.g., greenhouse gas (GHG) emissions) separately.** This recommendation arises directly from the variability caused by

assumptions made during construction of a composite index, a known limitation of composite indicators. Results should be interpreted in conjunction with a comprehensive literature review. PCFA partitions the total variance of the data structure into primary elements according to correlations among the set of variables (refer to appendix C), the variables in this case being the environmental sustainability performance indicators. In doing so, PCFA produces independent groups of similar indicators; such groupings provide effective policy measures for further analysis. These groupings offer an efficient approach for policy makers to quantify various areas of environmental sustainability performance. Composite indices are useful tools for generally comparing overall performance and for communicating results with the public, but a composite index should always be analysed with other policy subindices and individual indicators. In this way, reasons for a country's performance on the overall composite index become apparent. For example, Canada's poor performance on the environmental sustainability performance composite index is attributable to a poor performance on the waste and pollution subindex, and to a lesser extent poor performance on the sustainable energy policy subindex (refer to fig. 6.1).

2. The results indicate that the normalisation method and scale-effect adjustments decisions are significant sources of variation. Of the three methods the current study examines, excluding either the standardisation or re-scaling method (but retaining the ranking method) produces very similar patterns of variation. The standardisation and re-scaling methods retain more information from the underlying indicator values than does the ranking method. Once an analyst converts values to ranks, the distance between countries is unknown. Both the standardisation and re-scaling methods retain this type of information. In addition to these two methods, the reviewed studies also use three other techniques that retain such information (refer to table 2.2): distance-to-reference country, conversion-to-common unit, and proximity to target. However, each technique has a drawback that limits its applicability in many situations. The distance-to-reference-country technique can produce division-by-zero errors, while converting indicators to a common scale may not be

appropriate, and targets for all indicators are not available. Moreover, the re-scaling method of the current study, which employs a scale derived from the best and worst performing countries, produces easily interpretable results. Thus, the final construction of the current study's composite index employs the re-scaling method. **Rather than using outright ranking, studies should use a normalisation method that retains information from the raw indicator values and is easily interpretable.** Simple interpretation enables and supports communication with policy makers, as well as with a wider lay audience. This portion of the recommendation pertains to the formulation of the individual indicators, so is applicable to any study using performance indicators, even if not aggregated into a composite index.

The reviewed studies choose from among several scale-effect adjustments (refer to table 2.3), the choice of which imparts considerable variation in the final performance ranks. The sensitivity analysis provides no information to help select appropriate scale-effect adjustments; however, the literature review discussing population pressures in chapter 4 does provide some insight. Sources opine that population pressures likely influence environmental degradation more than economic activity, supporting the selection of per capita scale-effect adjustments over ones based on GDP (Ehrlich and Holden 1972; Kates 2000). Moreover, policy makers and other stakeholders understand per capita adjustments more clearly, thus easing communication challenges. **For these reasons, as well as for the connection between population and consumption discussed in chapter 4, certain indicators (for the current study, GHG emissions, sulphur oxides emissions, nitrogen oxides emissions, volatile organic compound emissions, and distance travelled; refer to table** 3.2**) should use the per capita scale-effect adjustments.** This portion of the recommendation pertains to the formulation of the individual indicators, so is applicable to any study using performance indicators, even if not aggregated into a composite index.

To illustrate, consider the debate surrounding carbon intensity targets, which focus on emissions per unit of GDP. One side argues that environmentally degrading impacts will be limited by relating carbon emissions to levels of economic activity, while the other argues that total emissions may continue to grow unabated even though intensities are decreasing. Between 1990 and 2000, the U.S. economy's carbon intensity declined by 17%, however total emissions grew by 14%.[31] Consequently, the level of emissions, rather than the intensity, determines the environmental impact.

In addition to the two decisions that are significant sources of variation, are three that are not: missing data treatment, weights, and aggregation method. While these decisions are non-influential and may be set at any value, several reasons provide support for the specific selections the current study employs. First, unlike the other three methods incorporated into this factor (unconditional mean, regression, and Markov chain Monte Carlo[32] imputation), the average around missing values method for handling missing data does not alter the original data set. Second, other studies frequently use equal weights, which may be the simplest option, particularly since a clearly superior option does not exist. Third, several conditions limit the application of the geometric mean method of aggregation and most other studies use the simple mean approach for aggregating composite indices. Also, the simple mean is an easily understood method for aggregating indices, which, in turn, enables clear communication with policy makers. For these reasons, studies should strongly consider using these methods when facing similar situations. The portion of the recommendation regarding missing data treatment pertains to the formulation of the individual indicators, so is applicable to any study using performance indicators, even if not aggregated into a composite index. However, the portions regarding weights and aggregation pertain to the formulation of the composite index, so are applicable only to studies using such an index.

3. Since the set of environmental indicators appears to induce considerable variation among performance ranks, an analyst should operate from a

[31] Earth Policy Institute website: http://www.earth-policy.org/index.php?/indicators/C52/carbon_emissions_2002; accessed 18 March 2010.

[32] Markov chain Monte Carlo is a sophisticated statistical technique used to estimate missing data. This technique substitutes missing values with ones drawn from a quasi-random distribution that depends on the correlations observed among data sets.

conceptual basis. A conceptual framework in conjunction with empirical results should aid with selection of environmental performance indicators, as well as guide other measurement efforts. For example, the current study employs a modified pressure-state-response framework that helps determine the relevance of various indicators that other studies include in an environmental reporting system (refer to fig. 1.2).

4. Interaction effects induced relatively large amounts of variation in rank distributions. When formulating an environmental reporting system, an analyst should use a sensitivity analysis that is capable of accounting for non-linear, non-additive interactions among decision points encountered when building a composite index. If these effects remain undetected, an analysis loses valuable information, thus increasing levels of uncertainty for policy makers.
5. When missing or incomplete data exclude important indicators, valuable information is lost from the policy analysis. National statistical agencies of the OECD-member countries should reaffirm their commitment to the organisation by ensuring data for environmental compendiums are available in a timely fashion, and kept current. Moreover, the OECD and these national agencies should strive to collect the necessary data to formulate the indicators in table 3.12. More information reduces uncertainty with measurement of environmental sustainability performance thereby strengthening conclusions regarding management actions or policy directions.

These recommendations provide further detail for the monitoring and reporting best practices guidelines (refer to table 1.1) and the indicators and targets management principle discussed in section 1.1 (refer to table 1.2). They illustrate how policy makers should build an environmental reporting system that strives to reduce the effects of uncertainty while providing valuable information supporting national sustainability development efforts. To reiterate, "what gets measured gets managed;" therefore, these recommendations offer refinements on how policy makers may assess environmental sustainability.

FUTURE RESEARCH

Researchers and policy makers need to:

1. investigate how environmental sustainability performance indicators vary among studies, as well as the reasons why the studies used the indicators that they did.
2. The cluster analyses results of the current study indicate that two high performing country clusters achieved their success in different ways, perhaps indicating two different development pathways. While cluster analyses on the Environmental Sustainability Index and Environmental Performance Index seem to suggest that peer groups of countries exist (Esty et al. 2005; Esty et al. 2006). Perhaps formulating performance indicators to reflect peer groups, such as level of development or level of governance (e.g., local, regional, national), would provide better information. The current study focuses on the national level of performance for highly developed countries.
3. identify the barriers that are excluding certain important indicators of important environmental policy areas from a national environmental performance evaluation system (refer to table 3.12).

7.2) HYPOTHESIS #2: SIGNIFICANT INFLUENTIAL FACTORS

The following section details the conclusions and recommendations pertaining to the second hypothesis. First, the discussion centres on the conclusions emerging from the results of the analyses in chapter 5, followed by a discussion of the recommendations arising from them, and an examination of areas for future research. Moreover, results from chapter 6 inform conclusions and recommendations pertaining to Canadian policy implications arising from the influential factors.

CONCLUSIONS

Repeated, for convenience, is the second hypothesis from chapter 1. Next, specific conclusions provide evidence to evaluate its validity.

H_2: Countries' environmental sustainability performances will depend, in part, on influential factors, either ungovernable, semi-governable, or governable.

1. Results suggest that several influential factors do affect OECD countries' environmental sustainability performances to varying degrees. These factors form four groups: major, minor, marginal, and trivial (refer to section 5.4 and fig. 5.4). **The major influential factors—energy prices, environmental governance, economic output—play crucial roles in shaping a country's environmental performance, demonstrating a relatively important affect on a variety of policy measures (environmental sustainability performance composite index (ESPCI), waste and pollution policy subindex (WPPS), sustainable energy policy subindex (SEPS), greenhouse gas (GHG) emissions).**[33] One should remember that the environmental governance factor relies solely on the perceptions of business leaders that may not fully capture the differences in regulatory effectiveness. The analytical results of the current study would probably change if perceptions substantially diverge from the true

[33] Major insights arising from the current study mentioned in the abstract appear in **boldface** type to allow readers to find this information easily.

effectiveness of a jurisdiction's environmental governance. Minor factors—population density, technological development—generally play a lesser role, but each is relatively important to one measure, SEPS and the sustainable cities policy subindex (SCPS) respectively. At the same time, marginal factors—climate, per capita pollution abatement and control (PAC) expenditures—provide some information regarding a country's environmental sustainability performance, but usually only small amounts, and only on one or two measures (SEPS, SCPS). As the name suggests, trivial factors—population growth, industrial structure—are not very important, supplying very limited information. Finally, per capita environmental pricing supplies redundant information.

Each policy measure of environmental performance possesses a different set of influential factors, with one usually emerging as relatively more important. **For the overall index of performance, ESPCI, energy prices are the most important factor, explaining about 37% of the variation (out of about 73% explained by all four factors). Energy prices is also the most important factor for GHG emissions, explaining about 55% out of about 81% accounted for by all three factors. Moreover, it is the only explanatory factor for WPPS, accounting for about 55% of the variation. The energy prices factor also accounts for about 20% of the variation on SEPS, out of the 70% explained by all six factors, making it slightly more important than population density.** Of the two factors important to the sustainable food policy subindex, population density is most important, accounting for about 47% out of the 60% explained by both factors. Finally, technological development appears to be the most important of seven factors for SCPS, explaining about 26% of the total 100% of variance explained; however, both climate (24%) and population density (21%) explain similar amounts of variation.

2. As illustrated by the current study's guiding conceptual framework (fig. 1.2), one may further characterise the emergent major, minor, and marginal influential factors as ungovernable, semi-governable, or governable. An ungovernable factor, one mainly beyond a country's sphere of policy influence, is climate, while semi-governable factors, those over which a government possesses some influence, are population

density, technological development, and economic output. Finally, governable factors, those over which a government has the most influence, are per capita PAC expenditures, environmental governance, and energy prices. Because per capita PAC expenditures account for a relatively small amount of variation on only one measure, environmental governance and energy prices are clearly the more important factors. **Of these two governable factors, results demonstrate that the energy prices factor is much more important to shaping environmental sustainability performance.** Again, the reader is cautioned that the environmental governance factor relies solely on the perceptions of business leaders that may not fully capture the differences in regulatory effectiveness. The conclusions of the current study could change if perceptions substantially diverge from the true effectiveness of a jurisdiction's environmental governance. This factor appears as a statistically significant, at the 95% level of confidence, factor for five out of seven performance measures (ESPCI, WPPS, SEPS, SCPS, and GHG emissions), and it is the most important factor in four out of the five subsets in which it occurs (ESPCI, WPPS, SEPS, and GHG emissions, but not SCPS).

3. Canada's lagging environmental performance mainly arises from a poor showing on WPPS, SEPS, and GHG emissions, thus, environmental governance and energy prices gain additional relevance. A sensitivity analysis (refer to table 6.1) altering Canadian levels of each of these factors illustrates their respective policy relevance to Canada. Marginally increasing levels of environmental governance, from above average to elite levels, produce small performance increases on relevant measures, those policy subindices for which governance is an important factor (ESPCI, SEPS, GHG emissions). On the other hand, substantially increasing energy prices, from among the lowest in the OECD to either the OECD median or the average of the OECD top three highest prices, improves Canada's environmental sustainability performance. Performance improvement is dramatic at the higher energy prices, placing Canada among the top three for those policy subindices for which it is an important factor (ESPCI, WPPS, SEPS, GHG emissions). Moreover, increasing both of these governable factors to the top-three average

pushes Canada into 1st place overall on ESPCI, as well as on SEPS. **Consequently, these results imply that Canadian policy makers should primarily focus on increasing energy prices to secure the largest improvement to environmental sustainability performance as quantified by ESPCI.** Canadian policy makers should have a secondary focus on environmental governance targeting specific lagging components: air pollution, water pollution, toxic waste disposal, and chemical waste (refer to table 6.3).

These discussion points provide much evidence to support the second hypothesis. Clearly, a country's environmental performance depends on several influential factors, notably, economic output, environmental governance, and energy prices. The latter two emerge as relevant governable factors that a government may alter to shape a country's environmental sustainability trajectory, with energy prices in particular coming forward as highly relevant to improving Canada's environmental performance.

RECOMMENDATIONS

Repeated, for convenience, is the second research question from chapter 1. It provides context and guidance for formulating specific recommendations emerging from the conclusions for the second hypothesis.

Q_2: How do influential factors—ungovernable, semi-governable, governable—affect a country's environmental sustainability performance? And, what are potential implications for policy makers?

1. Results indicate that two governable factors, energy prices and environmental governance, emerge as the most important influential factors. The capability of energy prices to affect a country's environmental sustainability is clearly superior to that of environmental governance. However, because the environmental governance factor relies solely on the perceptions of business leaders that may not fully capture the differences in regulatory effectiveness, the recommendations of the current study could change if perceptions substantially diverge from the

true effectiveness of a jurisdiction's environmental governance. Canadian prices for the energy types used in the current study range from about one-half to roughly two-thirds of respective OECD median prices (refer to table 6.2). **Therefore, policy makers have an opportunity to increase energy prices to influence behaviour, subsequently improving Canada's environmental sustainability performance across a variety of policy measures. Increasing energy prices would tend to improve performance on ESPCI, WPPS, GHG emissions, SEPS, and, to a lesser extent, SCPS.**

Policy makers should implement a carbon pricing strategy that increases energy prices (refer to section 6.4). Such a strategy is congruent with the ecological fiscal reform that Canada's national environmental policy group, National Round Table on the Environment and the Economy (NRTEE) recommends (NRTEE 2002; 2005). A strategy to price carbon can be either a carbon tax or a cap-and-trade system, but the likelihood of the United States pursuing a cap-and-trade system may influence Canadian policy maker preferences (NRTEE 2009). However, the key aspect remains placing a price on the environmental damage caused by consuming fossil fuels, thereby sending a more appropriate price signal to the market place and instigating behavioural changes. OECD's most recent environmental performance review for Canada supports this recommendation, as does NRTEE, and an independent review of Canadian environmental policy (OECD 2004; NRTEE 2009; Boyd 2003).

Specific percentage increases to energy prices examined by the current study compare well to those that Canada's National Climate Change Process develop to meet Kyoto targets (NRTEE 2007) (refer to section 6.4). To raise energy prices across energy types to the OECD median and to the OECD top-three average requires a percentage increase of 30% to 100% and 130% to 240% respectively. The National Climate Change Process indicates price increases of 13% to 35% for gasoline, 30% to 75% for household natural gas, and 2% to 84% for electricity. These levels of energy price increases will likely affect the Canadian economy very little, as a recent study suggests that an even steeper carbon price would likely only marginally reduce GDP growth (Rivers and Sawyer 2008). To further ease objections over increasing energy prices, policy makers should provide sufficient time prior to implementation allowing consumers a chance to plan for change. Policy makers should also phase these changes in over several years to provide flexibility to adaptation efforts. Moreover, carbon-pricing strategies should be as revenue neutral to government as possible, with offsetting cuts to such items as income taxes, corporate taxes, and payroll taxes to balance revenue streams.

In addition to funding tax cuts, revenue from a price on carbon could also support emerging alternative energy technologies (refer to section 6.4). Several countries—Sweden, United Kingdom, Denmark—provide examples of carbon and energy taxes used to fund research efforts into non-polluting technologies. Sweden collects U.S.$10 billion from energy taxes, with U.S.$1 billion from a carbon tax, the United Kingdom's Fossil Fuel Levy accrues U.S.$150 million, and Denmark has a gradually increasing carbon tax. Such cash infusions support the burgeoning alternative energy sectors, which, in turn, expand employment opportunities in these sectors. Using this approach, Germany and the United Kingdom have generated tens of thousands of jobs in the wind sector alone. For Canada, a recent study estimates that development of low-impact, renewable electricity could potentially create and sustain through 2020 12,700 to 26,900 jobs (NRTEE 2007).

2. While energy prices may be most influential, environmental governance also produces important effects for environmental sustainability performance. Canadian policy makers should target efforts on increasing the stringency of air pollution regulations, water pollution regulations, toxic waste disposal regulation, and, to a lesser extent, chemical waste regulations. Two recent assessments of Canadian environmental policy provide numerous and detailed recommendations in these policy areas (Boyd 2003; OECD 2004). Again, the environmental governance factor relies solely on the perceptions of business leaders that may not fully capture the differences in regulatory effectiveness and recommendations of the current study could change if perceptions substantially diverge from the true effectiveness of a jurisdiction's environmental governance.

These recommendations provide general guidance for policy makers to alter Canada's current dismal environmental sustainability trajectory. Indeed, if the "what gets measured gets managed" hypothesis is valid, these recommendations provide a basis for developing the management tools to respond to performance measures from an environmental reporting system.

FUTURE RESEARCH

Researchers and policy makers need to:

1. understand better the structure that a Canadian energy pricing mechanism should possess. Needed details include the pricing scheme, particularly initial and final carbon prices, preliminary lead time, phase-in time to final carbon price, and energy types covered. All elements should consider the extent of behavioural change required to achieve environmental sustainability. Furthermore, research should determine the economically efficient and socially beneficial options for shifting taxes from income and production to pollution. Finally, researchers and policy makers need to determine how to co-ordinate the Canadian carbon pricing mechanism with the one under development in the United States.
2. investigate the feasibility of extending Canadian pricing mechanisms to other pollutants, notably sulphur oxides emissions, nitrogen oxides emissions, ozone-depleting substances, volatile organic compounds, and nuclear waste, perhaps investigating the best practices emerging from environmental performance reviews of OECD-member countries.
3. examine OECD best practices for supporting alternative energy development for transference to encourage efforts to de-carbonise the Canadian economy.
4. review OECD best practices for managing and regulating air and water pollution, and toxic and chemical waste disposal for transference to the Canadian legislative and regulatory framework. Indeed, compared to the three best performers in the OECD, these components were relatively less effective in Canada's environmental governance.

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APPENDIX A:
ENVIRONMENTAL SUSTAINABILITY REPORTING SYSTEMS

This appendix reviews the environmental sustainability reporting methodologies used by a variety of studies.[34] It is not possible to review the large number of studies and reporting systems; therefore, this appendix reviews a selection that represents the available range. The 12 selected studies include ones done by international agencies focusing on multiple country assessments because they are most likely to include best practices of member countries. Also included are a number of evaluative frameworks from independent research organisations, as well as several included to reflect the Canadian context of this study. A comparison of the various frameworks provides a list of environmental indicators evaluated for inclusion in the current study in appendix B.

1. OECD Environmental Reporting System (Organisation for Economic Co-operation and Development (OECD) 1995; 2004)
2. *Canada vs. the OECD: an Environmental Comparison* (Boyd 2001)
3. *Alberta Genuine Progress Indicator Accounting (GPI) Project* (Anielski 2001)
4. *GPI Atlantic Natural Resource and Environmental Accounts* (Colman 2001)
5. *Environmental Trends in British Columbia* (B.C. 2002)
6. National Round Table on the Environment and the Economy (NRTEE) Sustainability Indicators Project (NRTEE 2003)
7. David Suzuki Foundation *Sustainability within a Generation* Framework (Boyd 2004)
8. Fraser Basin Council (FBC) *State of the Fraser Basin Report* (FBC 2004)
9. Conference Board of Canada (CBC) *Potential and Performance Review* (CBC 2004)
10. Yale Environmental Performance Index (Esty et al. 2008)
11. Simon Fraser University *Canada's Environmental Performance* (Gunton et al. 2005)
12. World Wide Fund *Living Planet Report* (World Wide Fund (WWF) 2006)

[34] The current research updates this list of indicator frameworks by replacing the Yale Environmental Sustainability Index (Esty et al. 2005) with the most recent Yale Environmental Performance Index (Esty et al. 2008), as well as adding the Gunton et al. (2005) study and a recent WWF *Living Planet Report* (WWF 2006).

A.1) OECD ENVIRONMENTAL REPORTING SYSTEM

The OECD tracks member countries' environmental performances and progress towards sustainable development. The objective of the OECD is to report member countries' environmental performances by using a common framework of environmental indicators. Such indicators help inform the public about key issues of common concern to OECD countries (OECD 2003).

The criteria used by the OECD to choose its indicators include policy relevance, analytical soundness, and measurability. In addition to these criteria, the OECD uses the pressure-state-response model, which highlights cause-and-effect relationships between humans and the environment. In 1985, the OECD started publishing on a biannual basis a compendium summarising environmental indicators for member countries. The OECD regularly updates the indicators as scientific knowledge, policy concerns, and data availability progress (OECD 2003). The OECD also publishes separate reports evaluating the environmental performance for each member country, with two reviews completed for Canada (OECD 1995; 2004). Table A.1 summarises current indicators used by the OECD.

Table A.1: OECD environmental performance review indictors

CATEGORY	INDICATOR	MEASUREMENT
Air Pollution	Sulphur oxides	kg/capita kg/U.S.$1,000 GDP
	Nitrogen oxides	kg/capita kg/U.S.$1,000 GDP
	VOCs	kg/capita
	Carbon monoxide	kg/capita
Agriculture	Pesticide use	Tonnes/km^2 of arable land
	Nitrogenous fertiliser use	Tonnes/km^2 of arable land
	Livestock population	# of sheep equivalents/capita
Surface Water Use	Water consumption	% of gross annual availability Cubic metres/capita
Climate Change	GHG emissions	Tonnes of CO_2 equivalents/capita Tonnes/U.S.$1,000 GDP
Transportation	Road vehicles	#/capita
	Vehicle distance travelled	Vehicle-km/capita
Waste	Public sewage treatment	% of population with sewage treatment
	Municipal waste	kg/capita
	Industrial waste	kg/U.S.$1,000 GDP
	Nuclear waste	kg/capita
	Pollution abatement	PAC expenditures as % of GDP
	Environmental taxes	Revenue as % of GDP
Energy Use	Energy efficiency	toe/U.S.$1,000 GDP toe/capita
	Energy supply source	% by type (oil, gas, nuclear, renewable)
Protected Areas/Forested Areas	Protected area status	% of land base protected
	Forests	% of land area forested Harvest to growth ratio Harvest
	Tropical wood imports	U.S.$/capita
Threatened Species	Mammals	% of known species
	Birds	% of known species
	Fish	% of known species
	Fisheries	% of world catch
Population	Population	% growth
Official Development Assistance	Development assistance	Development assistance as % of Gross National Income

Source: OECD 2004

A.2) CANADA VS. THE OECD: AN ENVIRONMENTAL COMPARISON

Canada vs. the OECD: an Environmental Comparison assesses Canada's environmental track record (Boyd 2001). This study's methodology uses a time-series analysis and a cross-sectional comparison of Canada's environmental performance, using the environmental indicators in table A.2 with data from an OECD Environmental Compendium. The time-series analysis reports the percent change in each indicator over two decades from 1980 to 1999, while the cross-sectional comparison ranks Canada's environmental performance for each indicator relative to other member nations of the OECD for the most recent year. The study ranks OECD countries from best to worst for each indicator with an overall average rank for each country calculated as the arithmetic mean of the country's rank for each of the indicators.

Table A.2: *Canada vs. the OECD* indicators

CATEGORY	INDICATOR	MEASUREMENT
Air Pollution	Sulphur oxides	kg/capita
	Nitrogen oxides	kg/capita
	Volatile organic compounds	kg/capita
	Carbon monoxide	kg/capita
Climate Change	Greenhouse gas emissions	tonnes of CO_2/capita
Water	Water consumption	m^3/capita
	Municipal sewage treatment	% of population served
Energy Use	Energy consumption	toe/capita
	Energy efficiency	toe /$1000 U.S. GDP
Waste	Municipal waste	kg/capita
	Recycling	% of glass and paper recycled
	Hazardous waste	kg/capita
	Nuclear waste	kg/capita
Ozone-Depleting Substances	Consumption of ODS	kg/capita
Agriculture	Pesticide use	tonnes of active ingredients/capita
	Fertiliser use	tonnes/capita
	Livestock	number of cattle, sheep, goats and pigs/capita
Biodiversity	Species at risk	number of species designated as at risk
	Protected areas	% of land designated as protected
	Fisheries	volume caught, kg per capita
	Forests	volume of forest logged, in m^3/capita
Transportation	Road vehicles	number of road vehicles per capita
	Distance travelled	road distance travelled per vehicle
Miscellaneous	Population	% growth in number of people
	Official Development Assistance	% of GDP

Source: Boyd 2001

A.3) ALBERTA GENUINE PROGRESS INDICATOR ACCOUNTING PROJECT

The *Alberta Genuine Progress Indicator Accounting Project* (AGPI), developed by the Pembina Institute's Green Economics team, provides a framework to quantify sustainability. The goal of the AGPI is to provide citizens and decision makers with a comprehensive measure of progress towards achieving economic, social, and environmental sustainability. The AGPI bases its framework (table A.3) on an integration of four indexes: the Genuine Progress Indicator (GPI) developed in the U.S., the Index for Sustainable Economic Welfare, the United Nations Human Development Index, and the Edmonton Social Health Index (Anielski 2001).

The calculation of the AGPI involves three components. First, the GPI provides data on over 50 sustainability and quality of life indicators. Second, the GPI balance sheet records current and historical conditions of all capital assets, liabilities, and net worth and provides this information in physical, qualitative, or monetary terms. Third, a GPI income statement provides a cost-benefit analysis of the economic, social, and environmental indicators compared to GDP. This step results in a GPI estimate of net sustainable income to determine total monetary costs and benefits associated with management or consumption of all forms of capital (Anielski 2001). The research team applied the GPI methodology to Alberta using data from 1961 to 1999.

Table A.3: Alberta GPI indicators

CATEGORY	INDICATOR	MEASUREMENT
Economy	Economic growth	GDP
	Economic diversity	Index where 1.0 represents Alberta's diversity as equal to federal diversity
	Balance of trade	% of total exports contributed by each industry or commodity group
	Real disposable income	CDN$/capita
	Personal consumption expenditures	GDP/capita
	Taxes	CDN$ paid in taxes/capita
	Debt	Total CDN$ value of household, government, business, farm debt/capita
	Savings rate	CND$ savings/capita
	Household infrastructure	CDN$ value of household infrastructure
	Public infrastructure	Net capital stock of public infrastructure
Society	Poverty	% living below low-income cut-off
	Income Inequality	Gini coefficient of income inequality
	Paid work time	# of hours of paid work
	Unemployment rate	# of people unemployed
	Underemployment rate	# of people underemployed
	Parenting and eldercare time	Hrs/person
	Leisure time	Hrs of free time
	Volunteer time	Hrs of unpaid work
	Commuting time	# of registered vehicles
	Family breakdown	# of marriages/divorces
	Crime	# of incidents/100,000 people
	Democracy	% participation of registered voters
	Intellectual/knowledge capital	% of population 15 yrs+ with some level of post secondary education
	Life expectancy	Years
	Infant mortality	# of deaths/1,000 births
	Premature mortality	Person-years of life lost/100,000 people
	Suicide	# of suicides/100,000 people
	Auto crashes	# of people killed/100,000 people
	Substance abuse	% of youth with drug abuse offences
	Gambling	CDN$ spent gambling
	Obesity	Body mass indices

Continued on next page

Table A.3—*Continued*

CATEGORY	INDICATOR	MEASUREMENT
Environment	Ecological footprint	Hectares/capita
	Ecosystem health	Forest fragmentation index
	Parks and Protected Areas	Area protected in km^2
	Energy demand	Primary energy demand/CDN$ millions of GDP
	GHG emissions	Million tonnes of GHG emissions
	Carbon budget deficit	Million tonnes of carbon equivalent
	Non-renewable conventional oil/gas reserve	Closing stock/annual production
	Oilsands reserve life	Closing stock/annual production
	Renewable energy	Not yet determined
	Agriculture sustainability: Irrigation use	# of acres Volume of water/irrigated acre
	Agriculture sustainability: Soil erosion	% of land at risk % of cultivated land
	Agriculture sustainability: Dryland salinity	Extent of average visible salinity in acres
	Agriculture sustainability: Organic soil loss	kg/hectare
	Organic agriculture	# of certified producers
	Timber sustainability	Total growth volume to total depletions ratio
	Wetlands	% lost/remaining
	Peatlands	Tonnes harvested
	Fish & wildlife species' health	Tonnes of commercially harvested fish # of red and blue listed species
	Air quality	% of increased risk of death
	Water quality	% of population with sewage treatment
	Hazardous waste production	Tonnes
	Landfill waste production	Tonnes waste disposed Tonnes waste disposed/capita

Source: Anielski 2001

A.4) THE GPI ATLANTIC NATURAL RESOURCE AND ENVIRONMENTAL ACCOUNTS

Founded in 1997, the *GPI Atlantic Natural Resource and Environmental Accounts* (*GPI Atlantic*) seeks to develop a more comprehensive measure of societal well-being. The *GPI Atlantic* bases its framework on the following four core principles:

- integration of sustainability as an overarching theme,
- utilisation of investment oriented accounting approaches that recognise natural resources as capital assets subject to depreciation and requiring potential re-investment, and
- application of the precautionary principle to economic valuation methods, and recognition of resource accounting and sustainability measures as a first step toward incorporating full cost accounting into existing financial and taxation structures, as well as eventually into market price mechanisms (Colman 2001: 2).

The *GPI Atlantic* links the economy with social and environmental variables to create a more comprehensive measurement tool. The *GPI Atlantic* accounts for the value of human, social, and natural capital in addition to conventional gauges of economic capital. The index also assigns value to assets like population health, educational attainment, community safety, voluntary work, and environmental quality.[35] The *GPI Atlantic* framework has 22 components distributed across five general categories (table A.4).

Application of the *GPI Atlantic* is still in progress. Researchers are completing separate reports on each indicator instead of integrating all information into a single, aggregate number. The final result will be an index consisting of the 22 components applied to a region of Nova Scotia. *GPI Atlantic* intends that the 'full cost accounting' method applied by this pilot project will provide a starting point for future applications at various levels of government.[36]

[35] GPI Atlantic website. www.gpiatlantic.org/; accessed 22 June 2005.
[36] Ibid.

Table A.4: The *GPI Atlantic* indicators

CATEGORY	INDICATOR
Time Use	Economic value of civic and voluntary work Economic value of unpaid housework and child care Work hours Value of leisure time
Natural Capital	Soils and agriculture Forests Marine environment/fisheries Energy
Environmental Quality	GHG emissions Sustainable transportation Ecological footprint analysis Air quality Water quality Solid waste
Socioeconomic	Income distribution Debt, external borrowing, and capital movements Valuations of durability Composite livelihood security index
Social Capital	Population health Educational attainment Costs of crime Human freedom index

Source: GPI Atlantic website. www.gpiatlantic.org/; accessed 22 June 2005.

A.5) *ENVIRONMENTAL TRENDS IN BRITISH COLUMBIA*

The B.C. provincial government began publishing a report summarising environmental trends in 1998, with three reports published to date (B.C. 2002). B.C. reporting of environmental trends revolves around six themes: biodiversity, water, stewardship, human health and the environment, toxic contaminants, and climate change. Each report outlines the status of each indicator for British Columbia, the importance of measuring the indicator, and actions taken to improve the current trend. The environmental trends reports chose indicators based on these criteria: representative, sensitive to environmental change, relevant to public policy, and easy to understand by a non-technical audience (B.C. 2002). The report uses 16 indicators that incorporate 64 separate measurements (table A.5). The report does not aggregate the indicators into a single index to quantify the overall state of environment.

Table A.5: *Environmental trends in British Columbia* 2002 indicators

CATEGORY	INDICATOR	MEASUREMENT
Air Pollution	Particulate matter (PM_{10})	% of communities exposed to health risks from PM_{10} for more than 18 days annually
		% of the time that PM_{10} concentration is greater then 50 ug/m^3
	Ground-level ozone	Average daily 8-hr maximum ozone concentration in parts per billion weighted by population living in affected areas
Other Health and Environmental Indicators	Mercury concentration in fish	Mean mercury concentration in parts per billion wet weight for bull trout and lake trout
	Landscape pesticide use	Tonnes of active ingredient
	Ultraviolet radiation exposure	# of days in each category 1. extreme – 15 min or less to burn 2. high – about 20 min to burn 3. moderate – about 30 min to burn 4. low – more than 1hr to burn
Surface Water Quality	Water quality	Provincial water quality index – # of monitoring stations/category (excellent, good, fair, borderline, poor)
	Stream crossings	#of crossings/km of stream
Surface Water Use	Water allocation restrictions	% of licensed stream length that has water allocation restrictions by decade
	Municipal water use	m^3/capita
Groundwater	Declining groundwater levels	% of observation wells with declining water levels primarily due to human activities
Toxic Contaminants	On-site toxic substance releases	Tonnes
	Absorbable organic halides discharged in pulp and paper effluent	Tonnes/day
Persistent Chemicals	Organochlorines	Concentration in mg/kg of organochlorines in great blue heron eggs
	Dioxins and furans	Parts per trillion in harbour seals
		Average combined Dixon and Furan levels in digestive gland of Dungeness crab toxic equivalents (picograms/gram)
	PCBs	Parts per million in harbour seals
Climate Change	GHG emissions	Tonnes CO_2 equivalent/capita
	Temperature change	Change in ambient average temperature over the last century
	Fraser River annual flow	Date of one-third of Fraser River annual flow
	Fraser River temperature	Average Fraser River temperature
Transportation	Total vehicles	# of vehicles sold
	Road vehicles	#/capita

Continued on next page

Table A.5—*Continued*

CATEGORY	INDICATOR	MEASUREMENT
Waste	Sewage treatment	% of population with secondary or tertiary wastewater treatment plants (%)
	Mining waste	# Metal leaching/acid rock drainage mine sites
	Municipal solid waste	Municipal per capita solid waste disposal and recycling rates
	Waste oil	Waste oil re-refined
	Lead acid batteries	# of lead acid battery units recycled
Energy Use	Conventional energy consumption	Conventional energy consumption
	Conventional energy intensity	Consumption/GDP
Linking Environment and Economy	Organic farming	# of certified organic producers and processors
	Provincial park revenue	GDP generated by provincial parks
	Environment industry employment	# of positions
Protected Areas/ Forest Areas	Protected areas	% of land base protected
	Protected ecosections	% of ecosections protected
	Size of protected areas	# of protected areas by size in hectares
	Forest protected areas	% of total provincial forested area)
	High-elevation forest	% of total high-elevation forested area
	Low-elevation forest	% of total low-elevation forested area
Species at Risk	Red-listed species	% of known species that are threatened or endangered, or are candidates for such designations
	Red- and blue-listed species	# of red and blue listed species in each ecological region
Habitat	Road density	km of road/km^2 of watershed area
	Coastal estuary use	Area licensed or managed for conservation use
Fisheries	Steel head conservation risk	Categorised as healthy, conservation concern, extreme conservation concern, or no steelhead
	Bulltrout conservation risk	Categorised as presumed healthy, conservation risk unknown, presumed conservation risk, or no historical presence
	White sturgeon age distribution	% of juveniles, sub-adults, and adults

Source: B.C. 2002

A.6) NATIONAL ROUND TABLE ON THE ENVIRONMENT AND THE ECONOMY

National Round Table on the Environment and the Economy (NRTEE) created the Environmental Sustainable Development Initiative (ESDI), a three-year multi-stakeholder program to develop sustainability indicators for Canada. The purpose of the indicators is to gauge Canada's progress toward achieving sustainability (NRTEE 2003). Establishing a framework based on the concept of economic capital linked to current macroeconomic indicators with proposed new indicators. The rationale for this framework is that types of capital not normally included in economic accounts, such as environmental assets that provide quality-of-life 'services,' are as important to the future economy as more traditional forms of capital, such as factories and machinery.

A 30-member steering committee that included non-governmental organisations, academics, government officials, business, and financial organisations developed the indicators. The steering committee also worked closely with Statistics Canada and Environment Canada. Criteria used to evaluate alternative indicators included: transparency, clarity, scientifically credibility, and understandability by a non-technical audience (NRTEE 2003). Based on its analysis, the ESDI steering committee recommended six indicators (table A.6). Moreover, the ESDI steering committee assessed the possibility of creating a single composite index by aggregating these indicators, but rejected the creation of a single index because the separate indicators used measurement units for capital that are not comparable, nor combinable into a single measure (NRTEE 2003).

Table A.6: National Round Table on the Environment and the Economy indicators

CATEGORY	INDICATOR	MEASUREMENT
Air Quality	Ground-level ozone	Average daily 8-hr maximum ozone concentration in parts per billion weighted by population living in affected areas
Fresh Water Quality	Water quality	Provincial water quality index – # of monitoring stations/category (excellent, good, fair, borderline, poor)
GHG Emissions	GHG emissions	All GHG (CO_2, CH_4, N_2O) sources in tonnes CO_2 equivalents
Forest Cover	Crown closure	Changes in area with a crown closure of greater than 10%
Extent of Wetlands	Wetlands	% area of wetlands over time
Human Capital	Educational attainment	% of the population between the ages of 25 and 64 that has gained upper-secondary and tertiary-level educational qualifications

Source: NRTEE 2003

A.7) SUSTAINABILITY WITHIN A GENERATION

The David Suzuki Foundation commissioned the report, *Sustainability within a Generation* (Boyd 2004), to provide a policy framework for achieving sustainability in Canada. The report includes a vision statement, goals, and specific policy recommendations to achieve a sustainable future. The primary objective of the report is to outline a plan to achieve sustainability and increase genuine wealth for Canadians. For each of the goals, the report presents the Canadian context of the problem and sets targets and timelines to achieve sustainability within a generation. Interim objectives allow Canadian's to monitor progress toward the goals.

The path to sustainability outlined in the report revolves around the nine goals in table A.7. Assessing progress in meeting these goals involves measuring specific environmental indicators; however, the report references potential indicators but does not provide a comprehensive set of indicators to quantify sustainability.

Table A.7: *Sustainability within a Generation* goals and potential indicators

GOAL	POTENTIAL INDICATOR
Genuine Wealth Index	Genuine wealth indicator
Improving Efficiency	Energy consumption Water consumption Material consumption
Shifting to Clean Energy	GHG emissions Low-impact, renewable energy
Reducing Waste and Pollution	Toxic substances/hazardous waste Nitrogen oxides emissions Sulphur oxides emissions Recycling Municipal waste Ozone depleting substances Nuclear waste
Protecting Water Quality	Water quantity Water quality Drinking water Waste water treatment
Producing Healthy Food	Organic agriculture Pesticide use Fertiliser use
Conserving and Protecting Nature	Terrestrial protected areas Marine protected areas Fisheries Forestry Ecosystem-based management Species at risk
Building Sustainable Cities	Green infrastructure funding Public transit use Loss of agricultural land
Promoting Global Sustainability	Official development assistance

Source: Boyd 2004

A.8) 2004 *STATE OF THE FRASER BASIN REPORT*

The vision of the Fraser Basin Council (FBC) is to build a community where "social well-being is supported by a vibrant economy and sustained by a healthy environment" (FBC 2004: 1). FBC works with stakeholders from the basin, including community groups, government, First Nations, business, academics, and labour groups. As part of their mandate, FBC assesses progress toward sustainability in the Fraser Basin and publishes results in an annual report (FBC 2004).

FBC developed the indicators it uses in consultation with government, the private sector, and community groups. FBC uses 17 indicators to assess social, economic, and environmental aspects of life in the Fraser Basin (table A.8). The annual assessment provides a link between each indicator and sustainability, along with relevant data outlining status and trends.

Table A.8: Fraser Basin sustainability indicators

CATEGORY	INDICATOR	MEASUREMENT
Aboriginal and Non-Aboriginal Relations	State of relations	% of responses by category (getting better, no change, getting worse, don't know)
	Level of satisfaction	% of responses by category (very satisfied, neutral, dissatisfied/very dissatisfied, too early to say, no response)
	Treaty process	# of First Nations at different stages of treaty process
	Benefits and challenges of agreements	Not available – indicator information not included in report
Agriculture	Productive land	% change
	Farm income	Net farm income in Fraser Basin ($)
	Soil conservation	% of farms reporting soil conservation practices
	Agricultural land reserve	Change in area protected by Agricultural Land Reserve
Air Quality	Particulate matter (PM_{10})	% of time PM_{10} > 50 $\mu g/m^3$
	$PM_{2.5}$ trends	$\mu g/m^3$
	Ozone trends	Parts per billion
Business and Sustainability	Corporate donors	% of companies surveyed that contributed to either the IMAGINE Campaign or the Matching Gift Campaign
	Real R&D spending to GDP	% of R&D spending
	Environmental industry	# of businesses
		# of people employed
Community Engagement	Volunteerism and charitable giving	% of population that has volunteered
	Sense of belonging within local community	% of responses by category (very strong, somewhat strong, somewhat weak, very weak, not stated)
	LRMP survey	% of responses that agree/disagree with set of questions
	Confidence in public institutions	Not available – indicator information not included in report
Community Sustainability	Population	% change in population
	Waste disposal	kg per capita waste disposed
Economic Diversification	Economic Indicators	Average % growth of six indicators (employment, sales, manufacturing shipments, international visitors, non-residential building permits, housing)
	Diversity Index	No unit of measurement
Education	Educational attainment	# of people/level of education
	Student-teacher ratios	% change in ratios
	Apprenticeship enrolment	# of students enrolled
	Adult training	# of adults in training

Continued on next page

Table A.8—*Continued*

CATEGORY	INDICATOR	MEASUREMENT
Energy and Climate Change	Energy use	% use by sector (community/institution/public, residential, total industrial, agricultural, transportation)
	Energy efficiency	% change
	Energy consumption	% by source (hydroelectricity, biomass, natural gas, petroleum)
	Growth in energy use	% change by source (petroleum, natural gas, hydroelectricity, biomass, coal and coke)
	GHG emissions	% by source (waste, agricultural and land use, fugitive emissions, industry, commercial and industrial, residential, transportation)
	Green energy	% by source (wind, biogas and sewage gas, solar photovoltatics, low-impact hydro)
Fish and Wildlife	Escapement	# valid escapement observations
	Chinook run	% of Chinook runs with increased escapement
	Sockeye run	% of sockeye runs showing increasing escapement
	Red- and Blue-listed species	% of known species
	Red- and Blue-listed species by region	# per region
Flood Hazard Management	Population	# of people and buildings located in the flood plain
Forests and Forestry	Ratio of area reforested	No unit of measurement
	Cumulative area certified	# of hectares
	Mountain pine beetle	# of affected hectares
	Forest vulnerability index	No unit of measurement
	Softwood lumber exported	Not available – indicator information not included in report
	Forest health	Not available – indicator information not included in report
Health	Life expectancy	Years
	Low weight births	% by region
	Self-rated health	% of responses by category (poor, fair, good, very good, excellent)
	Age standardized mortality rate	Not available – indicator information not included in report
	Change in age standardized mortality rate	Not available – indicator information not included in report
	Leisure time – physical activity	Not available – indicator information not included in report
Housing	Core housing need	%
	Vacancy	% vacant: apartment/row houses and urban/rural
	Tenure	Ownership/renter

Continued on next page

Table A.8—*Continued*

CATEGORY	INDICATOR	MEASUREMENT
Income and Employment	Household income	Average household income
	Income distribution	% of population by household income
	Employment rate	Employment rates by region
	Unemployment rates	Unemployment rates by region
Population	Age distribution	% of Fraser Basin population by age
	Mobility	# of migrants to the region
	Ethnicity	% of population by ethnic origin
	Aboriginal population	# of people
Water Quality and Quantity	Water use	% of total water use by sector)
	Water flow	Average flow in m^3/day
	Water quality	% of samples that achieve of water quality objectives
	Water quality	% of time water quality objectives are met

Source: FBC 2004

A.9) CONFERENCE BOARD OF CANADA: PERFORMANCE AND POTENTIAL STUDIES

Since 1999, Conference Board of Canada (CBC) publishes an annual report evaluating Canada's economic, social, and environmental performance relative to other OECD countries. The evaluation reports on 24 of 30 OECD countries, excluding five OECD countries from the analysis (Czech Republic, Hungary, Poland, Slovak Republic, and Turkey) because of lack of reliable data, and excluding Luxembourg due to its economic union with Belgium (CBC 2004). The CBC study uses 110 indicators organised into six categories: economy, innovation, environment, education and skills, health, and society, with 24 indicators in the environmental category (table A.9). CBC uses the following three criteria to determine which indicators to analyse (CBC 2004: 16).

1. Is there a general agreement that a movement in the indicator in one direction is better than in the other?
2. Are the data available for most of the countries?
3. Are the data comparable across countries?

Table A.9: Conference Board of Canada environmental indicators

CATEGORY	INDICATOR
Air Quality	Urban sulphur dioxide concentration Urban nitrogen dioxide concentration Urban particulate matter
Water Quality	Freshwater phosphorous concentration Freshwater suspended solids
Biodiversity	Threatened species – mammals Threatened species – birds Threatened species – fish Major protected areas - % of land base
Climate Change	Absolute greenhouse gas emissions Carbon dioxide emissions per capita Carbon dioxide emissions per unit of GDP
Air	Sulphur dioxide emissions per populated land area Nitrogen oxides emissions per populated land area Volatile organic compounds emissions per populated land area
Water	Nitrogenous fertiliser use Industrial organic pollutants % of country under severe water stress Internal renewable water per capita
Waste	Hazardous waste production per unit of GDP Municipal waste generated per capita Pesticide use per km^2 of arable land
Governance	Stringency of environmental regulations Quality of environmental governance

Source: CBC 2004

A.10) YALE ENVIRONMENTAL PERFORMANCE INDEX

The Yale Environmental Performance Index (EPI), incorporating 149 countries (including 29 OECD-member countries), centres on two broad environmental protection objectives: (1) reducing environmental stresses on human health, and (2) promoting ecosystem vitality and sound natural resource management (Esty et al. 2008). EPI gauges environmental health and ecosystem vitality by tracking 25 indicators in six policy categories: environmental health, air quality, water resources, natural resources, biodiversity and habitat, and climate change (table A.10). The selection process for the 25 indicators incorporates a broad-based review of the environmental policy literature, the policy consensus emerging from the Millennium Development Goal dialogue, the evidence from the Intergovernmental Panel on Climate Change and the Global Environmental outlook 4, and expert judgment.

Table A.10: Environmental Performance Index policy categories, indicators, and measures

POLICY CATEGORIES	INDICATORS	MEASUREMENT
Environmental Health	Environmental burden of disease	Years of life lost per 1,000 population
	Adequate sanitation	Percentage of population
	Drinking water	Percentage of population
	Indoor air pollution	Percentage of population using solid fuels
	Urban particulates	Micrograms/cubic metre
	Local ozone	Exceedance person ppb per capita
Air Pollution	Regional ozone	Exceedance square-kilometre-hours/square kilometre
	Sulphur dioxide emissions	Tonnes
Water	Water quality index	Proximity-to-Target
	Water stress	Percentage of national territory with water withdrawals exceeding 40% of available supply
Biodiversity and Habitat	Conservation risk index	Ratio
	Effective conservation	Percentage of territory
	Critical habitat protection	Percentage of territory
	Marine protected areas	Percentage of EEZ
Productive Natural Resources	Growing stock	cubic metres/hectare
	Marine trophic index	Slope of trend line
	Trawling intensity	Percentage of EEZ
	Irrigation stress	Percentage of irrigated area that is in water stressed areas
	Agriculture subsidies	Proximity-to-target, with 100 being the target, and 0 being the worst performer
	Intensive cropland	Percentage of cropland area that is in agriculture-dominated landscapes
	Burnt land area	Percentage of territory
	Pesticide regulation	22 point scale, with 0 representing the lowest score, and 22 the highest
Climate Change	Emissions/capita	Tonnes CO_2 equivalent/person
	Emissions/electricity generated	g CO_2/kWh
	Industrial carbon intensity	CO_2/\$1000 (U.S.D 1995 PPP)

Source: Esty et al. 2008

A.11) SIMON FRASER UNIVERSITY CANADA'S ENVIRONMENTAL PERFORMANCE

The Sustainable Planning Research Group with the School of Resource and Environmental Management at Simon Fraser University conducted this study (Gunton et al. 2005). To assess Canada's progress relative to other OECD-member countries, this study develops and applies an environmental sustainability reporting system, consisting of 29 indicators and two ranking systems. This study reviews the following 10 methodologies to compile a list of environmental indicators.

1. *OECD Environmental Performance Reviews for Canada* (OECD 1995; 2004)
2. *Canada vs. the OECD: an Environmental Comparison* (Boyd 2001)
3. *Alberta Genuine Progress Indicator Accounting (GPI) Project* (Anielski 2001)
4. *GPI Atlantic Natural Resource and Environmental Accounts* (Colman 2001)
5. *Environmental Trends in British Columbia* (B.C. 2002)
6. National Round Table on the Environment and the Economy (NRTEE) Sustainability Indicators Project (NRTEE 2003)
7. David Suzuki Foundation *Sustainability within a Generation* Framework (Boyd 2004)
8. Fraser Basin Council (FBC) *State of the Fraser Basin Report* (FBC 2004)
9. Conference Board of Canada (CBC) *Potential and Performance Review* (CBC 2004)
10. Yale Environmental Sustainability Index (Esty et al. 2005)

Next, this study evaluates the environmental indicators based on the four criteria listed below and selects 37 indicators, 29 of which have OECD data available for international comparisons (table A.11).

1. The indicator must provide a meaningful gauge of environmental sustainability.
2. The indicator must be generally understandable for a non-technical audience.
3. The data required for the indicator must be reliable and available in a timely fashion, as well as produced on a regular basis using consistent definitions for OECD countries.
4. The indicator should not directly replicate other indicators.

Table A.11: Simon Fraser University *Canada's Environmental Assessment* indicators

CHALLENGE	INDICATOR	MEASUREMENT
Environmental Efficiency	Energy consumption	toe per capita
	Energy intensity	toe/ U.S.$1,000 GDP
	Water consumption	Cubic metres of water consumption per capita
	Environmental pricing	% of GDP
Clean Energy	Greenhouse gas emissions	Tonnes CO_2 equivalent emissions per capita
	Electricity from renewable resources (w/ hydro)	% electricity from renewable resources (w/ hydro)
	Electricity from renewable resources (w/out hydro)	% electricity from renewable resources (w/out hydro)
Waste and Pollution	Sulphur oxides	Kilograms sulphur oxides emitted per capita
	Nitrogen oxides	Kilograms nitrogen oxides emitted per capita
	Volatile organic compounds	Kilograms volatile organic compounds emitted per capita
	Carbon monoxide	Kilograms carbon monoxide emitted per capita
	Ozone-depleting substances	Kilograms ozone-depleting substances emitted per capita
	Municipal waste	Kilograms municipal waste generated per capita
	Recycling	% material recycled from municipal waste
	Nuclear waste	Kilograms nuclear waste per capita
	PAC expenditures	% of GDP
Water Quality	Municipal sewage treatment	% population with sewage treatment
Healthy Food	Pesticide use	Tonnes pesticide used per square kilometre of arable land
	Fertiliser use	Tonnes fertiliser used per square kilometre of arable land
	Livestock	Sheep equivalents per square kilometre of arable and grassland
Nature Conservation	Number species at risk	Number species at risk
	% species at risk	% known species at risk
	Protected areas	% land designated as protected
	Forest harvested	Cubic metres timber harvested per square kilometre forestland
	Forest harvest to growth ratio	Timber harvested to forest growth ratio
	Per capita capture fishery	Kilograms per capita
	Fisheries harvest to world harvest	% world catch
Sustainable Cities	Distance travelled	Thousand vehicle-kilometres travelled per capita
Global Sustainability	Official development assistance	% of Gross National Income

Source: Gunton et al. 2005

A.12) WORLD WIDE FUND *LIVING PLANET REPORT*

WWF began its Living Planet Reports in 1998 to show the state of the natural world and the impact of human activity upon it. This report relies primarily on five indicators (table A.12) selected for ecological reasons. The Living Planet Index tracks the health of 1,313 vertebrate species from around the world as a composite index created from three separate indices that track trends in populations of 695 terrestrial species, 274 marine species, and 344 freshwater species. The Ecological Footprint demonstrates the extent of the demand human consumption exerts on these ecosystems. The Ecological Footprint analysis of this study encompasses 147 countries, including 28 OECD-member countries. The *Living Planet Report* includes freshwater consumption as a separate indicator due to comparability issues.

Table A.12: World Wide Fund *Living Planet Report* indicators

INDICATOR	MEASURE
Terrestrial species	% population of terrestrial species
Marine species	% population of marine species
Freshwater species	% population of freshwater species
Ecological footprint	Ecological footprint per capita
Water withdrawals	Withdrawals to availability ratio

Source: WWF 2006

APPENDIX B:
INDICATOR SELECTION MATRIX[37]

The assessment contained in the following table uses five criteria to determine which indicators compiled from appendix A are suitable for inclusion in the environmental indicator framework. This study only includes indicators that satisfy all five criteria; thus, once an indicator fails to satisfy one criterion it warrants no further consideration. The assessment applies the criteria in order from left to right, starting with the Relevance criterion.

1. **Relevance:** Does the proposed indicator capture a pertinent aspect of environmental sustainability?
2. **Measurability:** Is the phenomenon being appraised by the proposed indicator able to be reliably quantified with current techniques?
3. **Relationship:** Does the proposed indicator exhibit any a strong relationship or overlap with other indicators?
4. **Soundness:** Is the underlying data for the proposed indicator obtained with established and accepted methods?
5. **Coverage:** Do underlying data sources for the proposed indicator provide sufficient spatial coverage of the Organisation for Economic Co-operation and Development (OECD) countries for inclusion in the study?

The conceptual framework presented by figure 1.2 helps with determining the relevance of an indicator.

[37] This evaluation identifies 26 of the 29 performance indicators that Gunton et al (2005) used. Though one of the indicator frameworks uses them, environmental pricing, pollution abatement and control expenditures, and official development assistance have been removed from the compiled list. The current study recasts the first two indicators as factors and removes the third entirely. Refer to section 1.2, Environmental Sustainability Performance Indicators heading.

INDICATOR	RELEVANCE[1]	MEASURABILITY[2]	RELATIONSHIP[3]	SOUNDNESS[4]	COVERAGE[5]
Energy consumption	✓	✓	✓	✓	✓
Energy intensity	✓	✓	✓	✓	✓
Water consumption	✓	✓	✓	✓	✓
GHG emissions	✓	✓	✓	✓	✓
Renewable electricity w/ hydro	✓	✓	✓	✓	✓
Renewable electricity w/out hydro	✓	✓	✓	✓	✓
Sulphur oxides emissions	✓	✓	✓	✓	✓
Nitrogen oxides emissions	✓	✓	✓	✓	✓
VOC (non-methane) emissions	✓	✓	✓	✓	✓
Carbon monoxide emissions	✓	✓	✓	✓	✓
Ozone-depleting substances emissions	✓	✓	✓	✓	✓
Municipal waste	✓	✓	✓	✓	✓
Recycling of municipal waste	✓	✓	✓	✓	✓
Nuclear waste	✓	✓	✓	✓	✓
Municipal sewage treatment	✓	✓	✓	✓	✓
Pesticide use	✓	✓	✓	✓	✓
Fertiliser use	✓	✓	✓	✓	✓
Livestock	✓	✓	✓	✓	✓
Number of species at risk	✓	✓	✓	✓	✓
Percent of species at risk	✓	✓	✓	✓	✓
Protected areas	✓	✓	✓	✓	✓
Timber harvest	✓	✓	✓	✓	✓
Timber harvest/forest growth ratio	✓	✓	✓	✓	✓
Fisheries as % world catch	✓	✓	✓	✓	✓
Fisheries	✓	✓	✓	✓	✓
Distance travelled	✓	✓	✓	✓	✓

1 Does the proposed indicator capture a pertinent aspect of environmental sustainability?
2 Is the phenomenon being appraised by the proposed indicator able to be reliably quantified with current techniques?
3 Does the proposed indicator exhibit any a strong relationship or overlap with other indicators?
4 Is the underlying data for the proposed indicator obtained with established and accepted methods?
5 Do underlying data sources for the proposed indicator provide sufficient spatial coverage of OECD countries for inclusion in the study?

INDICATOR	RELEVANCE[1]	MEASURABILITY[2]	RELATIONSHIP[3]	SOUNDNESS[4]	COVERAGE[5]
Genuine Wealth Index	✓	✓	✓	✓	✗
Hazardous waste	✓	✓	✓	✓	✗
Particulate matter emissions	✓	✓	✓	✓	✗
Ecosystem-based management	✓	✓	✓	✓	✗
Organic agriculture	✓	✓	✓	✓	✗
Public transit	✓	✓	✓	✓	✗
Green infrastructure funding	✓	✓	✓	✓	✗
Loss of agricultural land	✓	✓	✓	✓	✗
Ecological footprint	✓	✓	✓	✗	
Carbon budget deficit	✓	✓	✓	✗	
Wetlands	✓	✓	✓	✗	
Mercury concentration in fish	✓	✓	✓	✗	
Stream crossings	✓	✓	✓	✗	
Water allocation restrictions	✓	✓	✓	✗	
On-site toxic substance releases	✓	✓	✓	✗	
Temperature change	✓	✓	✓	✗	
Forest protected areas	✓	✓	✓	✗	
Soil conservation	✓	✓	✓	✗	
Escapement	✓	✓	✓	✗	
Ratio of area reforested	✓	✓	✓	✗	
Water quality	✓	✓	✓	✗	
Water quality index	✓	✓	✓	✗	
Marine trophic index	✓	✓	✓	✗	
Trawling intensity	✓	✓	✓	✗	
Marine protected area	✓	✓	✓	✗	
Intensive cropland	✓	✓	✓	✗	

1 Does the proposed indicator capture a pertinent aspect of environmental sustainability?
2 Is the phenomenon being appraised by the proposed indicator able to be reliably quantified with current techniques?
3 Does the proposed indicator exhibit any a strong relationship or overlap with other indicators?
4 Is the underlying data for the proposed indicator obtained with established and accepted methods?
5 Do underlying data sources for the proposed indicator provide sufficient spatial coverage of OECD countries for inclusion in the study?

INDICATOR	RELEVANCE[1]	MEASURABILITY[2]	RELATIONSHIP[3]	SOUNDNESS[4]	COVERAGE[5]
Number of road vehicles	✓	✓	✗		
Conservation risk index	✓	✓	✗		
Effective conservation	✓	✓	✗		
Critical habitat protection	✓	✓	✗		
Forest growing stock	✓	✓	✗		
Pesticide regulation	✓	✓	✗		
Energy supply source	✓	✓	✗		
Non-renewable conventional oil/gas reserve	✓	✓	✗		
Peatlands	✓	✓	✗		
Air quality	✓	✓	✗		
Declining groundwater levels	✓	✓	✗		
Conventional energy consumption	✓	✓	✗		
Conventional energy intensity	✓	✓	✗		
Size of protected areas	✓	✓	✗		
Energy use	✓	✓	✗		
Energy efficiency	✓	✓	✗		
Growth in energy use	✓	✓	✗		
Water stress	✓	✗			
Internal renewable water per capita	✓	✗			
Biodiversity	✓	✗			
Regional ozone	✓	✗			
Ecosystem health	✓	✗			
Ground-level ozone	✓	✗			
Ultraviolet radiation exposure	✓	✗			
Waste oil	✓	✗			
Lead acid batteries	✓	✗			

1 Does the proposed indicator capture a pertinent aspect of environmental sustainability?
2 Is the phenomenon being appraised by the proposed indicator able to be reliably quantified with current techniques?
3 Does the proposed indicator exhibit any a strong relationship or overlap with other indicators?
4 Is the underlying data for the proposed indicator obtained with established and accepted methods?
5 Do underlying data sources for the proposed indicator provide sufficient spatial coverage of OECD countries for inclusion in the study?

INDICATOR	RELEVANCE[1]	MEASURABILITY[2]	RELATIONSHIP[3]	SOUNDNESS[4]	COVERAGE[5]
High-elevation forest	✓	✗			
Low-elevation forest	✓	✗			
Forest vulnerability index	✓	✗			
Material consumption	✓	✗			
Environmental pricing	✗				
PAC expenditures	✗				
Official development assistance	✗				
Population growth	✗				
Stringency of environmental regulations	✗				
Quality of environmental governance	✗				
% of households using solid fuels	✗				
Agricultural subsidies	✗				
Burnt land area	✗				
Drinking water	✗				
Environmental burden of disease	✗				
Tropical wood imports	✗				
Economic growth	✗				
Economic diversity	✗				
Balance of trade	✗				
Real disposable income	✗				
Personal consumption expenditures	✗				
Taxes	✗				
Debt	✗				
Savings rate	✗				
Household infrastructure	✗				
Public infrastructure	✗				

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INDICATOR	RELEVANCE[1]	MEASURABILITY[2]	RELATIONSHIP[3]	SOUNDNESS[4]	COVERAGE[5]
Poverty	✖				
Income inequality	✖				
Paid work time	✖				
Unemployment rate	✖				
Underemployment rate	✖				
Parenting and eldercare time	✖				
Leisure time	✖				
Volunteer time	✖				
Commuting time	✖				
Family breakdown	✖				
Crime	✖				
Democracy	✖				
Intellectual/knowledge capital	✖				
Life expectancy	✖				
Infant mortality	✖				
Premature mortality	✖				
Suicide	✖				
Auto crashes	✖				
Substance abuse	✖				
Gambling	✖				
Obesity	✖				
Oilsands reserve life	✖				
Agriculture sustainability: irrigation use	✖				
Economic value of unpaid housework	✖				
Debt, borrowing, and capital movements	✖				
Valuations of durability	✖				

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INDICATOR	RELEVANCE[1]	MEASURABILITY[2]	RELATIONSHIP[3]	SOUNDNESS[4]	COVERAGE[5]
Composite livelihood security index	✖				
Population health	✖				
Human freedom index	✖				
Absorbable organic halides discharged	✖				
Organochlorines	✖				
Dioxins and furans	✖				
PCBs	✖				
Fraser River annual flow	✖				
Fraser River temperature	✖				
Mining waste	✖				
Provincial park revenue	✖				
Environment industry employment	✖				
Road density	✖				
Coastal estuary use	✖				
Steel head conservation risk	✖				
Bulltrout conservation risk	✖				
White sturgeon age distribution	✖				
Aboriginal and non-Aboriginal relations	✖				
Productive land	✖				
Farm income	✖				
Corporate donors	✖				
Real R&D spending to GDP	✖				
Environmental industry	✖				
Sense of belonging within local community	✖				
LRMP survey	✖				
Confidence in public institutions	✖				

1 Does the proposed indicator capture a pertinent aspect of environmental sustainability?
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INDICATOR	RELEVANCE[1]	MEASURABILITY[2]	RELATIONSHIP[3]	SOUNDNESS[4]	COVERAGE[5]
Student-teacher ratios	✖				
Apprenticeship enrolment	✖				
Adult training	✖				
Chinook run	✖				
Sockeye run	✖				
Flood hazard management	✖				
Mountain pine beetle	✖				
Softwood lumber exported	✖				
Low weight births	✖				
Self-rated health	✖				
Age standardized mortality rate	✖				
Change in age standardized mortality rate	✖				
Core housing need	✖				
Vacancy	✖				
Tenure	✖				
Household income	✖				
Income distribution	✖				
Population	✖				
Water flow	✖				

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APPENDIX C:
METHODOLOGIES

This appendix provides further information regarding several methods that this research utilises. Specifically, appendix C details complex calculations, discusses necessary statistical assumptions, and reviews general methodology of the following techniques.

1. Principal components factor analysis
2. Regression analyses
3. Akaike's Information Criterion
4. The concept of suppression
5. Cluster analysis

C.1) PRINCIPAL COMPONENTS FACTOR ANALYSIS

Principal components analysis (PCA) parsimoniously partitions the total variance of the data structure into primary elements, thus defining the underlying dimensionality of the variable set (Stevens 2002; Bryant and Yarnold 1995). One extracts principal components from the sample correlation or covariance matrix as linear combinations of the original variables such that the number required to explain the data's observed variation is minimised. An analyst should use correlation matrices when the scales of the variables are not commensurable, but may use covariance matrices when the scales are similar. If variable scales are not commensurate, some variables may exert an undue influence on the formation of the principal components. Formally referred to as eigenvectors, the linear combinations specify how the variables load onto the components, with the variance they explain known as eigenvalues. The first principal component accounts for the largest amount of variance; therefore, it has the largest eigenvalue and no other linear combination of the variables explains a greater portion of the variation. Ensuing eigenvectors explain successively lower levels of variation and, as such, their eigenvalues diminish. Moreover, these eigenvectors are uncorrelated with and independent of each other and, therefore, are orthogonal; each component explains unique variation not captured by other linear combinations. The number of eigenvectors that explains all the variance is the rank, or true dimensionality, of the variable set.

Once a minimum number of components explains the total variance using PCA, a method referred to as principal components factor analysis (PCFA) helps with determining how many components to retain and with interpreting the nature of the retained components. Essentially, PCA extracts the components, while factor analysis determines the number to retain as well as characterises them. Two common stopping rules for deciding how many eigenvectors to retain are (Stevens 2002; Bryant and Yarnold 1995): Kaiser's (1960) stopping criterion and the scree test (Cattell 1966). When one uses a correlation matrix, Kaiser's stopping rule extracts all eigenvectors with eigenvalues of at least one. The scree test is a graphical procedure in which one plots eigenvalues successively against the component number, retaining eigenvalues, as well as their corresponding eigenvectors, in the steep part of the curve while excluding those eigenvalues at the transition and in the gradually descending curve. Stevens (2002: 390) and

Bryant and Yarnold (1995: 128) recommend using Kiaser's rule in situations with fewer than 30 variables, and when commonalities, which indicate the variance that variables have in common, are greater than 0.7.

Next, retained components require interpretation. In a best-case scenario, each component has a few variables with high factor-load coefficients while the rest of the variables have low coefficients. In such a situation, a component clearly assesses the attributes of the highly loaded variables; however, in most cases, identified eigenvectors are very difficult to interpret due to complex patterns of factor-load coefficients. A technique known as rotation may increase interpretability. Two of the most frequently used rotations are the quartimax and the varimax procedures (Bryant and Yarnold 1995). The quartimax rotation focuses on loading each variable mainly onto one component, but this approach tends to load most variables onto one component, rendering interpretation difficult (Stevens 2002). On the other hand, the varimax rotation tends to produce components with several highly loaded variables, while the rest of the variables are minimally loaded, thus, aiding interpretation of the resulting component.

A factor-load coefficient used to interpret a component should be statistically significant (Stevens 2002: 393). Usually, an analyst compares the coefficient values with the calculated standard error of a correlation coefficient to determine statistical significance; however, with components analysis and subsequent rotation of components, a considerable opportunity for results to occur by chance arises, especially with smaller sample sizes. Because of this capitalisation on chance, orthogonally rotated components very likely contain much more error than ordinary correlations. Consequently, Stevens (2002) recommends doubling the critical values in table C.1 for use with significance tests for extracted and rotated factor-load coefficients. With a sample size of 30, this study uses a critical value of 0.82 for determining statistical significance. The test uses a conservative level of significance of 0.01 to control for increases in experiment-wise Type I error rates (rejecting the null hypothesis when it is true) with multiple tests. This analysis considers these statistically significant loadings as only guides to the fundamental nature of the component; guides that an analyst best interprets in conjunction with other information, that being the largest non-significant loadings and other important secondary loadings.

Table C.1: Critical values for a correlation coefficient at α = 0.01 for two-tailed test

SAMPLE SIZE	CRITICAL VALUE
30	0.411[a]
50	0.361
80	0.286
100	0.256
140	0.217
180	0.192
200	0.182
250	0.163
300	0.149
400	0.129
600	0.105
800	0.091
1000	0.081

Source: Stevens 2002: 394

[a] This value extrapolated from: ((0.361 – 0.286)/(80 – 50))*(50 – 30) + 0.361

This study, similar to that conducted by Esty et al. (2006), uses the interpretation of PCFA results, in conjunction with a literature review, to guide grouping of the environmental sustainability performance indicators (ESPIs) during construction of the policy subcategories and related subindices used along with the overall composite index when evaluating the exogenous and endogenous factors. PCFA conducted by Esty et al. (2006) on 16 environmental performance indicators strongly identified three components the researchers interpreted as environmental health, sustainable energy, and biodiversity policy categories, and weakly identified three other policy categories interpreted as air quality, water resources, and natural resources.

C.2) REGRESSION ANALYSIS

After the uncertainty and sensitivity analyses, analytical focus shifts to the interactions among factors and indicators. Multiple regression analysis identifies and quantifies the pattern of relationships between many independent (predictor) variables and one dependent (criterion) variable. In the context of the current study, the factors influencing environmental performance form the independent variables used to explain the variance observed in the dependent composite indicator of environmental sustainability performance or related subindices of policy subcategories. Multivariate techniques, such as multiple regression, control increases in experiment-wise Type I error rates (rejecting the null hypothesis when it is true) that occurs when combining several bivariate tests, an important quality because it allows finer-scale findings to emerge (Stevens 2002). Experiment-wise error rates refer to the probability of a Type I error occurring anywhere within the analysis, as opposed to a single hypothesis test.

Multiple regression analysis generates an equation, known as the multiple regression equation (eq. C.1). It consists of weighted sums of two or more explanatory variables,

$$Y_i = \beta_0 + \sum_{j=1}^{k} x_{ij}\beta_j + \varepsilon_i . \tag{C.1}$$

The weights, β_j, known as partial regression coefficients, combine to predict scores of the criterion variable that are as close as possible to the observed values. A partial regression coefficient specifies, on average, the amount of change that occurs in the dependent variable per unit change in the explanatory or predictor variable, provided all other explanatory variables are statistically controlled. Selecting appropriate partial regression coefficients minimises the sum of the squared differences between the predicted and observed values. This technique is the ordinary least squares solution (Stevens 2002; Spicer 2005). This technique assumes the error term, ε_i, must fulfil several criteria, although the analysis can withstand a certain amount of deviation from these ideal criteria and still yield valid statistical results. These errors must have a mean of zero and must have equal variances across all values of the explanatory variables (i.e., are homoscedastic). Error terms must also be uncorrelated with each other and with the explanatory variables and must be normally distributed (Stevens 2002; Licht

1995; Spicer 2005). Bivariate regression analysis possesses similar assumptions. Moderate violations of these assumptions are not usually problematic for interpreting results; a researcher checks these assumptions visually with histograms and scatter plots of residuals. Data for the current research display only minor variations from the ideal set of assumptions.

Multiple regression analysis may take one of three forms: standard, sequential, and statistical (Tabachnik and Lidell 2007; Spicer 2005; Stevens 2002). These approaches differ only on how the analysis includes additional explanatory variables. With standard multiple regression analysis, all explanatory variables enter the regression equation simultaneously, but each explanatory variable is evaluated as if it was entered into the regression after all other variables. In other words, this type of regression assesses what each explanatory variable adds to the predictability of the criterion that is different from the other explanatory variables. Thus, a significant explanatory variable might appear unimportant because the other variables are masking its presence. With sequential, often referred to as hierarchical, multiple regression analysis, the researcher selects the order that the explanatory variables enter the regression equation, and each variable is assessed in terms of what it adds to the equation at its point of entry. Thus, the challenge lies in ascertaining the correct order of entry into the regression equation for each explanatory variable.

In contrast to standard regression, statistical regression analyses techniques enter explanatory variables based solely on statistical criteria. These techniques use forward selection, backward deletion, or stepwise regression to determine the next explanatory variable for inclusion, or exclusion, in the regression equation (Tabachnik and Lidell 2007; Spicer 2005; Stevens 2002; Licht 1995; Cohen and Cohen 1983). In forward selection, the analysis starts without any explanatory variables entered and adds one at a time based on statistical criteria. Importantly, once an explanatory variable enters the regression equation it can not be removed. Usually, the explanatory variable with the highest simple correlation enters the equation first followed by variables with the largest partial correlations with the dependent variable. Thus, the analysis enters additional variables that contribute the most to R^2.

In backward deletion, the analysis starts with all explanatory variables entered and deletes variables one at a time that do not contribute significantly to

R^2. Thus, this method excludes variables at each step with the smallest partial correlations with the dependent variable. This technique compares a partial F value, calculated for every explanatory variable as if it was the last one entered into the analysis, with an F to remove to determine the next variable to exclude from the analysis. Stepwise regression offers a compromise between these two procedures in which the analysis starts empty with explanatory variables added if they meet statistical criteria. If the equation contains independent variables, stepwise regression removes the variable with the largest probability of F if the value is larger than p_{out} and recalculates the equation without the variable, repeating the process until no more independent variables are candidates for removal. Then, stepwise regression enters the independent variable not in the equation with the smallest probability of F if the value is smaller than p_{in} and again re-examines all variables in the equation for removal. This process continues until no variables in the equation are candidates for removal and no variables not in the equation are eligible for entry. Consequently, stepwise regression reassesses the importance of each explanatory variable, thus the regression can remove previously included variables that cease contributing significantly to R^2.

C.3) AKAIKE'S INFORMATION CRITERION

This analysis uses stepwise and backward regression techniques to form candidate subsets of influential factors for further investigation. The influential factors form the complete set of independent variables from which one withdraws subsets for multiple regression with the various composite indices, as well as the greenhouse gas indicator. Used either singly or in conjunction with one another, these commonly used regression techniques often produce several significant sets of explanatory variables. Consequently, an analyst faces the challenge of selecting the best model from among many candidates.

A commonly used metric for selecting among variable sets is Akaike's Information Criterion (AIC) (Burnham and Anderson 2004; Cetin and Erar 2002; Kaibala 2002), which balances predictive power of the regression equation with parsimony of independent variables. In essence, AIC penalises a model for adding too many explanatory variables. Minimising the number of explanatory variables not only reduces experiment-wise Type I error rates by lowering the number of hypothesis tests, it also increases the statistical power thus decreasing the probability of Type II errors, failing to reject the null hypothesis when it is false (Cohen and Cohen 1983: 170). AIC, with a foundation in information theory, selects the most appropriate model based on the loss of Kullback-Leibler information, usually estimated with the maximum likelihood function. In the special case of least squares estimation with normally distributed errors AIC becomes

$$\mathrm{AIC} = n\log\left(\frac{\mathrm{SSE}}{n}\right) + 2k, \tag{C.2}$$

where n is the number of observations, k is the number of parameters in the regression equation including the constant (intercept), and SSE is the sum of squared errors.

According to Burnham and Anderson (2004: 12), researchers often neglect the effects of sample size when applying AIC. Such neglect may lead researchers to conclude that AIC overfit their model by including too many explanatory variables. Therefore, when n/k is less than 40, Burnham and Anderson (2004: 12) recommend using an AIC corrected for sample size ($\mathrm{AIC_C}$),

$$\mathrm{AIC_C} = \mathrm{AIC} + \frac{2k(k+1)}{n-k-1}. \tag{C.3}$$

As n gets large AIC_C converges to AIC, thus, a researcher should use AIC_C routinely. Therefore, the predictor subset with the smallest (most negative) AIC_C best balances parsimony of included explanatory variables with predictive power of the regression equation, given the size of the sample analysed, and is the most appropriate subset to carry forward into the next stage of the regression analysis.

C.4) THE CONCEPT OF SUPPRESSION

To determine factor importance, analysts often use two statistics: standardised partial regression coefficients and squared semi-partial correlation coefficients (Tabachnick and Fidell 2007; Stevens 2002; Licht 1995). Partial regression coefficients specify the amount the dependent variable changes, on average, per unit change in an explanatory variable while statistically controlling all other explanatory variables. When standardised (converted to *z*-scores), a partial regression coefficient's magnitude indicates the associated factor's relative importance. At the same time, semi-partial correlation coefficients quantify the correlation between a specific explanatory variable and the dependent variable while partialling out influences of all other explanatory variables from the specific explanatory variable, but not out of the dependent variable. Thus, squared semi-partial correlation coefficients represent the unique proportion of variance that respective factors explain in the dependent variable, which theoretically allows one to determine the relative importance of each explanatory variable. However, correlated explanatory variables do not necessarily sum to the coefficient of multiple determination, usually totalling to a smaller value. When the sum of the squared semi-partial correlation coefficients is less than the coefficient of multiple determination, the difference is attributable to the proportion of explained variance shared by the explanatory variables (Tabachnick and Fidell 2007: 146). Figure C.1 illustrates this situation with a Venn diagram, whereby neither of the squared semi-partial correlation coefficients of the explanatory variables x_1 and x_2 accounts for area c, the shared contribution, thus, the coefficients sum to something less than R^2.

On the other hand, when this sum is larger, a phenomenon known as suppression may be occurring. According to Friedman and Wall (2005), who survey the literature on suppression to reconcile the many different terms used to refer to this phenomenon, suppression is a combination of three different aspects: redundancy, enhancement, and suppression. A redundant explanatory variable, when included in the multiple regression analysis, explains less of the dependent variable's observed variation than one would expect given its correlation, and its standardised partial regression coefficient is also smaller than expected signifying that a redundant explanatory variable is less important than the correlation implies. With an enhancing explanatory variable the amount of the explained variation and the standardised partial regression coefficient are both larger than one would expect given the correlation between the variables, thus demonstrating that an enhancing explanatory variable is more important than indicated by the correlation. Meanwhile a suppressor explanatory variable's standardised partial regression coefficient is larger than its corresponding correlation with the dependent variable, usually because the correlation is near zero, and the overall explained variance is smaller than if the situation were enhancement, but still larger than without the suppressor variable (Friedman and Wall 2005; Tabachnick and Fidell 2007).

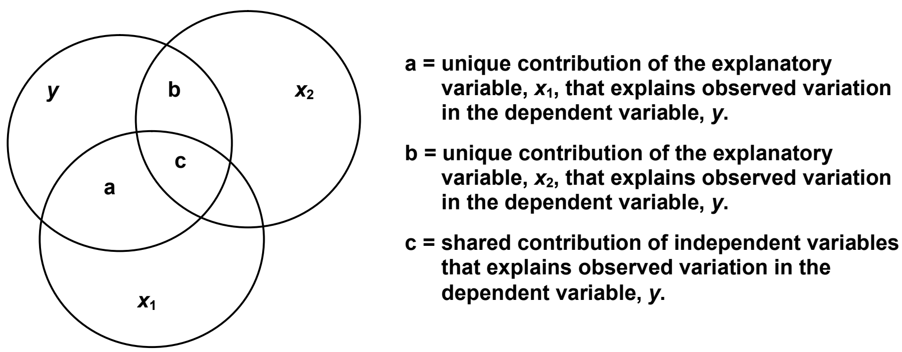


Figure C.1: Venn diagram with circles that represent a variable's variance demonstrating how overlapping correlated explanatory variables may produce lower sums of squared semi-partial correlation coefficients than the coefficient of multiple determination

Both enhancement and suppression variables increase the magnitude of the explained variation of a dependent variable. Such variables accomplish this feat by removing, or suppressing, irrelevant variation not associated with the dependent variable in one or more of the other explanatory variables (Tabachnick and Fidell 2007; Cohen and Cohen 1983; Stevens 2002). Clearly, analysts should exclude redundant variables from the regression analysis because of the decrease in the variation explained for a dependent variable. However, both enhancement and suppression variables are desirable because they increase the explanatory power of the analysis by increasing the explained portion of a dependent variable's variance.

Many efforts aimed at identifying suppression variables typically discuss methods involving only two predictor variables (Velicer 1978; Hamilton 1987; Malgady 1987; Smith et al. 1992; Sharpe and Roberts 1997; Maassen and Bakker 2001; Shieh 2001; Friedman and Wall 2005). Nevertheless, one recent effort develops a method for more than two predictor variables (Shieh 2006). Essentially, the candidate variable is one explanatory variable while the analyst treats the group of other explanatory variables as the second explanatory variable to calculate the Γ (pronounced gamma) statistic, defined as

$$\Gamma = r_{Y(j.h)}/r_{Yj}, \tag{C.4}$$

where $r_{Y(j.h)}$ represents the semi-partial correlation coefficient of y with x_j, which controlles for all other x_h, and r_{Yj} represents the coefficient of correlation between y and x_j. When squared, the ratio Γ determines how the unique variation that the specified explanatory variable explains on the dependent variable changes from the situation of no other predictors to one where all predicators are present. Enhancement occurs when Γ^2 is greater than 1 while suppression occurs when Γ^2 is greater than 1 - R^2_{jh}, but still less than 1, where R^2_{jh} represents the coefficient of multiple determination for x_j with (x_1, …,x_{j-1}, x_{j+1},…, x_p), that is the set of all other explanatory variables not including x_j.

Table C.2 applies this framework to the various composite indices with a sum squared semi-partial correlation coefficients greater than R^2. This suppression analysis provides three benefits. First, the nature of how enhancing and suppressor variables remove variation from other explanatory variables may have implications for policy recommendations directed at improving a country's environmental sustainability performance, which chapter 6 further explores. Second, suppression analysis helps to identify, in conjunction with the analysis of multicollinearity discussed in the limitations section of chapter 5, redundant variables that interfere with the multiple regression analysis. As table C.2 shows, the analysis uncovers no redundant variables, with all explanatory variables classified as either enhancement or suppression. In fact, most explanatory variables for these composite indices are enhancing, except economic output and energy prices for the environmental sustainability performance composite index (ESPCI), and population density for the sustainable cities policy subindex (SCPS), which are suppressor variables.

Lastly, such an analysis supplies further information for interpreting multiple regression statistics, specifically, the squared semi-partial correlation coefficients contained in table 5.3. These coefficients, which should sum to the coefficient of multiple determination, but, in each case, produce a greater summand, have values that strongly depend on the type of suppression present. Referring to table 5.3, the squared semi-partial correlation coefficients for ESPCI produce a summand about 16% greater than the corresponding coefficient of multiple determination; meanwhile, the squared semi-partial correlation coefficients pertaining to the sustainable energy policy subindex (SEPS) and SCPS provide summands with a much larger percent increase, each summand is greater than the corresponding coefficient of multiple determination by about 64% and 120% respectively. Such a result should not be surprising, given that predictors for SEPS and SCPS are predominantly enhancing variables, which provides a much greater boost to explanatory power than do the suppressor variables associated with ESPCI. Thus, suppression is producing effects that influence and confound the assessment of relative importance of each explanatory factor to environmental sustainability performance.

Table C.2: Analysis and identification of types of suppression

Policy Measure	X_1	X_2	Γ^2	$1-R_{jh}^2$	Type of Suppression
ESPCI	Population Density	Environmental Governance Energy Prices Economic Output	5.105	0.949	Enhancement
	Economic Output	Population Density Environmental Governance Energy Prices	0.800	0.486	Suppression
	Energy Prices	Economic Output Population Density Environmental Governance	0.862	0.690	Suppression
	Environmental Governance	Energy Prices Population Density Economic Output	85.551	0.492	Enhancement
Sustainable Energy	Climate (total degree days)	Environmental Governance Population Density Population Growth Energy Prices Economic Output	3.692	0.666	Enhancement
	Population Growth	Climate (total degree days) Energy Prices Population Density Economic Output Environmental Governance	1.693	0.778	Enhancement
	Population Density	Population Growth Economic Output Climate (total degree days) Energy Prices Environmental Governance	1.769	0.853	Enhancement
	Economic Output	Population Density Environmental Governance Population Growth Energy Prices Climate (total degree days)	2.026	0.470	Enhancement
	Energy Prices	Economic Output Population Density Population Growth Climate (total degree days) Environmental Governance	2.442	0.641	Enhancement
	Environmental Governance	Energy Prices Climate (total degree days) Population Density Population Growth Economic Output	66.035	0.386	Enhancement
Sustainable Cities	Climate (total degree days)	Technological Development Industrial Structure Population Density Energy Prices PAC Expenditures (per capita) Economic Output	1.402	0.482	Enhancement

Continued on next page

Table C.2—*Continued*

POLICY MEASURE	x_1	x_2	Γ^2	$1-R_{jh}^2$	TYPE OF SUPPRESSION
	Population Density	Climate (total degree days) Industrial Structure Energy Prices Economic Output PAC Expenditures (per capita) Technological Development	0.752	0.372	Suppression
	Economic Output	Population Density Industrial Structure Climate (total degree days) Energy Prices PAC Expenditures (per capita) Technological Development	20.077	0.176	Enhancement
	Energy Prices	Industrial Structure Climate (total degree days) Population Density Economic Output Technological Development PAC Expenditures (per capita)	3.898	0.553	Enhancement
	Industrial Structure	Technological Development Population Density PAC Expenditures (per capita) Climate (total degree days) Energy Prices Economic Output	9.325	0.604	Enhancement
	PAC Expenditures (per capita)	Energy Prices Climate (total degree days) Industrial Structure Population Density Economic Output Technological Development	7689.8 85	0.200	Enhancement
	Technological Development	Economic Output Population Density Industrial Structure Climate (total degree days) Energy Prices PAC Expenditures (per capita)	3.639	1.000	Enhancement

Suppression: $1 - R_{jh}^2 < \Gamma^2 < 1$

Enhancement: $\Gamma^2 > 1$

$\Gamma = r_{Y(j.h)} / r_{Yj}$,

Γ^2 represents how the unique variation that the specified explanatory variable explains on the dependent variable changes from the situation of no other predictors to one where all predicators are present.

R_{jh}^2 represents the coefficient of multiple determination for x_j with (x_1, …,x_{j-1}, x_{j+1},…, x_p), that is the set of all other explanatory variables not including x_j.

C.5) CLUSTER ANALYSIS

In addition to the regression analyses, this study also examines the underlying group structure of the performance indicators. Cluster analysis classifies large sets into subgroups with similar characteristics using a series of multivariate techniques based on a single characteristic or on multiple characteristics. The classification aims to reduce the dimensionality of a data set by exploiting the similarities (or dissimilarities) between subgroups. Cluster analysis techniques are hierarchical if the classification has an increasing number of nested classes, or non-hierarchical, as is the case when deciding the number of clusters before the analysis begins, as with the *k*-means clustering method (Nardo et al. 2005; Hair and Black 2000; Aldenderfer and Blashfield 1984). Hierarchical procedures are either agglomerative, where each object starts as its own cluster subsequently combining similar clusters to form fewer clusters, or divisive, where all objects start as one large cluster that is divide by splitting off dissimilar objects. In practice, one generally uses agglomerative techniques because divisive methods are simply the reverse of these techniques.

A researcher delineates distinct clusters by assessing distances between data points, or as in the case of Ward's method, an *F*-test (Nardo et al. 2005). A distance measure is an appraisal of the degree of similarity, or dissimilarity, between cases in the set, where a small distance is equivalent to a large similarity. Refer to table C.3 for a list of commonly used distance measures. After selecting a distance measure, a clustering algorithm assigns cluster membership (table C.4). One of the biggest problems with cluster analysis is identifying the optimum number of clusters: the amalgamation process fuses increasingly dissimilar clusters thus creating increasingly artificial classifications. Deciding upon the optimum number of clusters is largely subjective; although looking at the plot of linkage distance across fusion steps may help (Hair and Black 2000; Milligan and Cooper 1985; Aldenderfer and Blashfield 1984). Such a plot, referred to as a dendrogram, or tree graph, depicts the construction of the clusters as existing clusters are joined to form larger clusters; therefore, one may readily observe the steps at which disparate groups join to from larger groups.

Table C.3: Distance measures commonly used in cluster analysis

DISTANCE MEASURE	FORMULA	DESCRIPTION
Euclidean	$D(x,y)=\left(\frac{\sum_{i=1}^{N_d}(x_i-y_i)^2}{N_d}\right)^{1/2}$	This measure is the geometric distance in a multi-dimensional space and is usually computed from raw data (prior to any normalisation). This measure is not affected by the addition of new objects such as outliers. However, it is highly affected by the difference in scale (e.g., whether the same object is quantified in centimetres or in metres the *D*(*x*,*y*)).
Squared Euclidean	$D(x,y)=\frac{\sum_{i=1}^{N_d}(x_i-y_i)^2}{N_d}$	This measure places progressively greater weight on objects that are further apart. Usually this value is computed from raw data and shares the same advantages and disadvantages of the Euclidean distance.
City-block (Manhattan)	$D(x,y)=\frac{\sum_{i=1}^{N_d}\lvert x_i-y_i\rvert}{N_d}$	This distance is the average of distances across dimensions and it yields similar results to the Euclidean distance. In this measure, the effect of outliers is less pronounced, since it is not squared.
Chebychev	$D(x,y)=\text{Max}\lvert x_i-y_i\rvert$	This measure is mostly used when one wants to define objects as 'different' if they are different in any one of the dimensions.
Power	$D(x,y)=\left(\frac{\sum_{i=1}^{N_d}(x_i-y_i)^P}{N_d}\right)^{1/r}$	This distance measure is useful when one wants to increase, or decrease, the progressive weight placed on one dimension, for which the respective objects are very different. The parameters *r* and *p* are user-defined, such that p controls the progressive weights placed on differences on individual dimensions, and *r* controls the progressive weight placed on larger differences between objects. Note that for *p* = *r* = 2 corresponds to the Euclidean distance.

Source: Nardo et al. 2005: 47; Hair and Black 2000: 166-167; Aldenderfer and Blashfield 1984: 24-25

A non-hierarchical method of clustering that does not require multiple stages building upon each other is the *k*-means algorithm. This method is useful when the aim is to divide a sample into *k* clusters of greatest possible distinction (Nardo et al. 2005; Hair and Black 2000; Aldenderfer and Blashfield 1984). In such an analysis one decides the parameter *k* ex ante, or prior to starting the analysis. The algorithm starts with *k* random clusters and moves the objects in and out of the clusters with the aim of (i) minimising the variance of elements within the clusters, and (ii) maximising the variance of elements outside the clusters. Esty et al. (2005) tested hierarchical agglomerative and divisive clustering methods as well as different distance measures, employing the *k*-means algorithm only after estimating the number of clusters with their best performing clustering algorithm, Ward's method. Milligan (1980) recommends such an approach when conducting a cluster analysis.

Table C.4: Popular clustering algorithms for delineating group membership

ALGORITHM	DESCRIPTION
Single Linkage (nearest neighbour)	The distance between the two closest elements in the different clusters determines the distance between two clusters. Used with poorly delineated clusters, this rule produces clusters chained together by single objects.
Complete Linkage (farthest neighbour)	The greatest distance between any two objects belonging to different clusters determines the distance between two clusters. This method usually performs well when objects naturally form distinct groups. This technique eliminates the snaking problem identified with single linkage whereby single objects link clusters together.
Average Linkage	The distance between two clusters is the average distance between all pairs of objects in the two clusters. This method usually performs well when objects naturally form distinct groups, but tends to produce clusters with similar variances. A variation of this method uses the centroid of a cluster, an appraisement of a cluster's centre that accounts for multi-dimensional space.
Weighted Average Linkage	Similar to the unweighted pair-group average (centroid included) but uses the number of objects in a cluster as a weight for the average distance. This method is useful when cluster sizes are very different.
Ward's Method	The variance of elements determines cluster membership (i.e., the sum of the squared deviations from the mean of the cluster). An element belongs to a cluster if it produces the smallest possible increase in the variance. This procedure tends to combine clusters with low membership and also tends to produce clusters with similar numbers of observations.

Source: Nardo et al. 2005: 48; Hair and Black 2000: 178-180; Aldenderfer and Blashfield 1984: 38-45

This research follows a similar course to that of Esty et al. (2005), as recommended by Milligan (1980). Testing various hierarchical clustering methods and distance measures chooses the best performer for estimating the number of clusters for the *k*-means algorithm. This research clusters on all the ESPIs, subsequently using factor profiles to conduct further statistical analysis (Hair and Black 2000). Typically, Wilks's lambda compares average-score profiles across the clusters, the categorical dependent variable, while the factors are the explanatory variables; thus, the emphasis is on the characteristics that are significantly different across groups. Wilks's lambda is a test statistic that compares the equality of the cluster means as a group; it assumes relatively small values if one of the cluster means is significantly different from the others while it is closer to a value of one when all cluster means are relatively equal. Wilks's lambda is a ratio of within group variance divided by total variance, and, as such, small values indicate that the amount of variance not explained by the respective factor is small and is evidence of a treatment effect (Stevens 2002; Weinfurt 1995). Lower values indicate larger mean differences among the cluster means, thus indicating stronger group separation. In order to determine the statistical significance of Wilks's lambda, one transforms it into an *F* statistic.

APPENDIX D:
REGRESSION ANALYSES SPSS OUTPUT

This appendix provides SPSS output from the regression analyses of this study. Specifically, appendix D presents the raw output from SPSS (version 17) for various results from multiple regression analysis. The output includes model summaries, ANOVA (ANalysis Of VAriance) results that assess the significance of the relationships among explanatory and dependent variables, and coefficients that calculate predicted values for the dependent variable, as well as the various correlations between explanatory and dependent variables that arise from multiple regression.

D.1) MODEL SUMMARIES

ESPCI

MODEL[a]	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE[38]
1	.854	.730	.678	.040594

a = Constant, Environmental Governance, Population Density, Energy Prices, Economic Output.

WASTE AND POLLUTION

MODEL[a]	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.743	.553	.534	.119260

a = Constant, Energy Price.

SUSTAINABLE ENERGY

MODEL[a]	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.838	.702	.608	.069318

a = Constant, Environmental Governance, Population Density, Population Growth, Energy Prices, Climate (total degree days), Economic Output.

SUSTAINABLE FOOD

MODEL[a]	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.776	.601	.572	.113498

a = Constant, Economic Output, Population Density.

NATURE CONSERVATION

MODEL[a]	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.134	.018	-.023	.076162

a = Constant, Technological Development.

[38] In these model summary tables, the standard error of the estimate provides an estimate of the dispersion of the prediction errors that an analyst may use to determine a confidence interval for values predicted by the regression equation. A predicted value is likely to vary within plus or minus one standard error of the estimate 68% of the time. Extending the range to plus or minus two standard errors of the estimate increases this confidence about the variability of the predicted value to 95%. One method for calculating the standard error of the estimate is as the square root of the mean square error.

SUSTAINABLE CITIES

MODEL[a]	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	1.000	1.000	1.000	.000000

a = Constant, Pollution Abatement and Control Expenditures (using per capita), Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Technological Development, Economic Output.

GREENHOUSE GAS EMISSIONS

MODEL[a]	R	R SQUARE	ADJUSTED R SQUARE	STD. ERROR OF THE ESTIMATE
1	.899	.808	.780	.115406

a = Constant, Environmental Governance, Energy Prices, Economic Output.

D.2) MULTIPLE REGRESSION ANOVA RESULTS

ESPCI

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	*F*	SIG.
1	Regression	.093	4	.023	14.165	.0000094
	Residual	.035	21	.002		
	Total	.128	25			

Constant, Environmental Governance, Population Density, Energy Prices, Economic Output

WASTE AND POLLUTION

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	*F*	SIG.
1	Regression	.422	1	.422	29.645	.0000135
	Residual	.341	24	.014		
	Total	.763	25			

Constant, Energy Prices

SUSTAINABLE ENERGY

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	*F*	SIG.
1	Regression	.215	6	.036	7.474	.0003225
	Residual	.091	19	.005		
	Total	.307	25			

Constant, Environmental Governance, Population Density, Population Growth, Energy Prices, Climate (total degree days), Economic Output

SUSTAINABLE FOOD

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	*F*	SIG.
1	Regression	.525	2	.262	20.372	.0000040
	Residual	.348	27	.013		
	Total	.873	29			

Constant, Economic Output, Population Density

NATURE CONSERVATION

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	*F*	SIG.
1	Regression	.003	1	.003	.441	.513
	Residual	.139	24	.006		
	Total	.142	25			

Constant, Technological Development

SUSTAINABLE CITIES

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	*F*	SIG.
1	Regression	.355	7	.051	.	.
	Residual	.000	15	.000		
	Total	.355	22			

Constant, Pollution Abatement and Control Expenditures (using per capita), Climate (total degree days), Energy Prices, Industrial Structure, Population Density, Technological Development, Economic Output

GREENHOUSE GAS EMISSIONS

MODEL		SUM OF SQUARES	DF	MEAN SQUARE	*F*	SIG.
1	Regression	1.176	3	.392	29.441	.0000001
	Residual	.280	21	.013		
	Total	1.456	24			

Constant, Environmental Governance, Energy Prices, Economic Output

D.3) MULTIPLE REGRESSION COEFFICIENTS AND CORRELATIONS

ESPCI

MODEL		UNSTANDARDISED COEFFICIENTS		STANDARDISED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	.236	.085		2.774	.011			
	Population Density	-.0002	.0001	-.237	-2.036	.055	-.102	-.406	-.231
	Economic Output	-.00001	.000001	-.605	-3.721	.001	-.472	-.630	-.422
	Energy Prices	.0002	.00004	.717	5.246	.00003	.641	.753	.595
	Environmental Governance	.006	.001	.726	4.486	.0002	-.055	.700	.509

WASTE AND POLLUTION

MODEL		UNSTANDARDISED COEFFICIENTS		STANDARDISED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	.225	.098		2.309	.030			
	Energy Prices	.001	.0001	.743	5.445	.00001	.743	.743	.743

SUSTAINABLE ENERGY

MODEL		UNSTANDARDISED COEFFICIENTS		STANDARDISED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	-.204	.160		-1.278	.217			
	Climate (total degree days)	-.00005	.00002	-.395	-2.575	.019	-.168	-.509	-.322
	Population Growth	6.346	2.834	.318	2.239	.037	.215	.457	.280
	Population Density	-.0005	.0001	-.477	-3.518	.002	-.331	-.628	-.440
	Economic Output	-.000007	.000003	-.516	-2.823	.011	-.248	-.544	-.353
	Energy Prices	.0003	.00008	.631	4.037	.001	.323	.679	.505
	Environmental Governance	.013	.003	1.010	5.014	.00008	.077	.755	.628

SUSTAINABLE FOOD

MODEL		UNSTANDARDISED COEFFICIENTS		STANDARDISED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	1.106	.066		16.640	<.0001			
	Population Density	-.001	.0002	-.678	-5.575	.000007	-.695	-.732	-.677
	Economic Output	-.000008	.000003	-.345	-2.834	.009	-.378	-.479	-.344

NATURE CONSERVATION

MODEL		UNSTANDARDISED COEFFICIENTS		STANDARDISED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	.596	.042		14.322	<.0001			
	Technological Development	.071	.106	.134	.664	.513	.134	.134	.134

SUSTAINABLE CITIES

MODEL		UNSTANDARDISED COEFFICIENTS		STANDARDISED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	-.104	.00000		.	.			
	Climate (total degree days)	-.00006	.00000	-.426	.	.	.250	-1.000	-.296
	Population Density	-.001	.00000	-.539	.	.	.379	-1.000	-.329
	Economic Output	-.00003	.00000	-1.824	.	.	-.171	-1.000	-.765
	Technological Development	1.711	.00000	1.932	.	.	.450	1.000	.859
	Industrial Structure	3.171	.00000	.569	.	.	.145	1.000	.443
	Energy Prices	.0003	.00000	.606	.	.	.228	1.000	.450
	PAC Expenditures (per capita)	.001	.00000	1.201	.	.	-.006	1.000	.537

GREENHOUSE GAS EMISSIONS

MODEL		UNSTANDARDISED COEFFICIENTS		STANDARDISED COEFFICIENTS	T	SIG.	CORRELATIONS		
		B	STD. ERROR	BETA			ZERO-ORDER	PARTIAL	PART
1	(Constant)	-.528	.246		-2.144	.044			
	Economic Output	-.00002	.000004	-.577	-4.207	.0004	-.607	-.676	-.402
	Energy Prices	.001	.0001	.738	6.546	.000002	.793	.819	.626
	Environmental Governance	.014	.004	.487	3.599	.002	-.262	.618	.344

APPENDIX E:
CLUSTER PROFILES

This appendix profiles identified clusters with means, standard deviations, minima, and maxima. Specifically, appendix E details the cluster profiles of the performance composite subindices and the influential factors assessed.

E.1) POLICY MEASURE CLUSTER PROFILES

		ESPCI	WPPS	SEPS	SFPS	NCPS	SCPS
1	Mean	0.494	0.295	0.356	0.871	0.609	0.336
	SD	0.048	0.098	0.041	0.138	0.027	0.190
	Min	0.443	0.183	0.315	0.714	0.577	0.170
	Max	0.540	0.358	0.397	0.971	0.628	0.543
2	Mean	0.646	0.823	0.448	0.551	0.667	0.641
	SD	0.095	0.064	0.117	0.218	0.171	0.177
	Min	0.496	0.754	0.327	0.357	0.387	0.510
	Max	0.678	0.869	0.535	0.779	0.716	0.834
3	Mean	0.599	0.757	0.371	0.701	0.548	0.572
	SD	0.074	0.059	0.118	0.249	0.108	0.093
	Min	0.496	0.688	0.188	0.357	0.387	0.465
	Max	0.677	0.835	0.482	0.947	0.643	0.675
4	Mean	0.679	0.794	0.529	0.756	0.662	0.603
	SD	0.034	0.087	0.095	0.126	0.044	0.065
	Min	0.635	0.660	0.406	0.538	0.621	0.516
	Max	0.722	0.916	0.717	0.924	0.772	0.725
5	Mean	0.590	0.660	0.495	0.886	0.521	0.353
	SD	NA	NA	NA	NA	NA	NA
	Min	0.590	0.660	0.495	0.886	0.521	0.353
	Max	0.590	0.660	0.495	0.886	0.521	0.353
6	Mean	0.675	0.809	0.495	0.904	0.618	0.508
	SD	0.037	0.112	0.093	0.040	0.070	0.057
	Min	0.625	0.558	0.393	0.829	0.545	0.392
	Max	0.728	0.915	0.669	0.944	0.735	0.573

E.2) FACTOR CLUSTER PROFILES

		CL	POP GR	POP DEN	ECON OUT	TECH DEV	IND STR	ENER PR	ENV GOV	PACE (GDP)	PACE (CAP)	ENV PR (GDP)	ENV PR (CAP)
1	Mean	3124.1	0.0099	92.99	$28,293.31	0.418	0.0957	$539.05	59.4	0.012	$339.71	0.014	$383.34
	SD	1500.5	0.0008	7.82	$3,572.75	0.014	0.0055	$68.03	2.4	0.004	$159.45	0.006	$107.22
	Min	1666.7	0.0091	87.06	$24,991.10	0.408	0.0905	$493.77	56.7	0.008	$199.93	0.009	$288.77
	Max	4664.3	0.0107	101.85	$32,085.93	0.428	0.1015	$617.28	61.2	0.016	$513.37	0.020	$499.82
2	Mean	2819.5	0.0032	309.62	$20,761.94	0.467	0.1107	$1,030.01	54.0	0.013	$258.46	0.026	$467.69
	SD	424.4	0.0029	118.97	$5,180.00	0.185	0.0086	$156.15	4.2	0.003	$94.93	0.008	$45.85
	Min	2438.5	0.0006	186.95	$15,075.57	0.272	0.1049	$796.88	49.8	0.009	$201.06	0.023	$512.57
	Max	3223.5	0.0063	422.45	$24,870.72	0.619	0.1214	$1,121.95	59.3	0.015	$348.19	0.034	$512.57
3	Mean	3721.7	0.0024	144.38	$27,326.95	0.415	0.1414	$883.70	57.4	0.012	$246.69	0.027	$737.11
	SD	907.1	0.0084	119.61	$10,746.01	0.114	0.0286	$87.82	8.0	0.005	$90.04	0.003	$320.19
	Min	2995.6	-0.0084	33.61	$13,979.02	0.327	0.1172	$796.88	48.2	0.006	$180.29	0.023	$405.39
	Max	5259.5	0.0151	334.16	$43,468.47	0.571	0.1892	$1,004.57	68.2	0.017	$376.57	0.030	$1,260.59
4	Mean	3368.0	0.0053	156.14	$24,416.85	0.444	0.0988	$813.07	64.5	0.015	$376.22	0.029	$707.15
	SD	818.4	0.0041	121.19	$2,502.94	0.091	0.0051	$132.19	3.2	0.006	$156.62	0.009	$247.53
	Min	1774.1	0.0009	37.72	$19,446.56	0.355	0.0910	$532.24	60.0	0.007	$153.22	0.016	$311.14
	Max	4577.9	0.0149	419.84	$27,765.54	0.618	0.1069	$972.20	68.3	0.024	$593.00	0.047	$1,234.91
5	Mean	5071.3	0.0105	88.20	$26,388.89	0.434	0.0912		62.7	0.000	$0.00	0.025	$659.72
	SD	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	Min	5071.3	0.0105	88.20	$26,388.89	0.434	0.0912	$0.00	62.7	0.000	$0.00	0.025	$659.72
	Max	5071.3	0.0105	88.20	$26,388.89	0.434	0.0912	$0.00	62.7	0.000	$0.00	0.025	$659.72
6	Mean	2679.8	0.0054	99.76	$12,210.38	0.202	0.1167	$1,011.99	46.2	0.011	$127.21	0.024	$291.48
	SD	819.0	0.0065	18.08	$4,428.32	0.075	0.0238	$250.99	5.3	0.004	$49.96	0.007	$115.24
	Min	1712.0	-0.0024	71.24	$6,035.94	0.045	0.0879	$699.95	36.2	0.007	$56.26	0.017	$136.64
	Max	3819.2	0.0154	123.28	$18,606.03	0.278	0.1581	$1,500.92	53.1	0.020	$184.35	0.038	$470.48

APPENDIX F:
INDIVIDUAL COUNTRY RESULTS

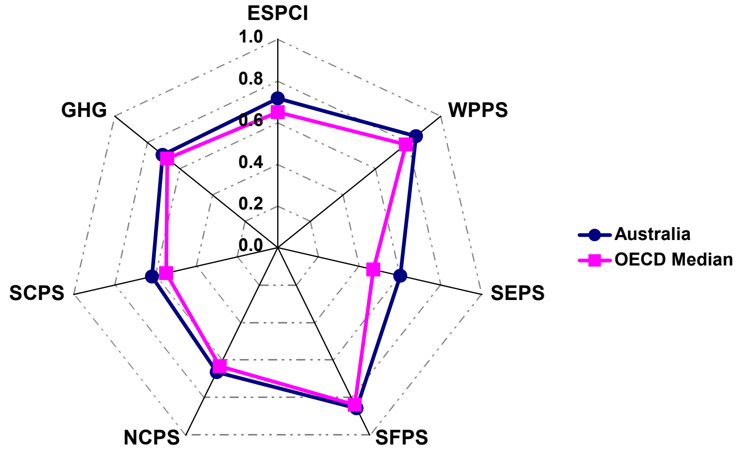
This appendix contains individual results for the 30 countries that are members of the Organisation for Economic Co-operation and Development (OECD). Each page displays one country's results as

- a radar diagram comparing that country's performance across policy measures with the OECD median, OECD best (1.0), and OECD worst (0.0)[39],
- a line-bar graph comparing that country's performance across environmental sustainability performance indicators with the OECD median, maximum (1.0), and minimum (0.0), and
- a table comparing that country's significant influential factor values—main, minor, marginal—with the OECD median and the average of the three highest countries.

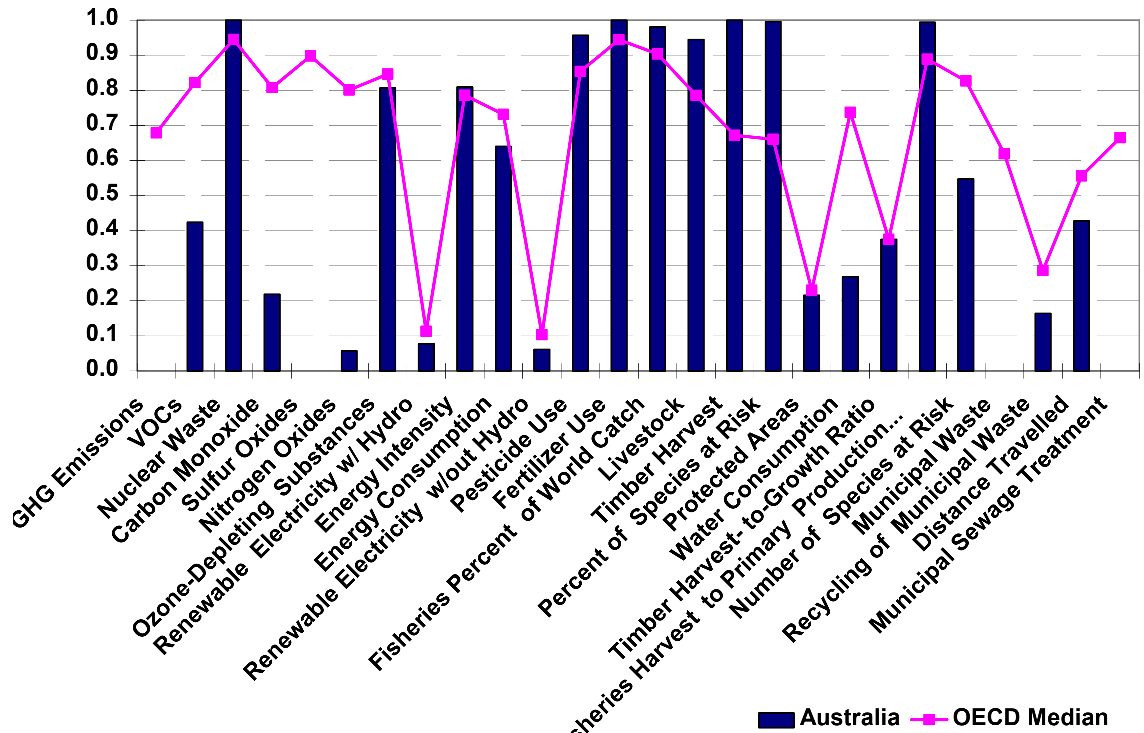
[39] Across all policy measures depicted in the radar diagram, indicator values that fall below the median exhibit poor performance; the further below the median, the worse the relative environmental performance.

COUNTRY RESULTS FOR AUSTRALIA

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

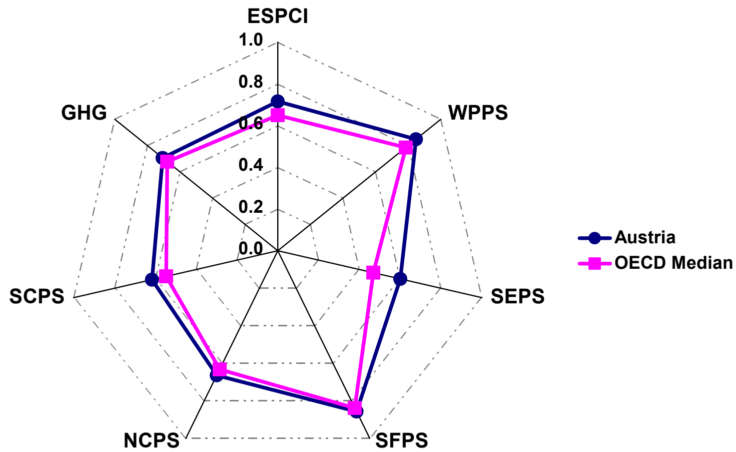


Country factors compared with OECD median and average of three highest countries

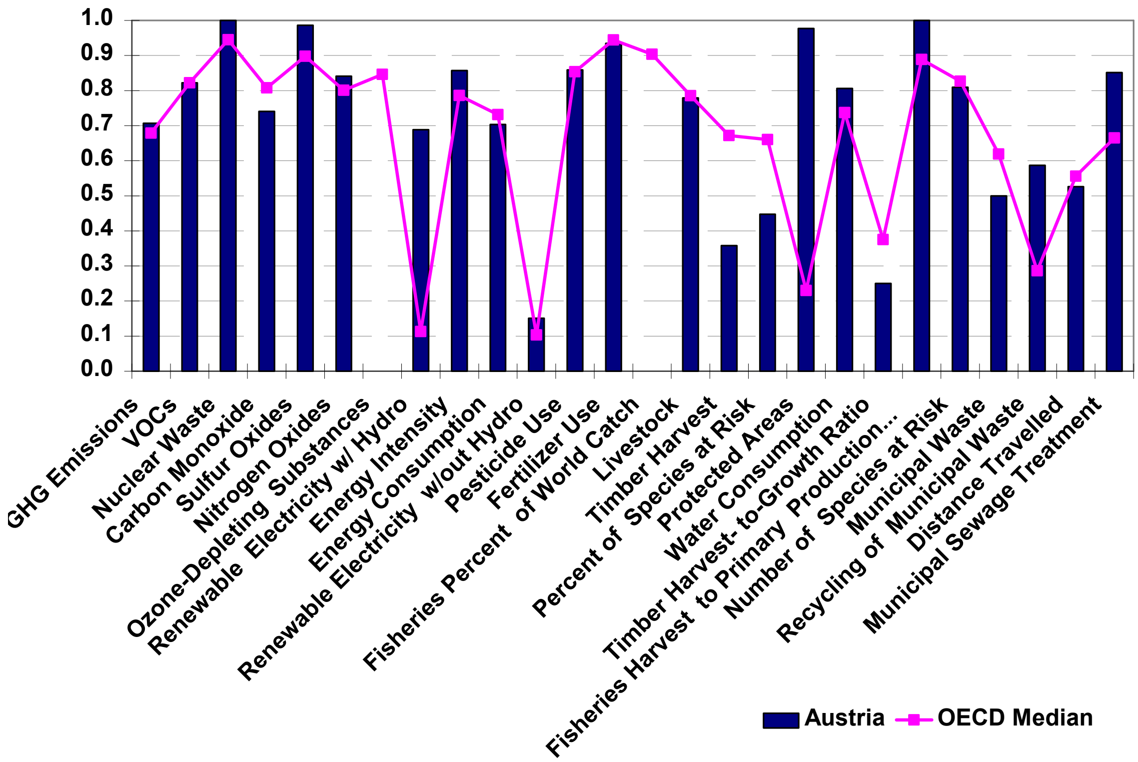
FACTOR	UNITS	OECD	TOP 3 AVG	AUSTRALIA
Climate	total degree days	3167.1	4998.3	**1666.7**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**101.85**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$24,991**
Technological Development	2002 dimensionless index	0.360	0.603	**0.408**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1015**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$617.28**
Environmental Governance	2002 dimensionless index	59.7	68.1	**60.3**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$199.93**

COUNTRY RESULTS FOR AUSTRIA

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

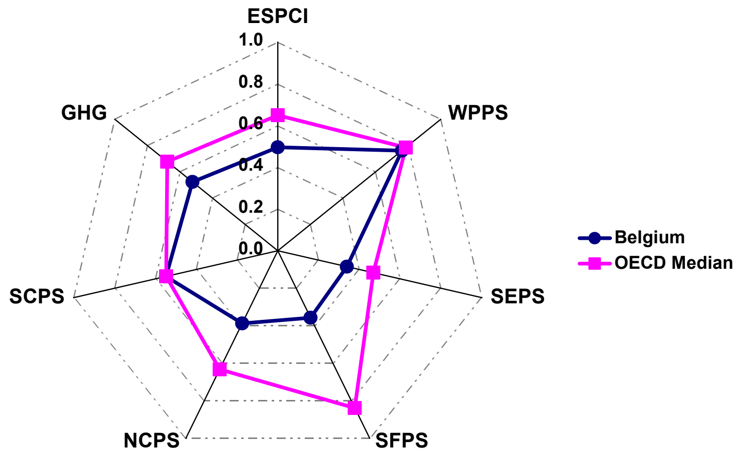


Country factors compared with OECD median and average of three highest countries

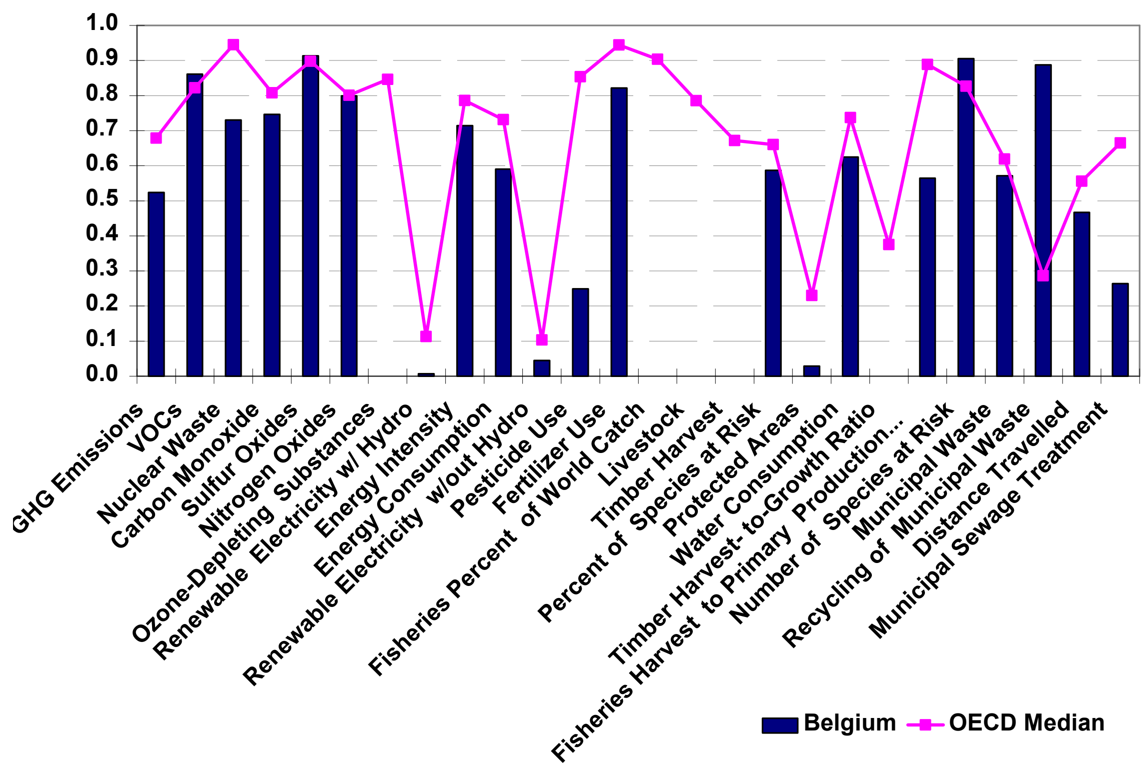
FACTOR	UNITS	OECD	TOP 3 AVG	AUSTRIA
Climate	total degree days	3167.1	4998.3	**3618.6**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**96.95**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$24,708**
Technological Development	2002 dimensionless index	0.360	0.603	**0.355**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0967**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$829.29**
Environmental Governance	2002 dimensionless index	59.7	68.1	**64.9**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$593.00**

COUNTRY RESULTS FOR BELGIUM

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

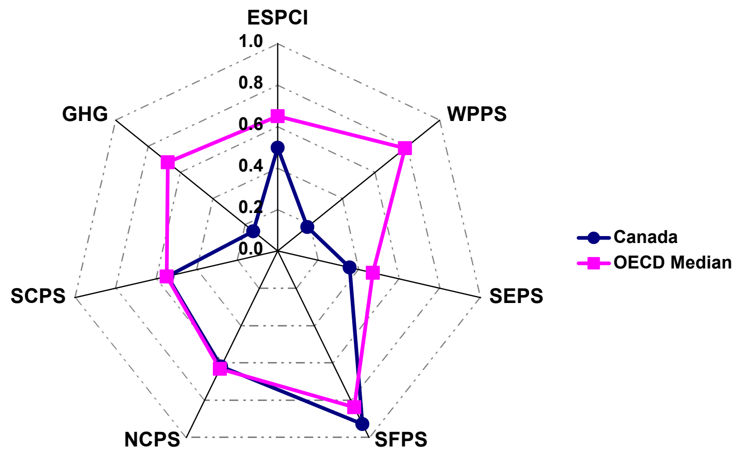


Country factors compared with OECD median and average of three highest countries

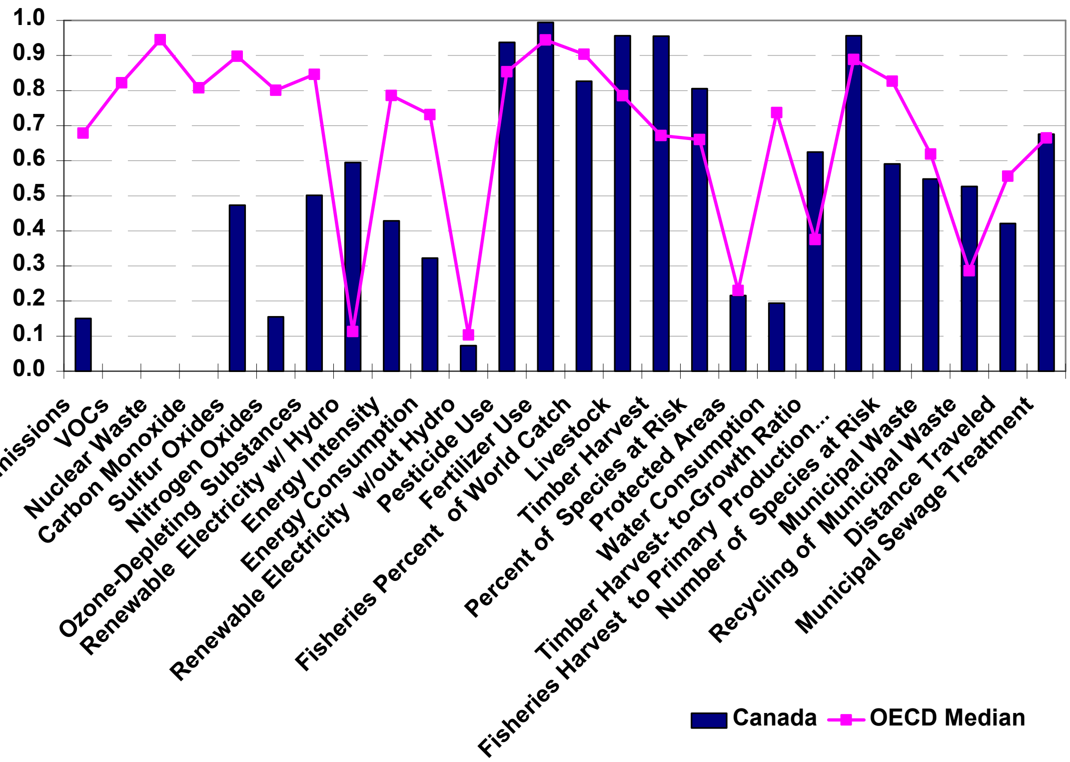
FACTOR	UNITS	OECD	TOP 3 AVG	BELGIUM
Climate	total degree days	3167.1	4998.3	**3110.7**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**334.16**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$25,105**
Technological Development	2002 dimensionless index	0.360	0.603	**0.332**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1172**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$796.88**
Environmental Governance	2002 dimensionless index	59.7	68.1	**58.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$376.57**

COUNTRY RESULTS FOR CANADA

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

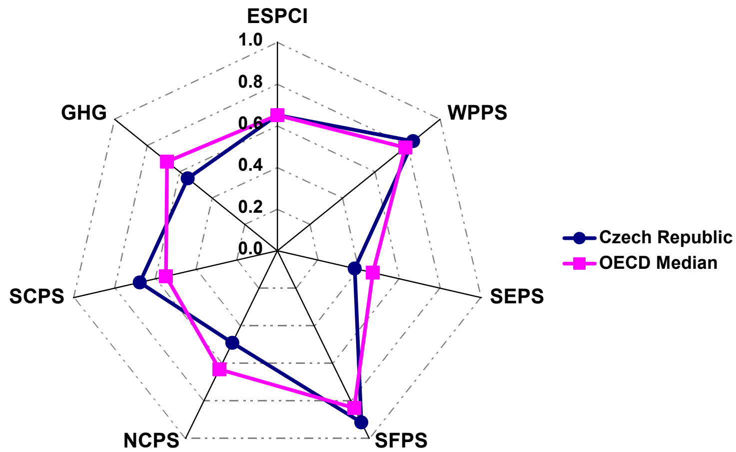


Country factors compared with OECD median and average of three highest countries

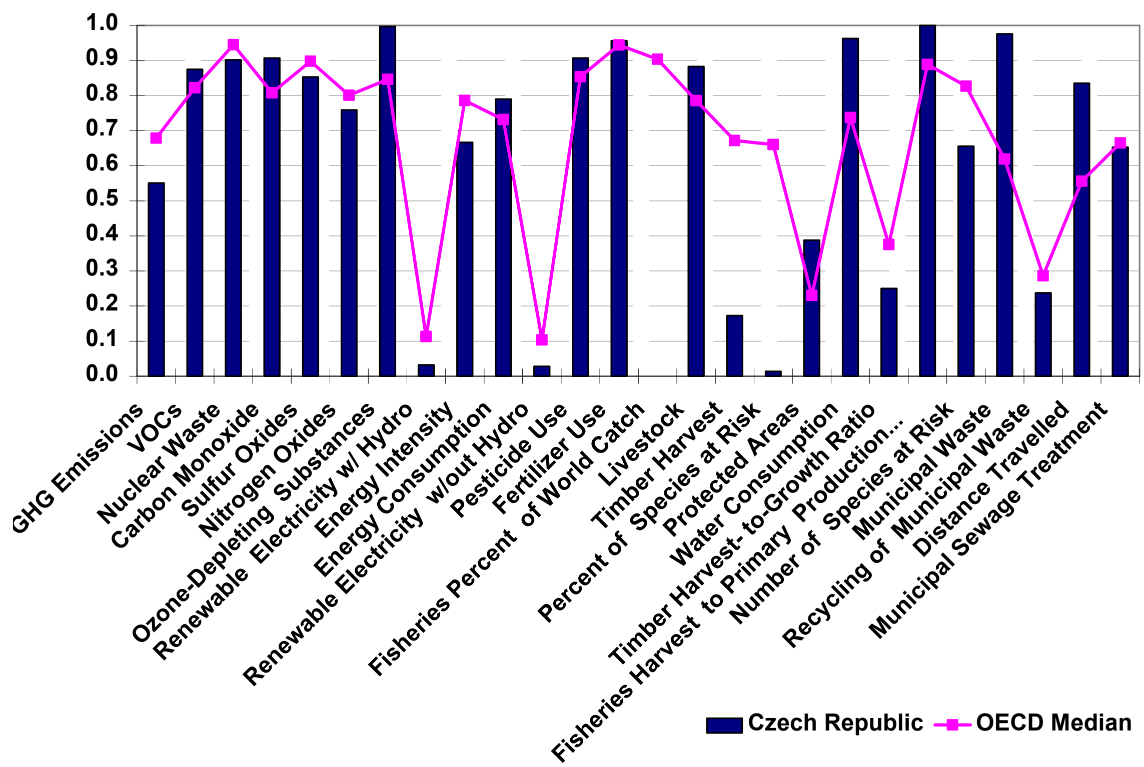
FACTOR	UNITS	OECD	TOP 3 AVG	CANADA
Climate	total degree days	3167.1	4998.3	**4664.3**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**90.05**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$27,803**
Technological Development	2002 dimensionless index	0.360	0.603	**0.428**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0950**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$493.77**
Environmental Governance	2002 dimensionless index	59.7	68.1	**61.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$305.83**

COUNTRY RESULTS FOR CZECH REPUBLIC

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

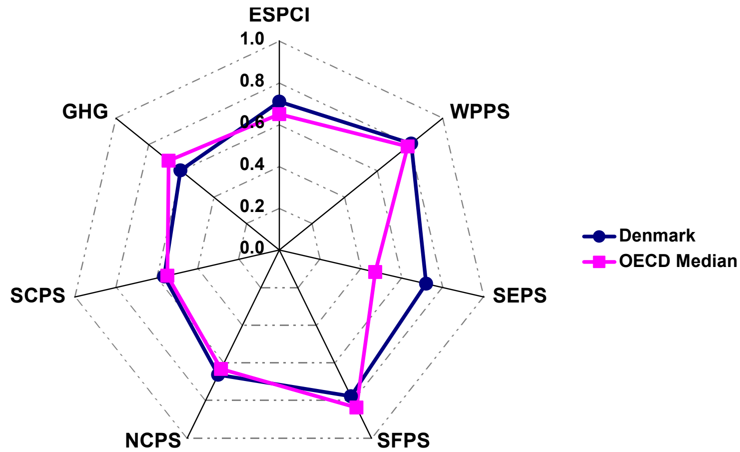


Country factors compared with OECD median and average of three highest countries

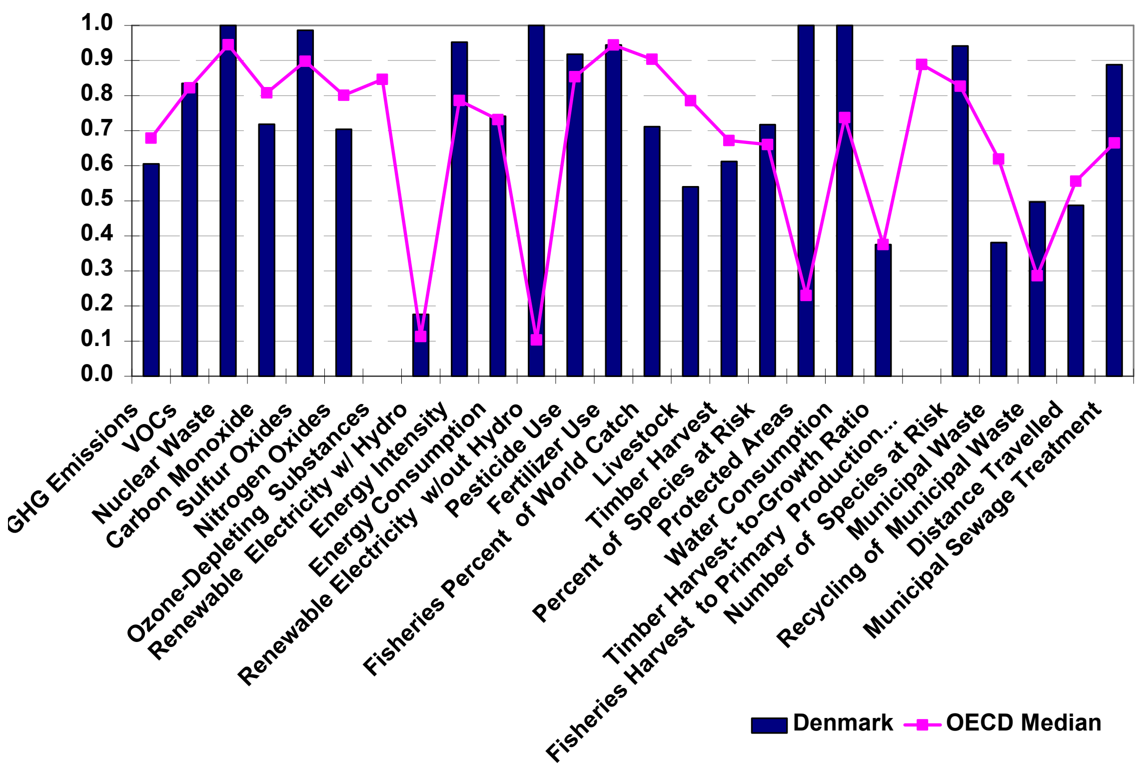
FACTOR	UNITS	OECD	TOP 3 AVG	CZECH REP.
Climate	total degree days	3167.1	4998.3	**3676.9**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**131.23**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$13,979**
Technological Development	2002 dimensionless index	0.360	0.603	**0.327**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1441**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$1,004.57**
Environmental Governance	2002 dimensionless index	59.7	68.1	**51.3**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$237.64**

COUNTRY RESULTS FOR DENMARK

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

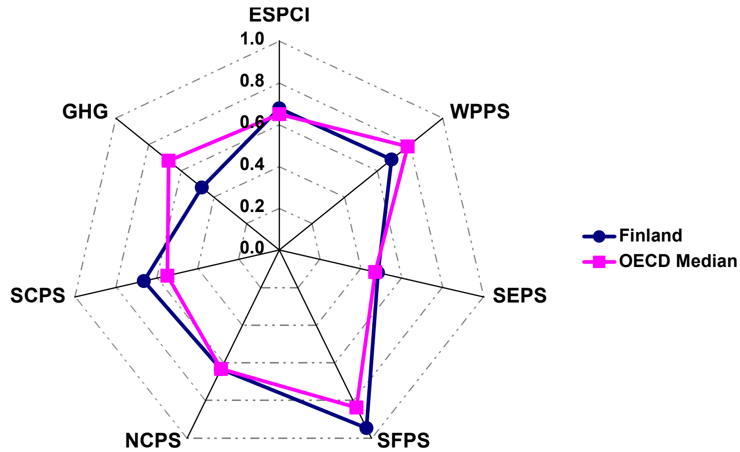


Country factors compared with OECD median and average of three highest countries

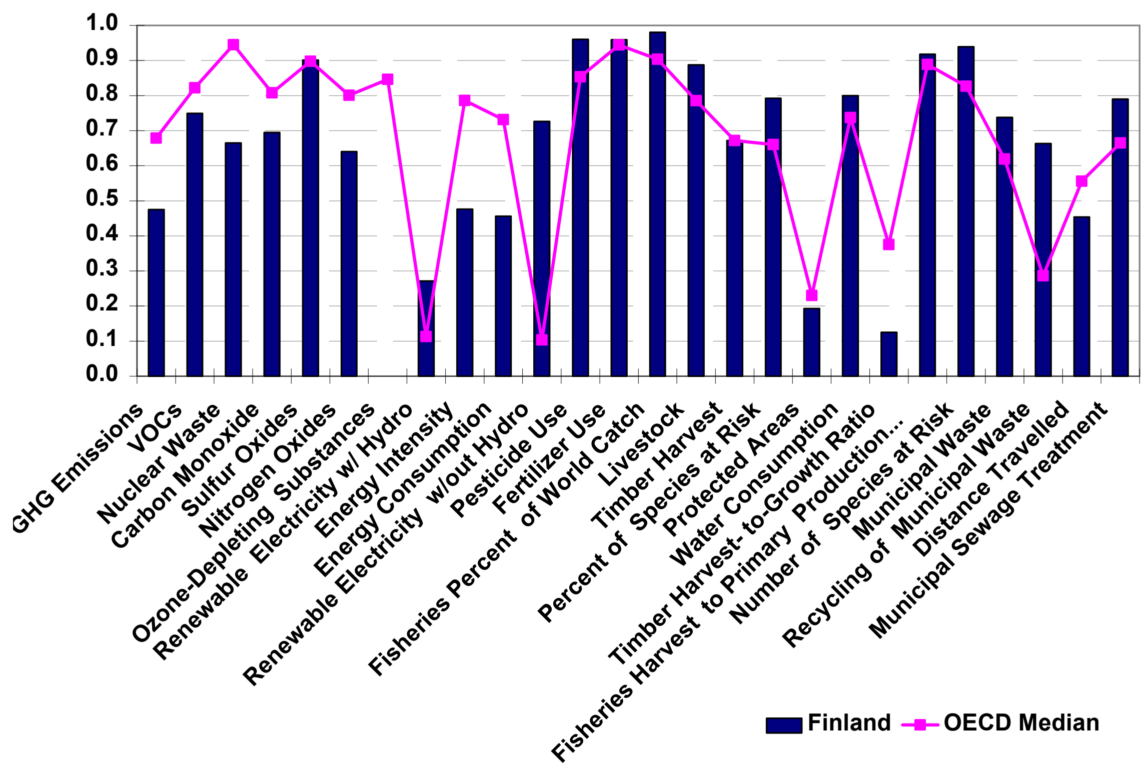
FACTOR	UNITS	OECD	TOP 3 AVG	DENMARK
Climate	total degree days	3167.1	4998.3	**3661.0**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**103.50**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$26,275**
Technological Development	2002 dimensionless index	0.360	0.603	
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1005**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	
Environmental Governance	2002 dimensionless index	59.7	68.1	**67.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$0.00**

COUNTRY RESULTS FOR FINLAND

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

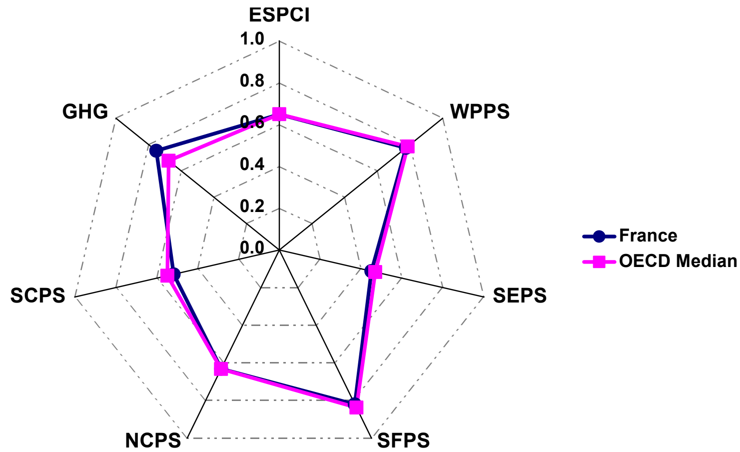


Country factors compared with OECD median and average of three highest countries

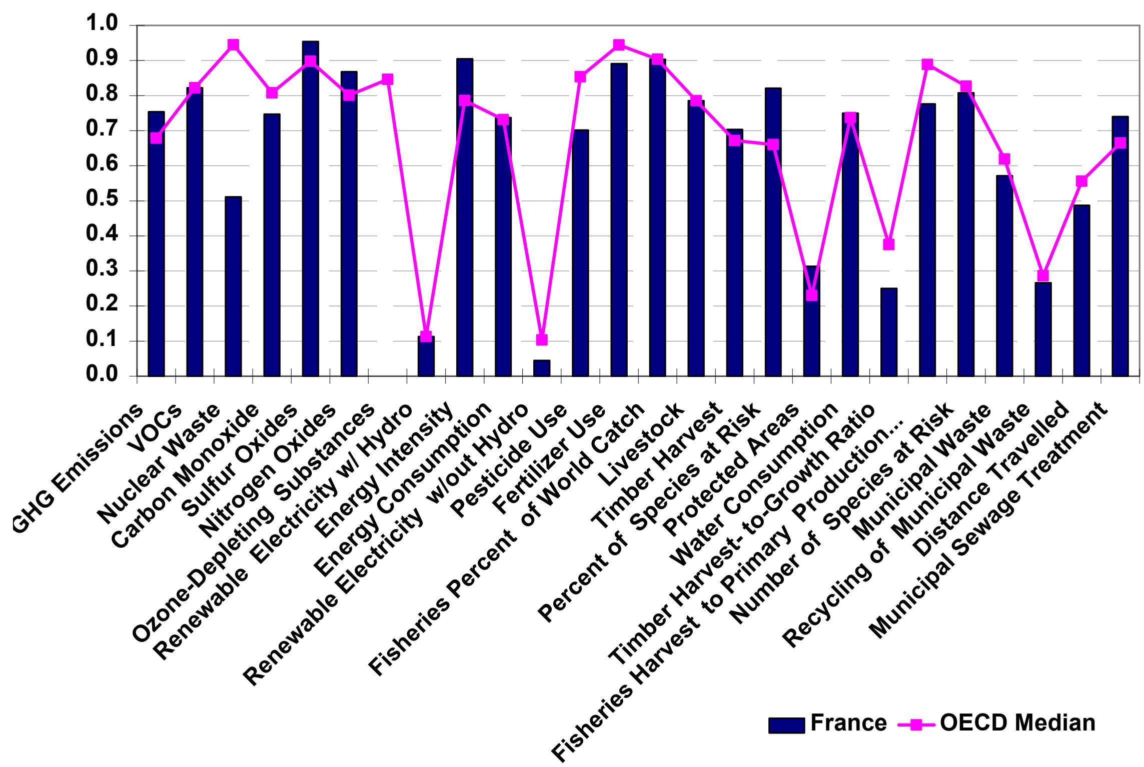
FACTOR	UNITS	OECD	TOP 3 AVG	FINLAND
Climate	total degree days	3167.1	4998.3	**5259.5**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**33.61**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$24,034**
Technological Development	2002 dimensionless index	0.360	0.603	**0.571**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1233**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$852.35**
Environmental Governance	2002 dimensionless index	59.7	68.1	**68.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$192.27**

COUNTRY RESULTS FOR FRANCE

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

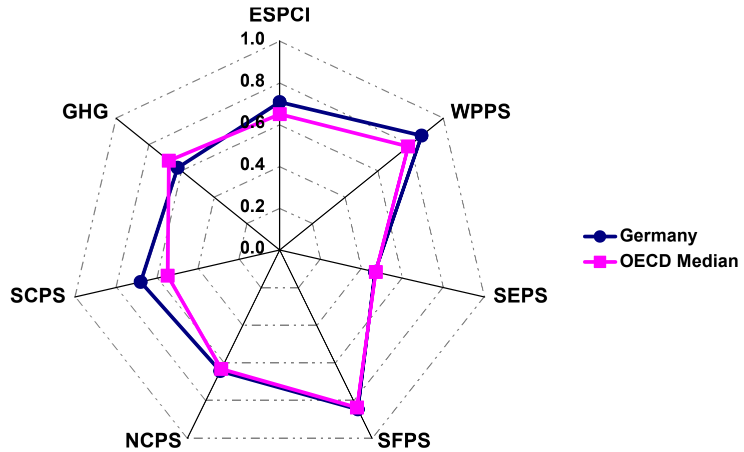


Country factors compared with OECD median and average of three highest countries

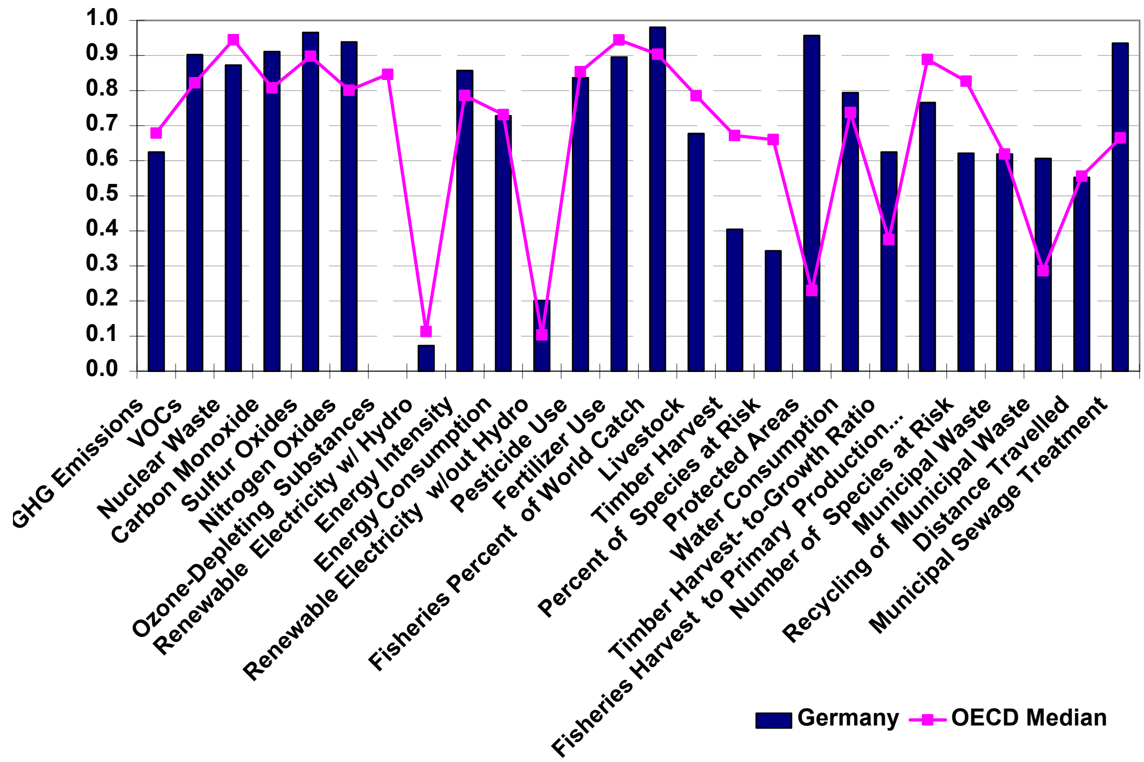
FACTOR	UNITS	OECD	TOP 3 AVG	FRANCE
Climate	total degree days	3167.1	4998.3	**2719.6**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**112.16**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$23,821**
Technological Development	2002 dimensionless index	0.360	0.603	**0.357**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0955**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$859.38**
Environmental Governance	2002 dimensionless index	59.7	68.1	**60.3**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$381.13**

COUNTRY RESULTS FOR GERMANY

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

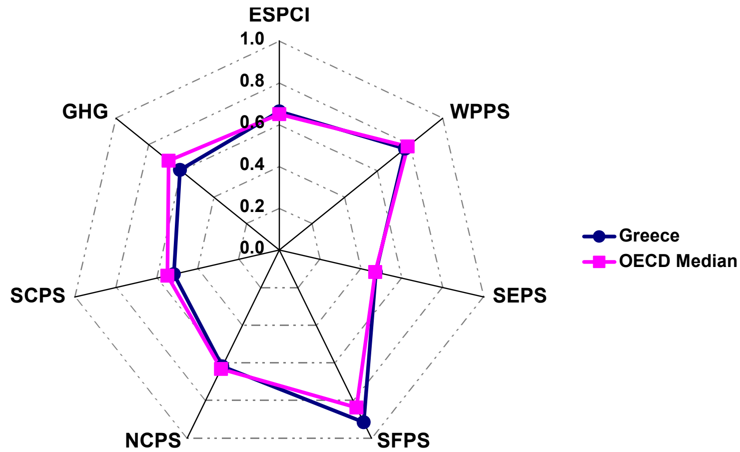


Country factors compared with OECD median and average of three highest countries

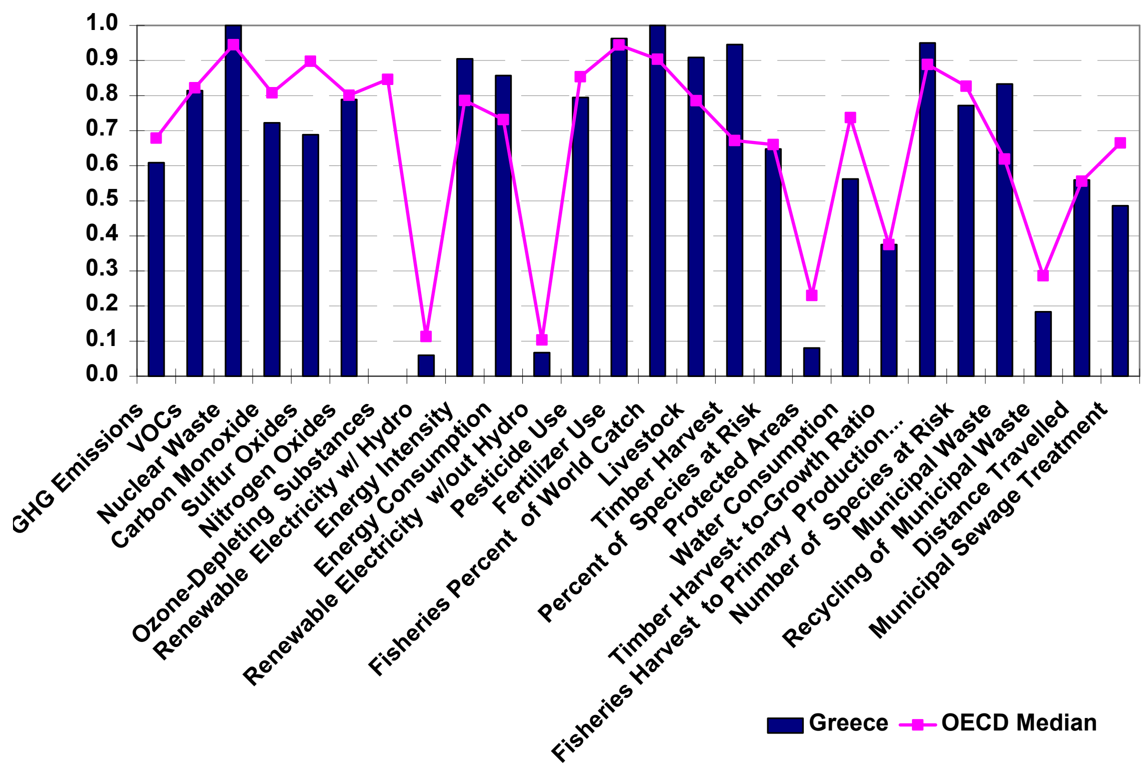
FACTOR	UNITS	OECD	TOP 3 AVG	GERMANY
Climate	total degree days	3167.1	4998.3	**3373.7**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**227.53**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$23,343**
Technological Development	2002 dimensionless index	0.360	0.603	**0.448**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0956**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$875.47**
Environmental Governance	2002 dimensionless index	59.7	68.1	**68.3**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$373.49**

COUNTRY RESULTS FOR GREECE

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

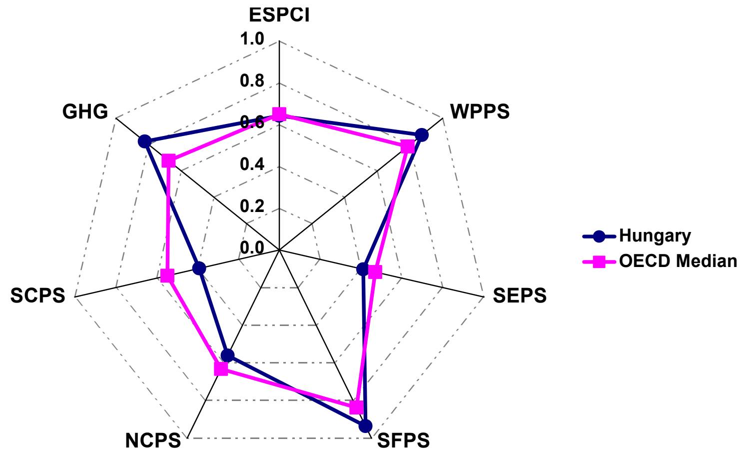


Country factors compared with OECD median and average of three highest countries

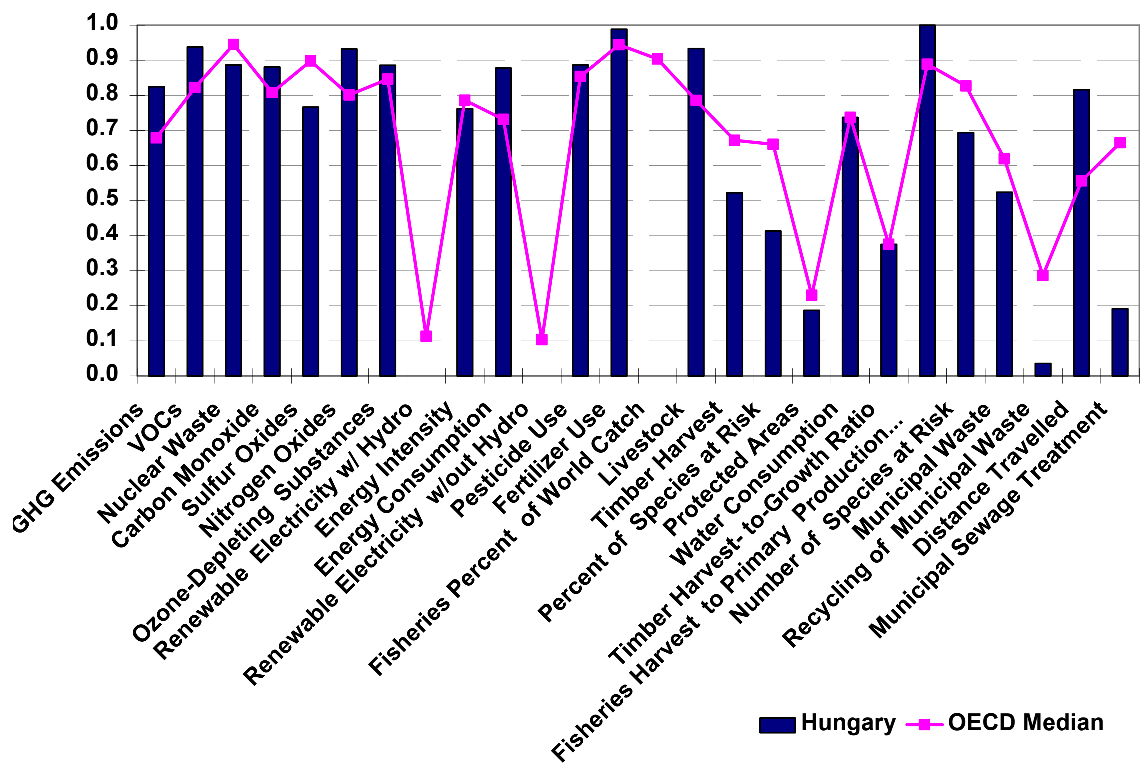
FACTOR	UNITS	OECD	TOP 3 AVG	GREECE
Climate	total degree days	3167.1	4998.3	**2191.9**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**71.24**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$16,113**
Technological Development	2002 dimensionless index	0.360	0.603	**0.278**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1024**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$934.12**
Environmental Governance	2002 dimensionless index	59.7	68.1	**45.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$161.13**

COUNTRY RESULTS FOR HUNGARY

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

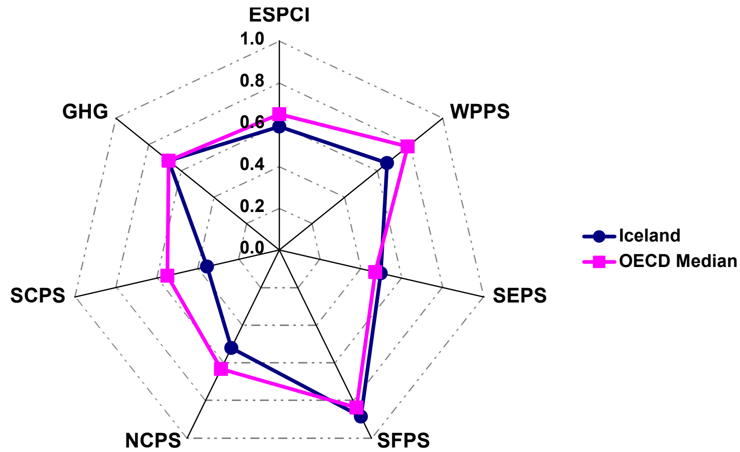


Country factors compared with OECD median and average of three highest countries

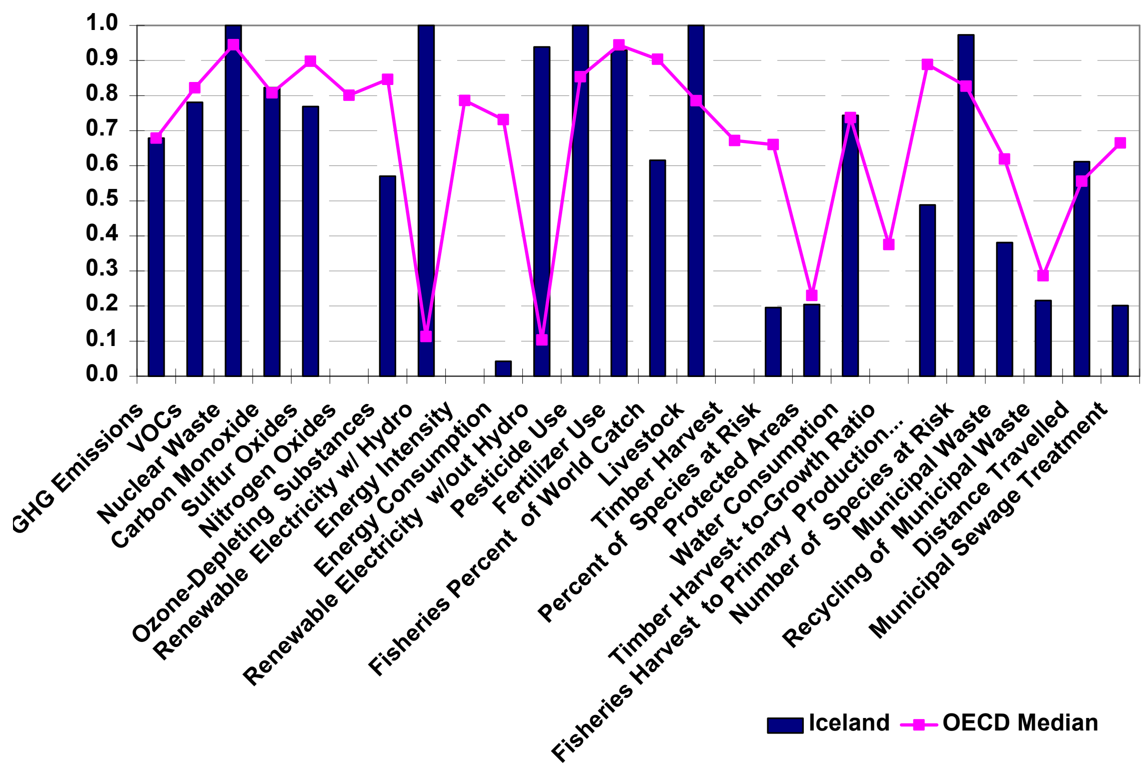
FACTOR	UNITS	OECD	TOP 3 AVG	HUNGARY
Climate	total degree days	3167.1	4998.3	**3313.1**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**109.57**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$11,905**
Technological Development	2002 dimensionless index	0.360	0.603	**0.271**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1195**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$856.91**
Environmental Governance	2002 dimensionless index	59.7	68.1	**47.7**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$178.57**

COUNTRY RESULTS FOR ICELAND

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

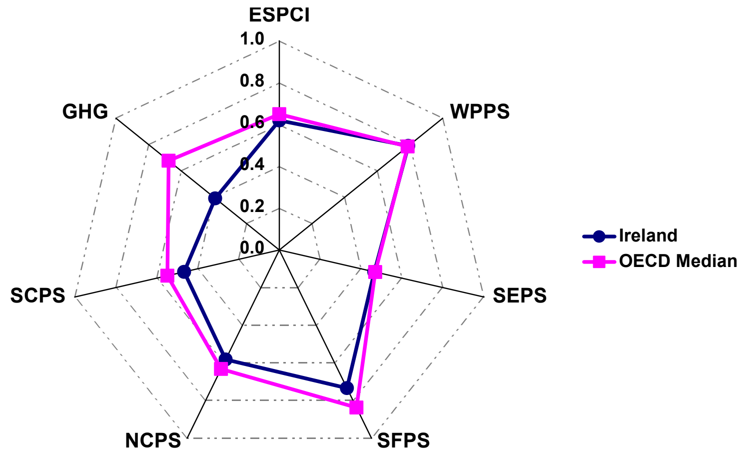


Country factors compared with OECD median and average of three highest countries

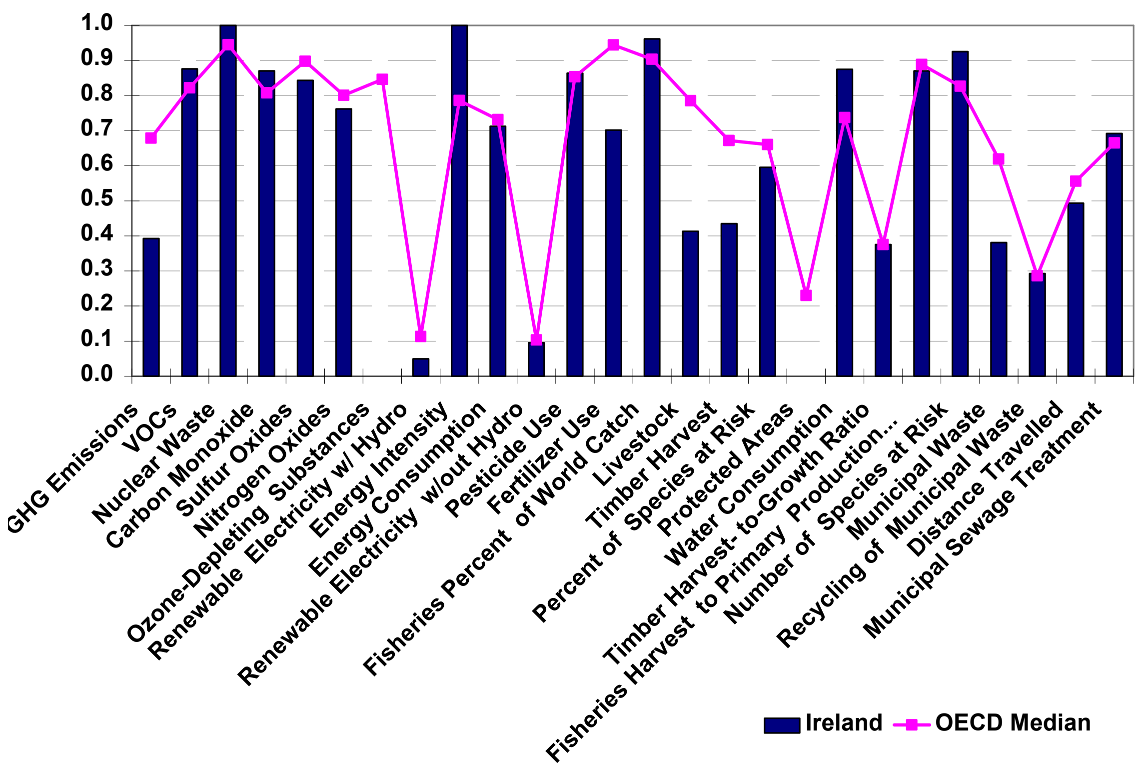
FACTOR	UNITS	OECD	TOP 3 AVG	ICELAND
Climate	total degree days	3167.1	4998.3	**5071.3**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**88.20**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$26,389**
Technological Development	2002 dimensionless index	0.360	0.603	**0.434**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0912**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	
Environmental Governance	2002 dimensionless index	59.7	68.1	**62.7**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$0.00**

COUNTRY RESULTS FOR IRELAND

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

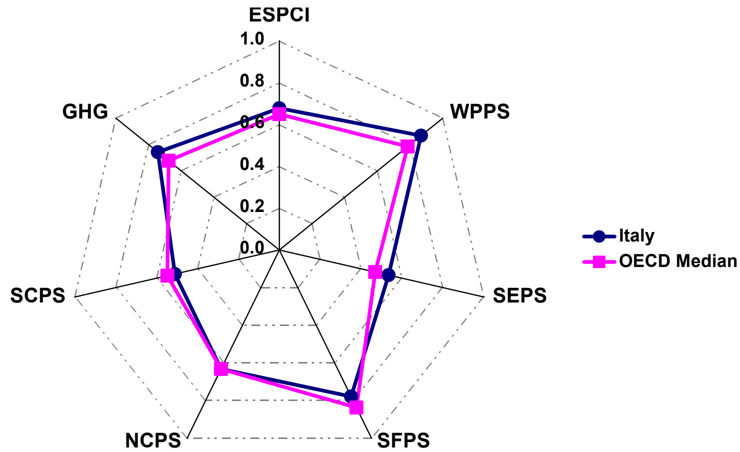


Country factors compared with OECD median and average of three highest countries

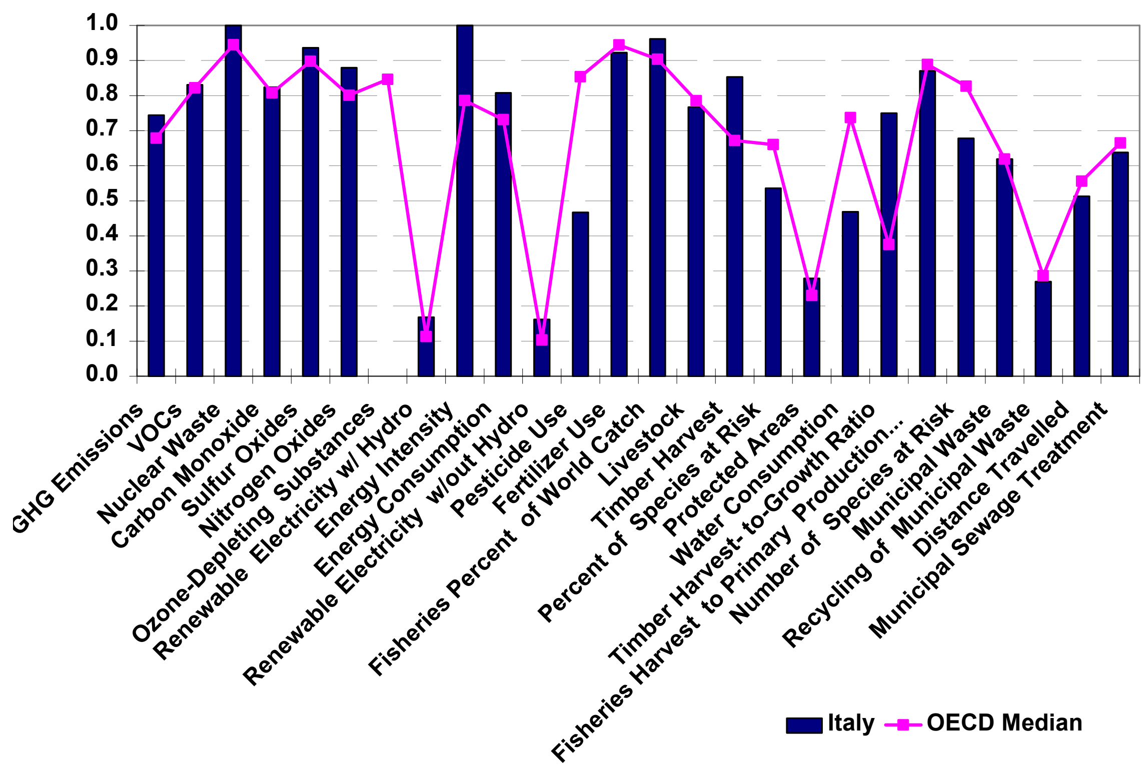
FACTOR	UNITS	OECD	TOP 3 AVG	IRELAND
Climate	total degree days	3167.1	4998.3	**2995.6**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**54.03**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$30,049**
Technological Development	2002 dimensionless index	0.360	0.603	**0.430**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1892**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$881.01**
Environmental Governance	2002 dimensionless index	59.7	68.1	**48.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$180.29**

COUNTRY RESULTS FOR ITALY

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

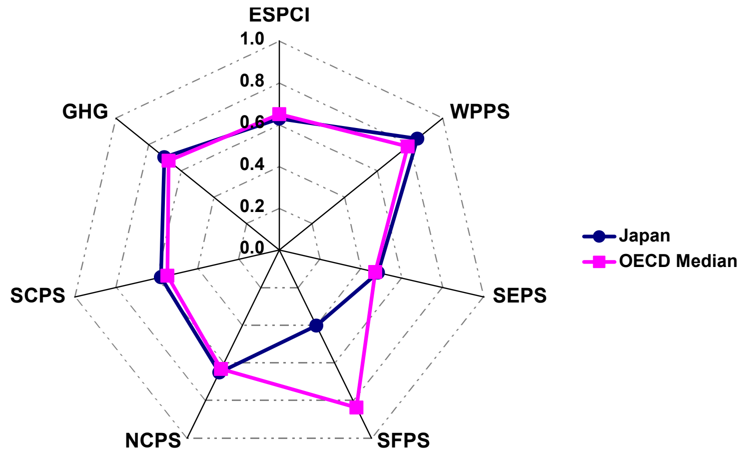


Country factors compared with OECD median and average of three highest countries

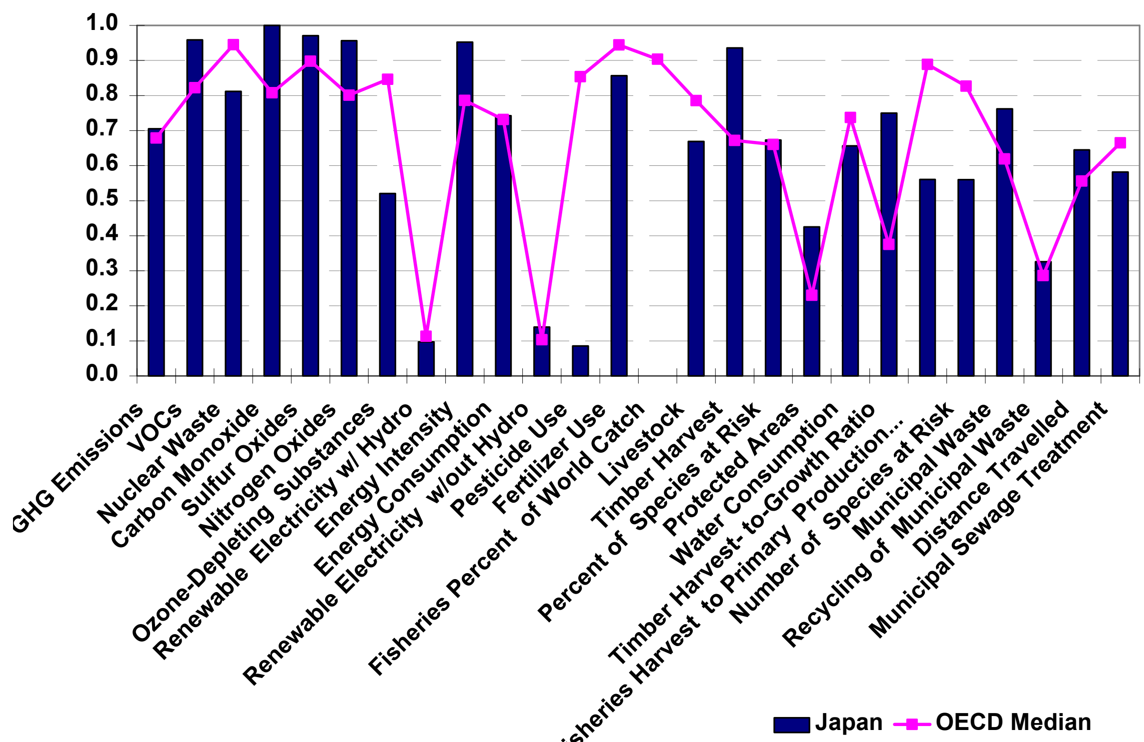
FACTOR	UNITS	OECD	TOP 3 AVG	ITALY
Climate	total degree days	3167.1	4998.3	**2438.5**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**186.95**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$22,340**
Technological Development	2002 dimensionless index	0.360	0.603	**0.272**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1049**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$1,096.76**
Environmental Governance	2002 dimensionless index	59.7	68.1	**52.9**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$201.06**

COUNTRY RESULTS FOR JAPAN

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

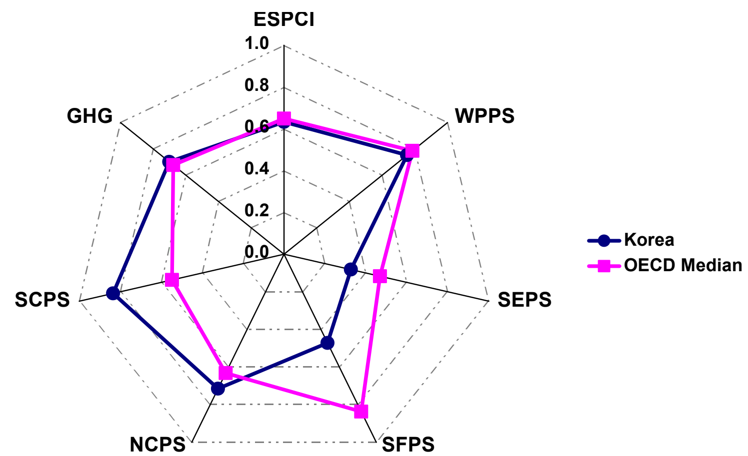


Country factors compared with OECD median and average of three highest countries

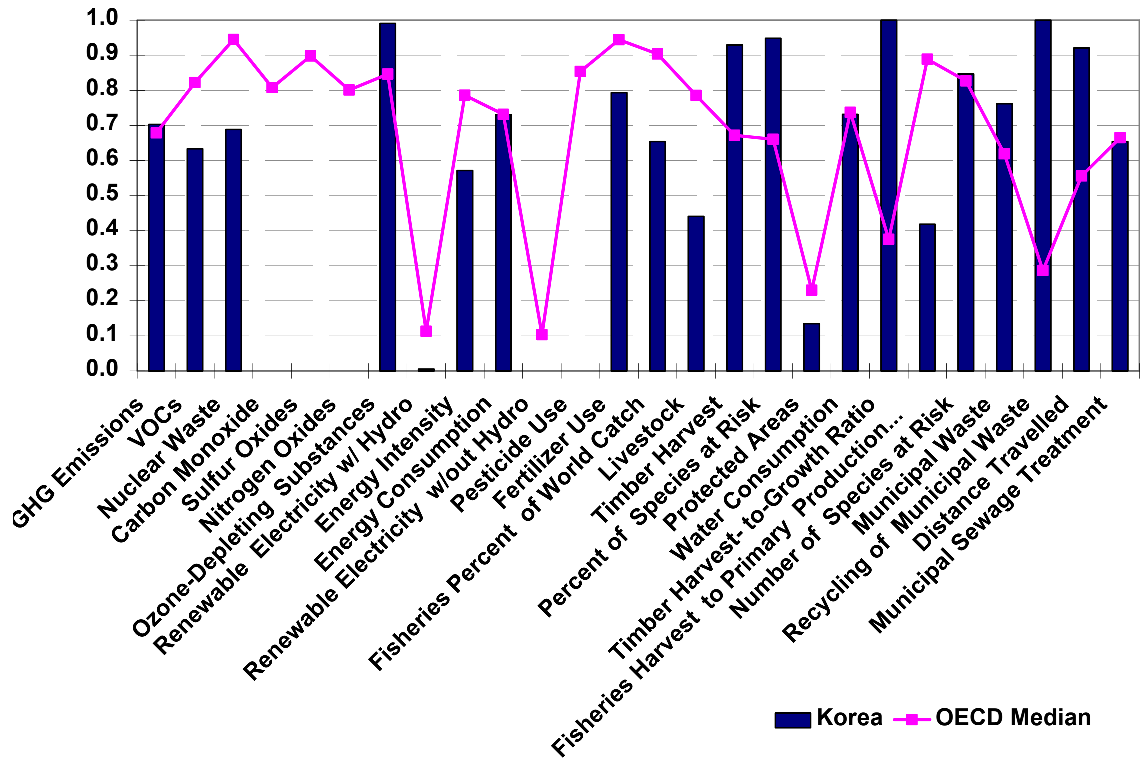
FACTOR	UNITS	OECD	TOP 3 AVG	JAPAN
Climate	total degree days	3167.1	4998.3	**2796.6**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**319.45**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$24,871**
Technological Development	2002 dimensionless index	0.360	0.603	**0.511**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1057**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$1,121.95**
Environmental Governance	2002 dimensionless index	59.7	68.1	**59.3**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$348.19**

COUNTRY RESULTS FOR KOREA

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

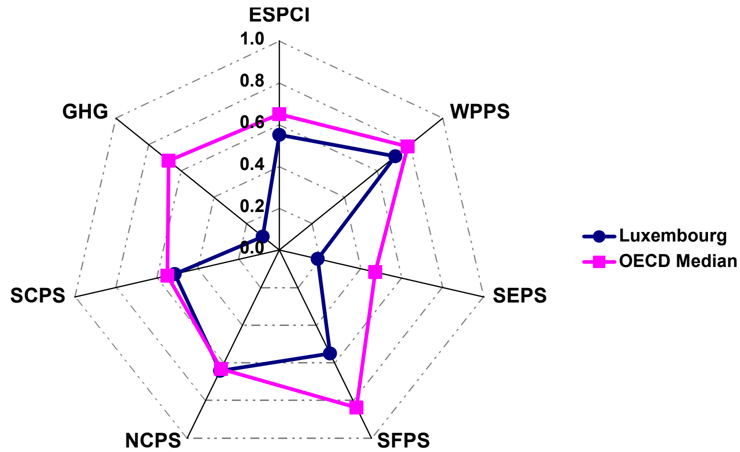


Country factors compared with OECD median and average of three highest countries

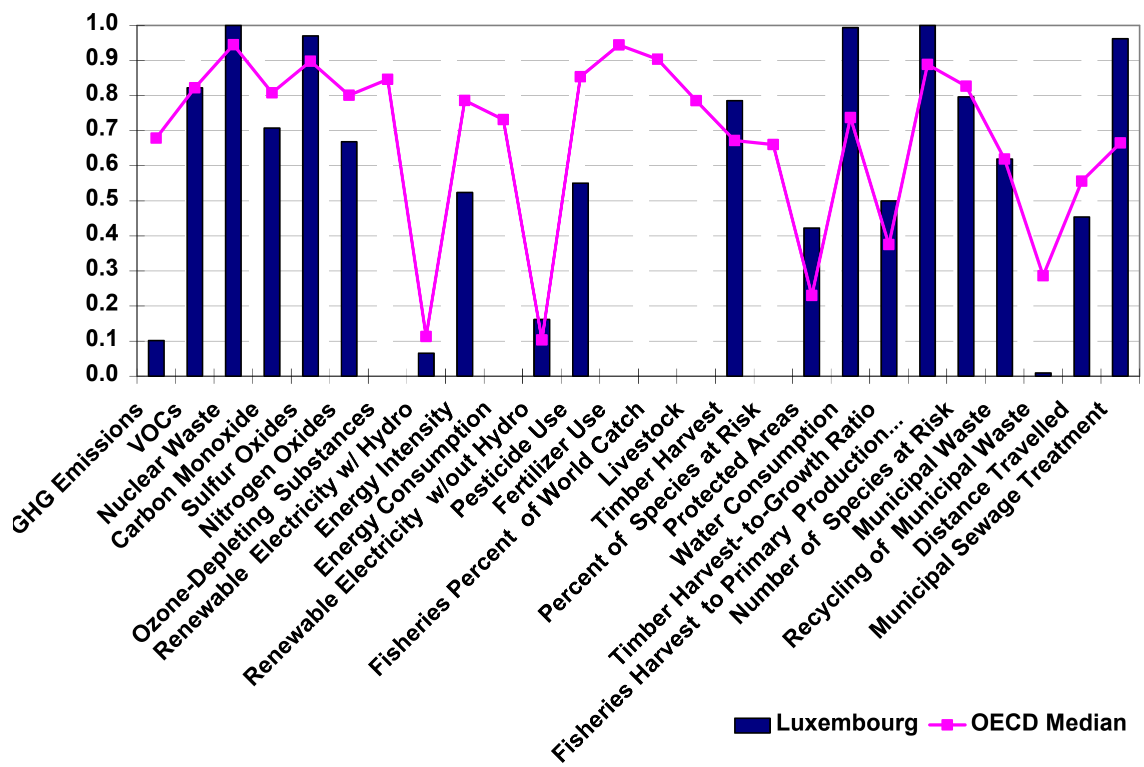
FACTOR	UNITS	OECD	TOP 3 AVG	KOREA
Climate	total degree days	3167.1	4998.3	**3223.5**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**422.45**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$15,076**
Technological Development	2002 dimensionless index	0.360	0.603	**0.619**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1214**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$871.32**
Environmental Governance	2002 dimensionless index	59.7	68.1	**49.8**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$226.13**

COUNTRY RESULTS FOR LUXEMBOURG

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

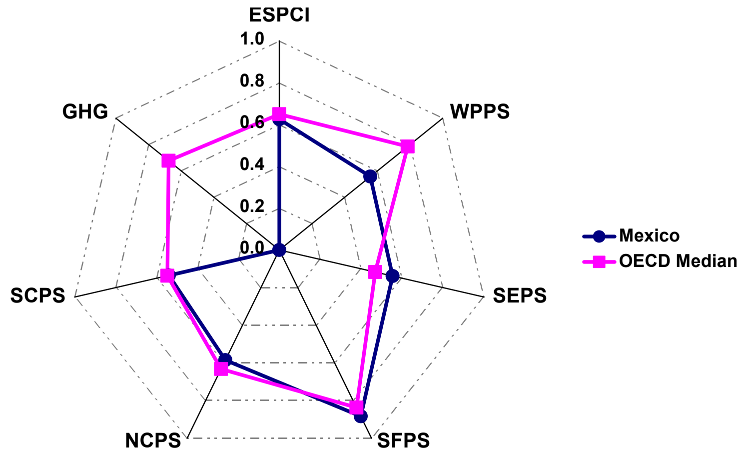


Country factors compared with OECD median and average of three highest countries

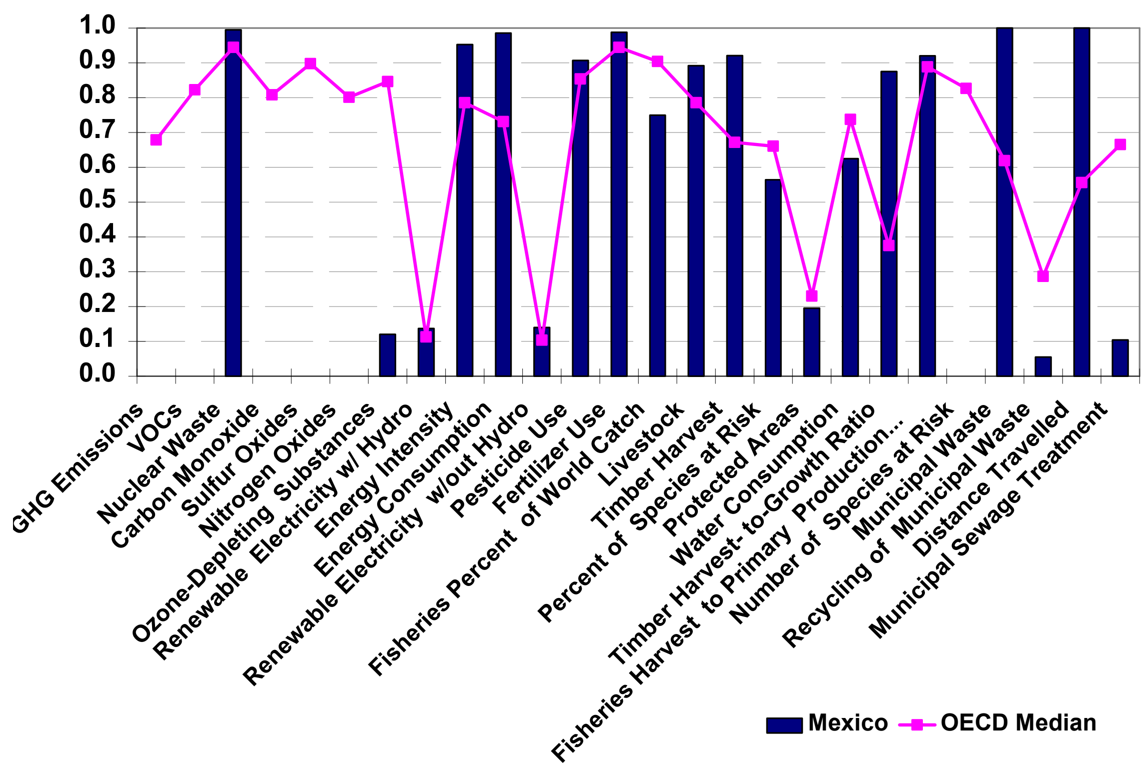
FACTOR	UNITS	OECD	TOP 3 AVG	LUXEMBOURG
Climate	total degree days	3167.1	4998.3	**3565.8**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**168.89**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$43,468**
Technological Development	2002 dimensionless index	0.360	0.603	
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1330**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	
Environmental Governance	2002 dimensionless index	59.7	68.1	**61.1**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$0.00**

COUNTRY RESULTS FOR MEXICO

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

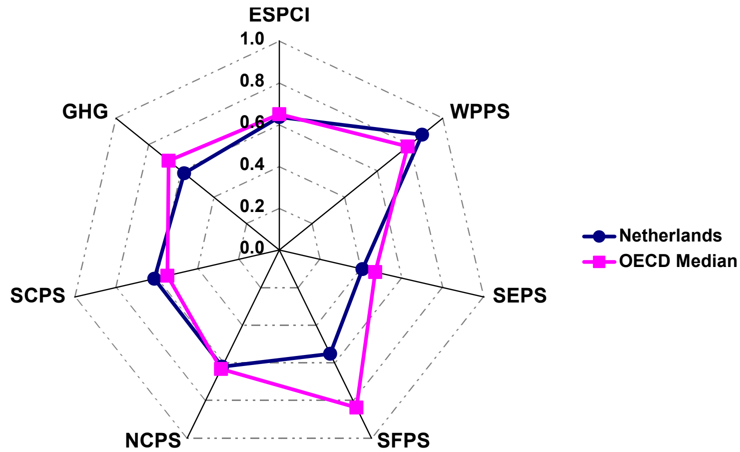


Country factors compared with OECD median and average of three highest countries

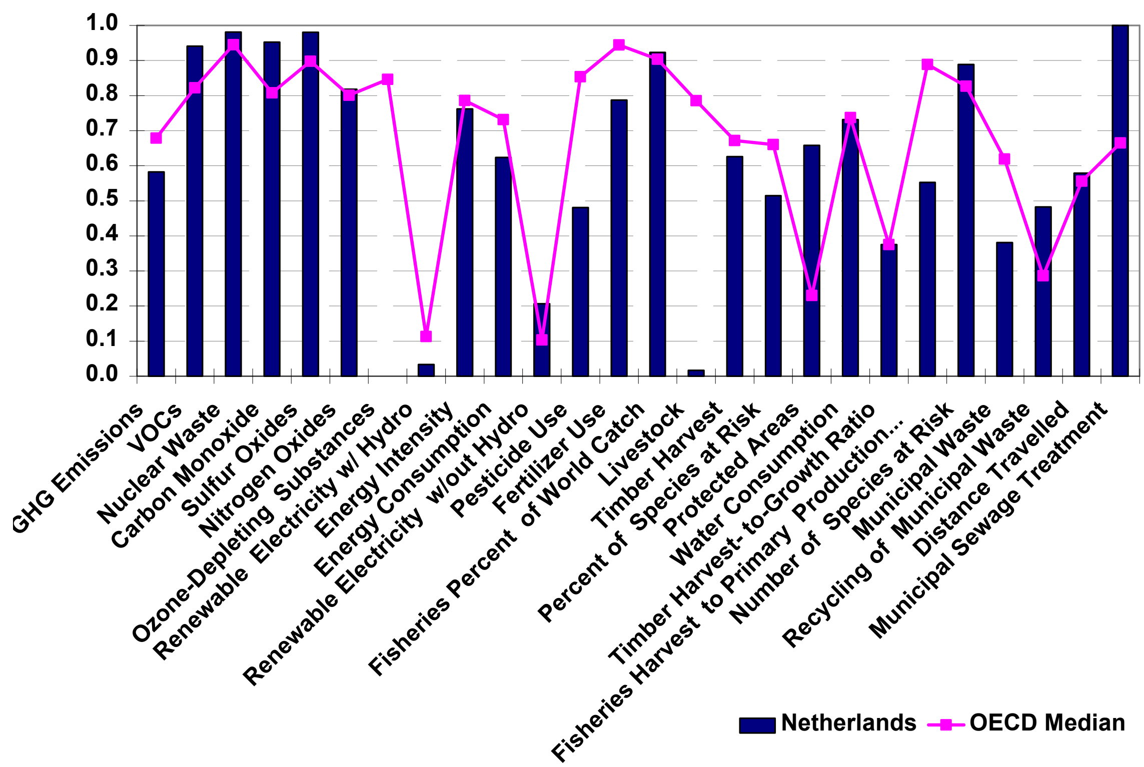
FACTOR	UNITS	OECD	TOP 3 AVG	MEXICO
Climate	total degree days	3167.1	4998.3	**1924.6**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**80.91**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$8,038**
Technological Development	2002 dimensionless index	0.360	0.603	**0.178**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1339**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$699.95**
Environmental Governance	2002 dimensionless index	59.7	68.1	**43.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$56.26**

COUNTRY RESULTS FOR NETHERLANDS

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

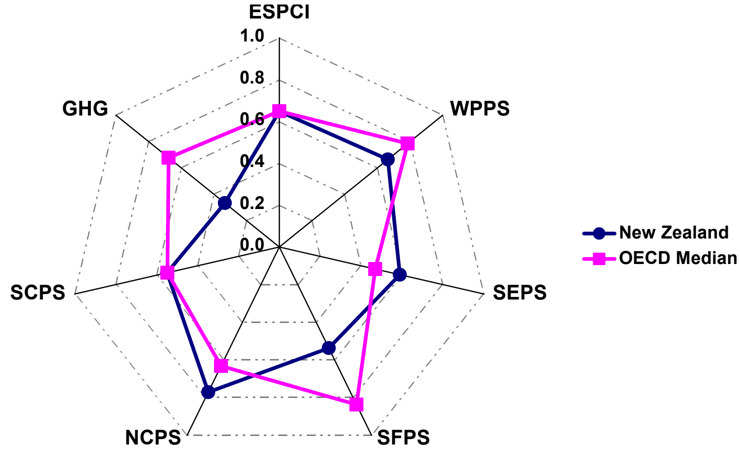


Country factors compared with OECD median and average of three highest countries

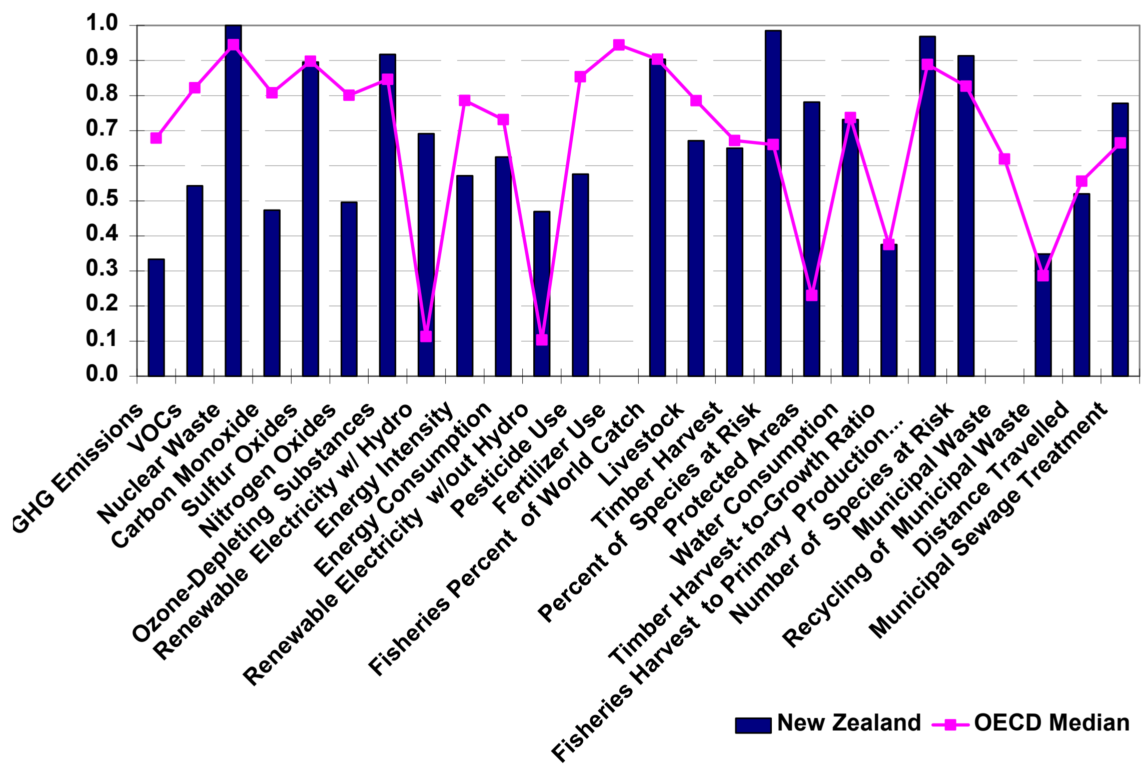
FACTOR	UNITS	OECD	TOP 3 AVG	NETHERLANDS
Climate	total degree days	3167.1	4998.3	**3102.4**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**419.84**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$24,862**
Technological Development	2002 dimensionless index	0.360	0.603	**0.444**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0981**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$826.27**
Environmental Governance	2002 dimensionless index	59.7	68.1	**64.7**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$497.24**

COUNTRY RESULTS FOR NEW ZEALAND

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

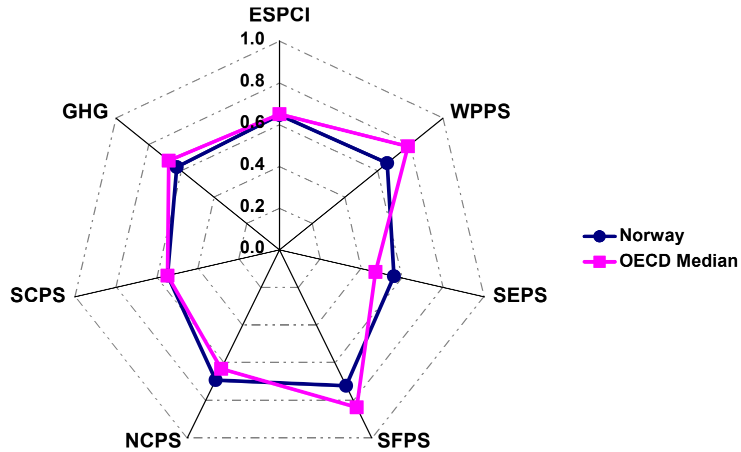


Country factors compared with OECD median and average of three highest countries

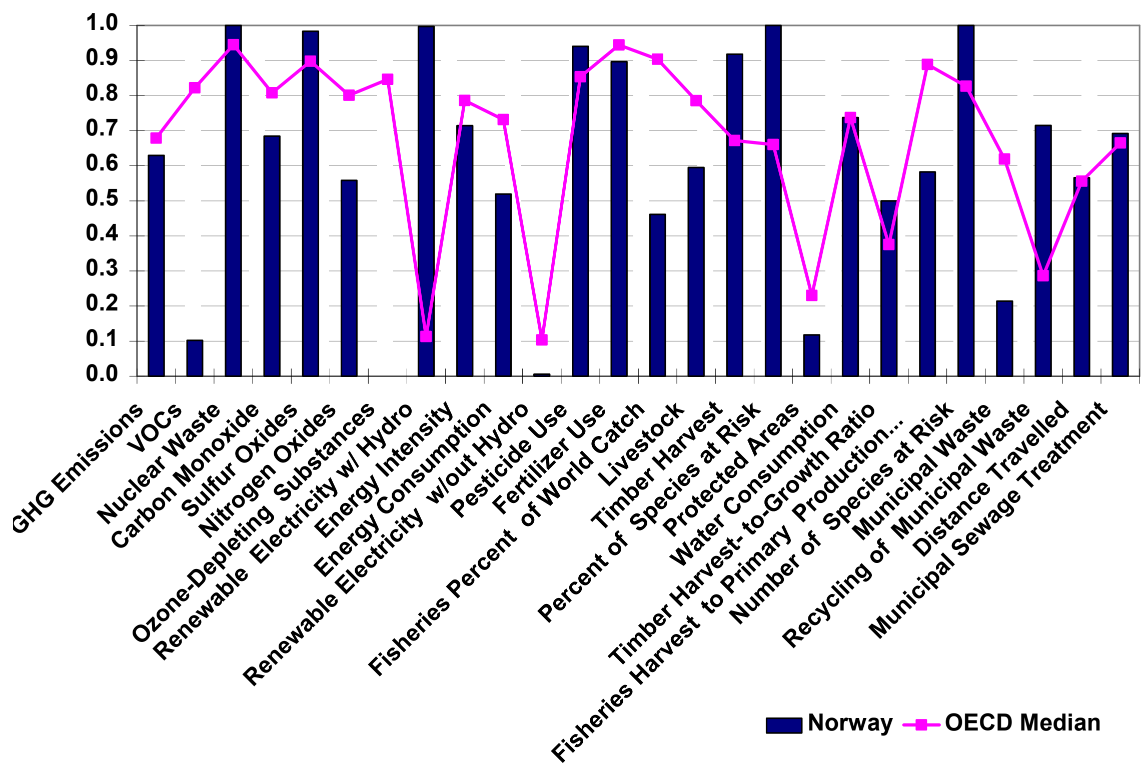
FACTOR	UNITS	OECD	TOP 3 AVG	NEW ZEALAND
Climate	total degree days	3167.1	4998.3	**1774.1**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**65.63**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$19,447**
Technological Development	2002 dimensionless index	0.360	0.603	**0.362**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0910**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$532.24**
Environmental Governance	2002 dimensionless index	59.7	68.1	**60.7**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$0.00**

COUNTRY RESULTS FOR NORWAY

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

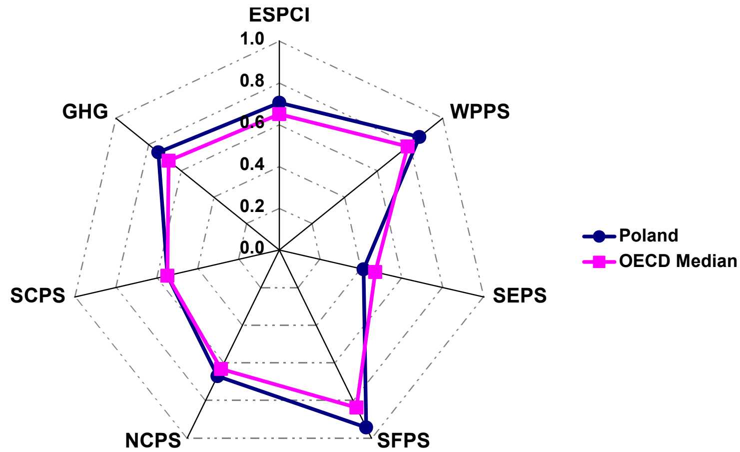


Country factors compared with OECD median and average of three highest countries

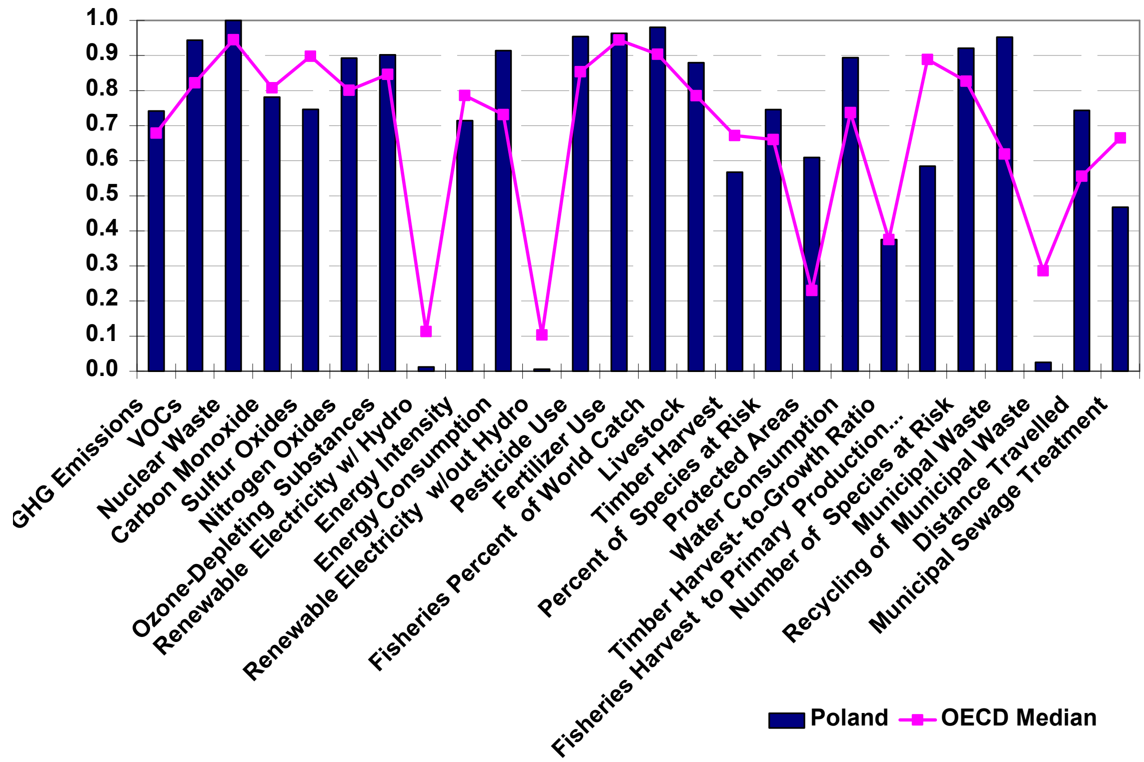
FACTOR	UNITS	OECD	TOP 3 AVG	NORWAY
Climate	total degree days	3167.1	4998.3	**4577.9**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**37.72**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$27,766**
Technological Development	2002 dimensionless index	0.360	0.603	**0.518**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0954**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$728.92**
Environmental Governance	2002 dimensionless index	59.7	68.1	**63.7**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$0.00**

COUNTRY RESULTS FOR POLAND

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

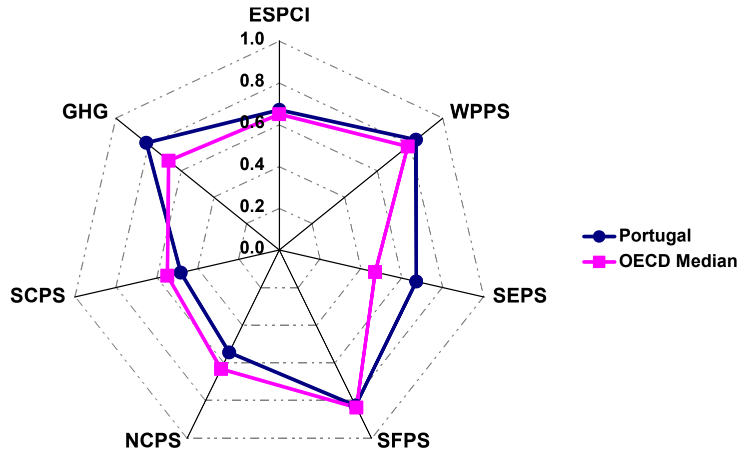


Country factors compared with OECD median and average of three highest countries

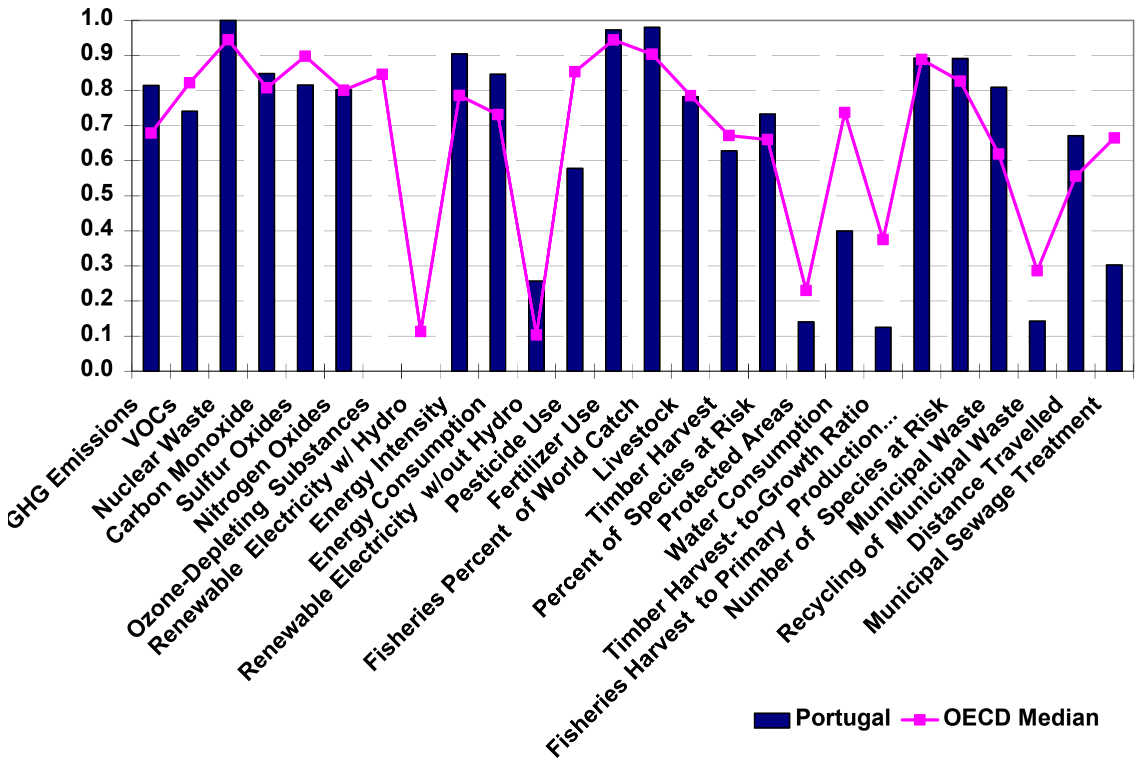
FACTOR	UNITS	OECD	TOP 3 AVG	POLAND
Climate	total degree days	3167.1	4998.3	**3819.2**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**123.28**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$9,217**
Technological Development	2002 dimensionless index	0.360	0.603	**0.175**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0981**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$1,113.69**
Environmental Governance	2002 dimensionless index	59.7	68.1	**44.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$184.35**

COUNTRY RESULTS FOR PORTUGAL

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

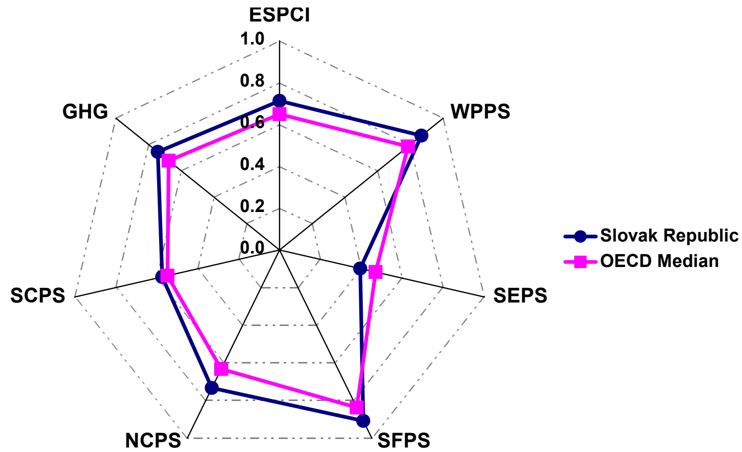


Country factors compared with OECD median and average of three highest countries

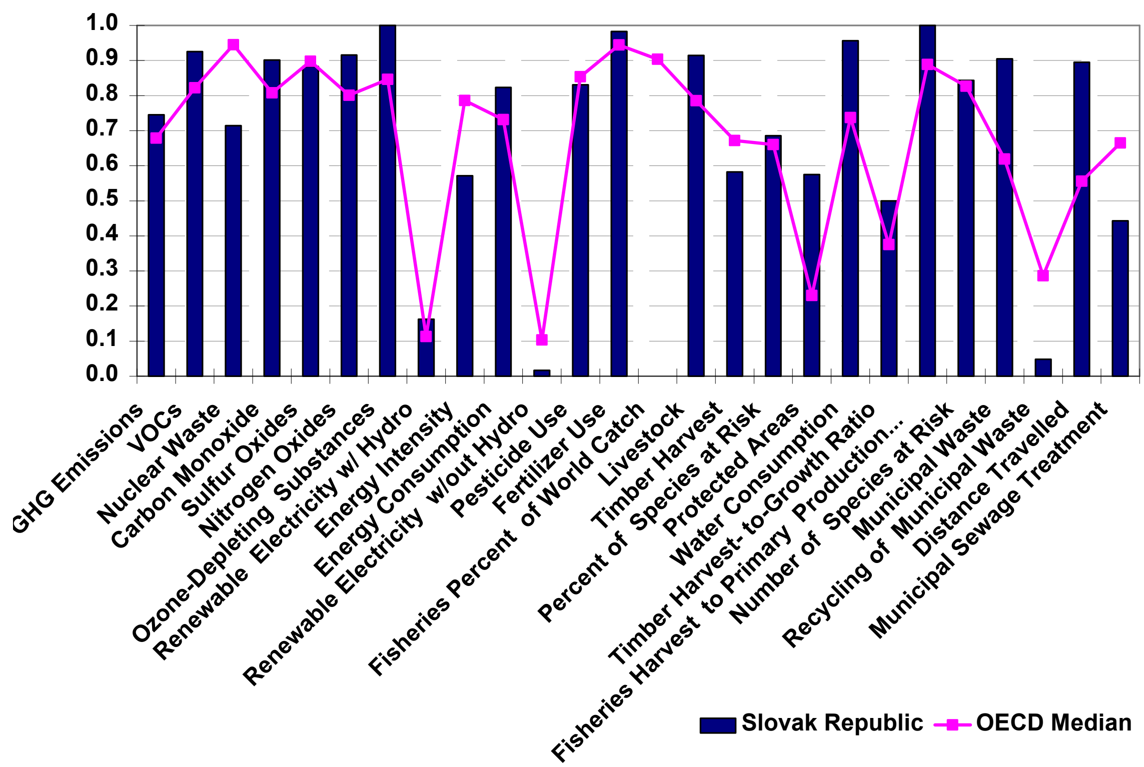
FACTOR	UNITS	OECD	TOP 3 AVG	PORTUGAL
Climate	total degree days	3167.1	4998.3	**1712.0**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**114.38**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$16,224**
Technological Development	2002 dimensionless index	0.360	0.603	**0.206**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0879**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$1,201.96**
Environmental Governance	2002 dimensionless index	59.7	68.1	**49.4**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$129.79**

COUNTRY RESULTS FOR SLOVAK REPUBLIC

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

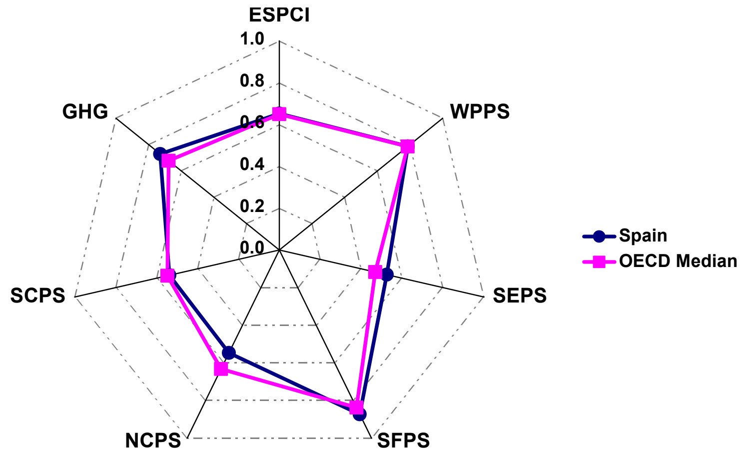


Country factors compared with OECD median and average of three highest countries

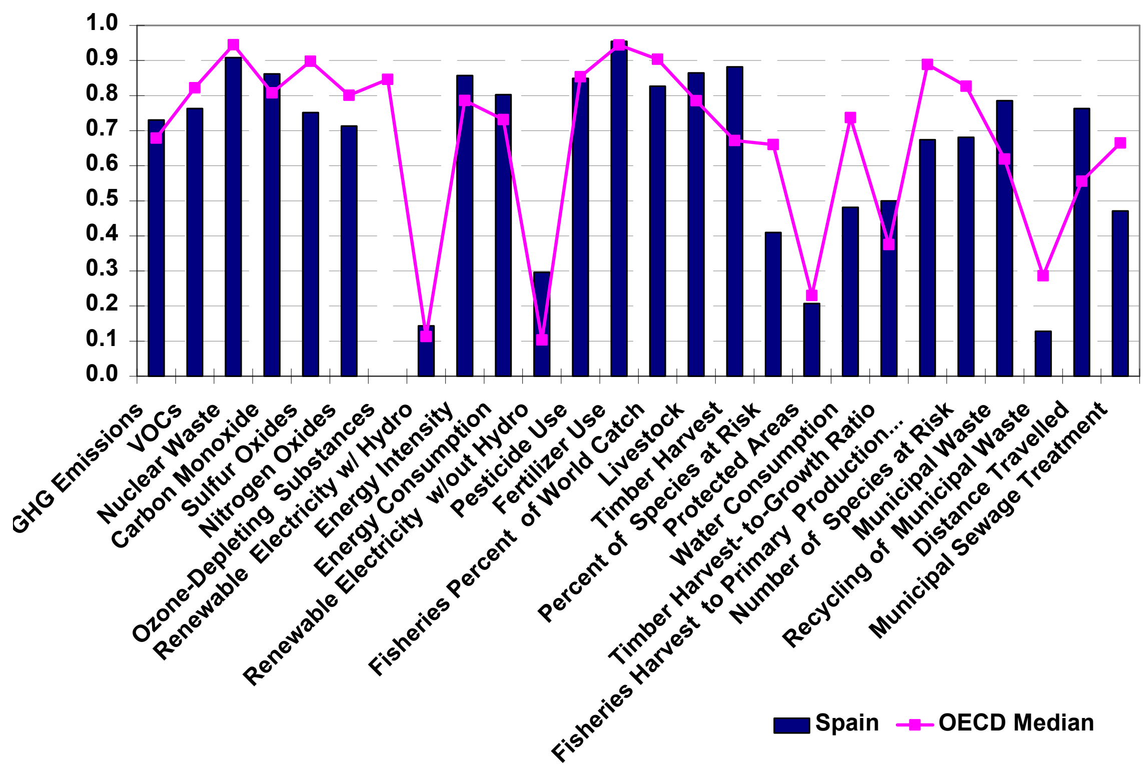
FACTOR	UNITS	OECD	TOP 3 AVG	SLOVAK REP.
Climate	total degree days	3167.1	4998.3	**3655.4**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**110.99**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$11,545**
Technological Development	2002 dimensionless index	0.360	0.603	**0.210**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1581**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$883.39**
Environmental Governance	2002 dimensionless index	59.7	68.1	**53.1**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$92.36**

COUNTRY RESULTS FOR SPAIN

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

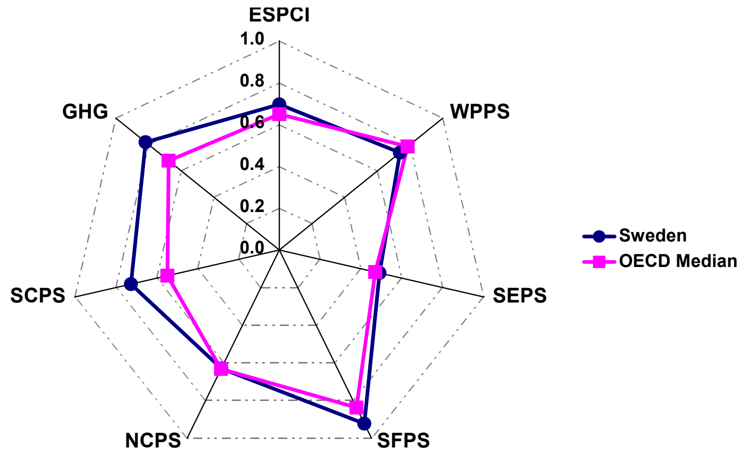


Country factors compared with OECD median and average of three highest countries

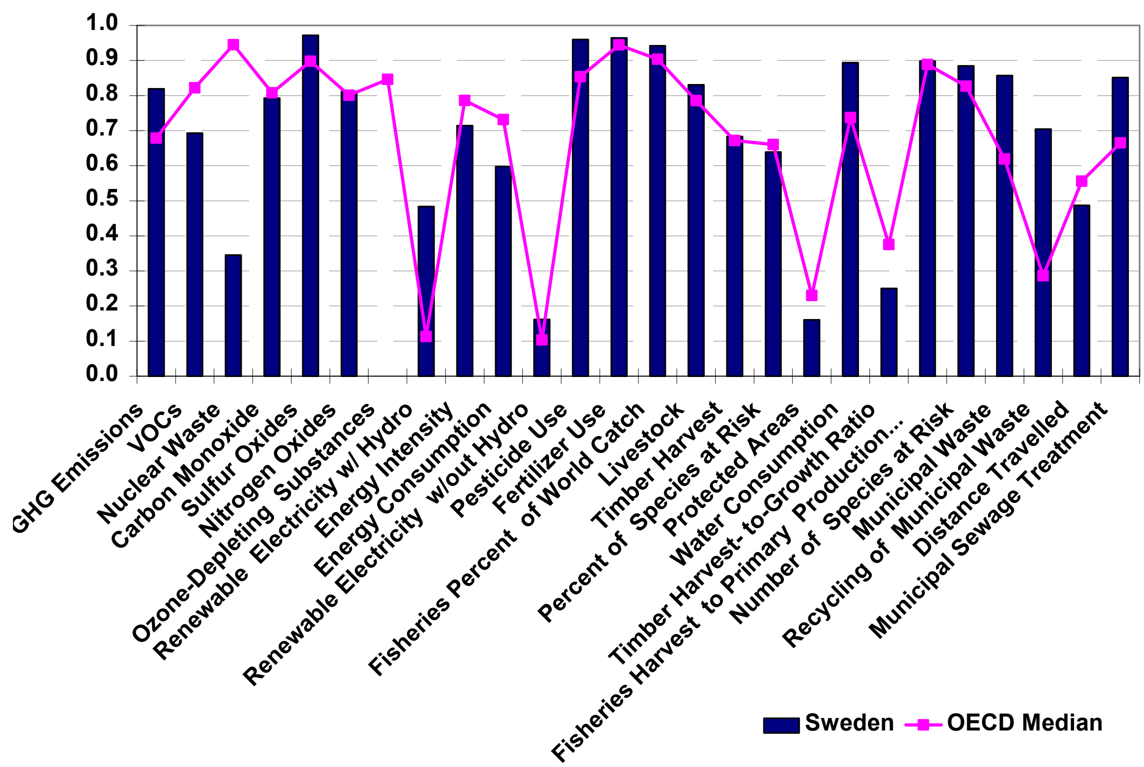
FACTOR	UNITS	OECD	TOP 3 AVG	SPAIN
Climate	total degree days	3167.1	4998.3	**2132.4**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**99.33**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$18,606**
Technological Development	2002 dimensionless index	0.360	0.603	**0.254**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1168**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$904.95**
Environmental Governance	2002 dimensionless index	59.7	68.1	**50.6**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$148.85**

COUNTRY RESULTS FOR SWEDEN

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

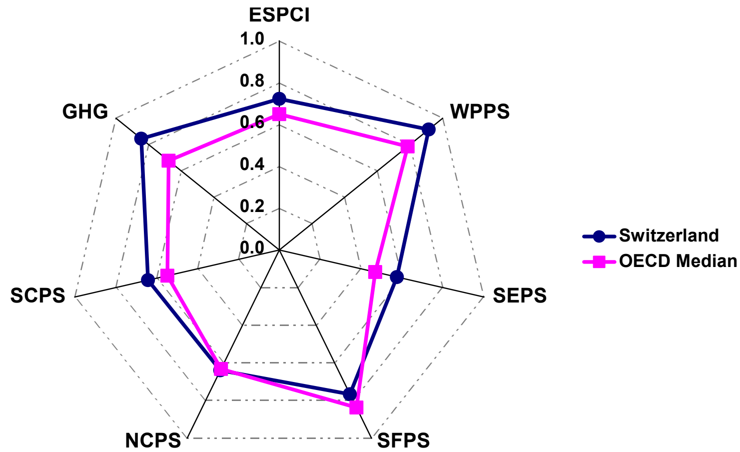


Country factors compared with OECD median and average of three highest countries

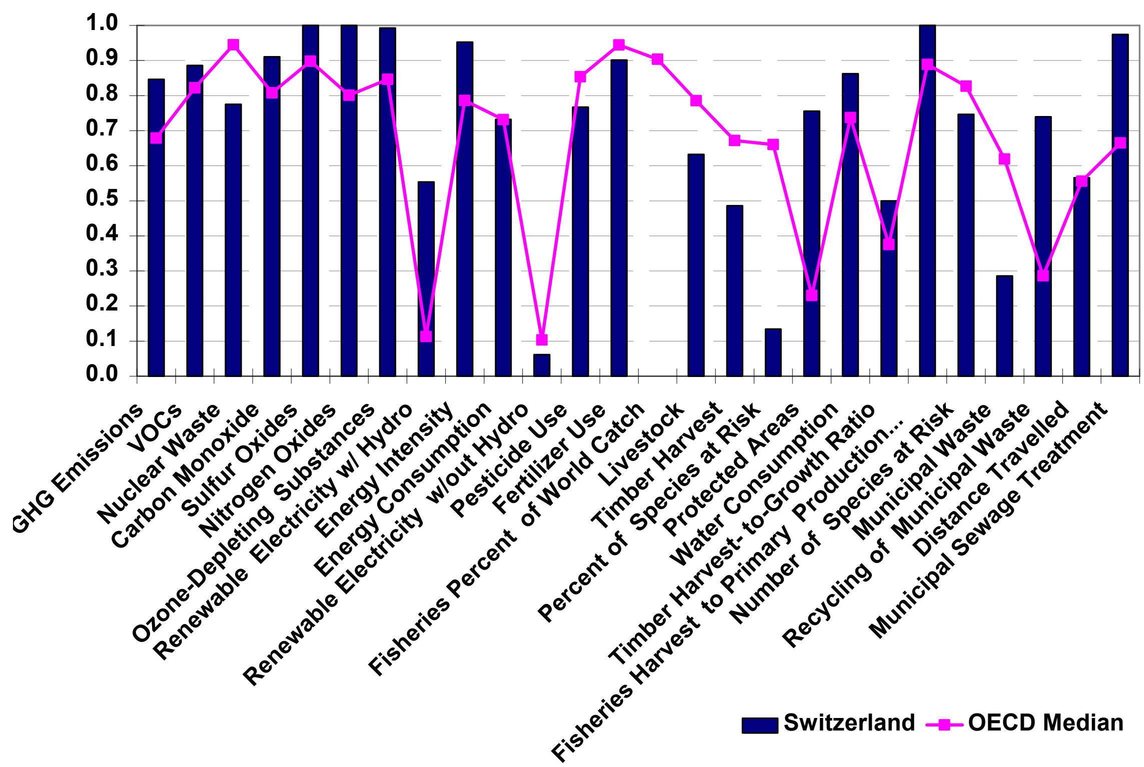
FACTOR	UNITS	OECD	TOP 3 AVG	SWEDEN
Climate	total degree days	3167.1	4998.3	**4420.3**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**39.25**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$24,683**
Technological Development	2002 dimensionless index	0.360	0.603	**0.618**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1067**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	
Environmental Governance	2002 dimensionless index	59.7	68.1	**67.8**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$197.47**

COUNTRY RESULTS FOR SWITZERLAND

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

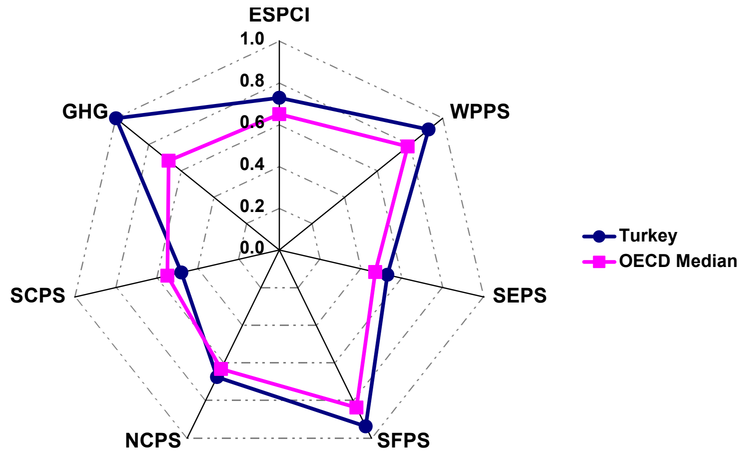


Country factors compared with OECD median and average of three highest countries

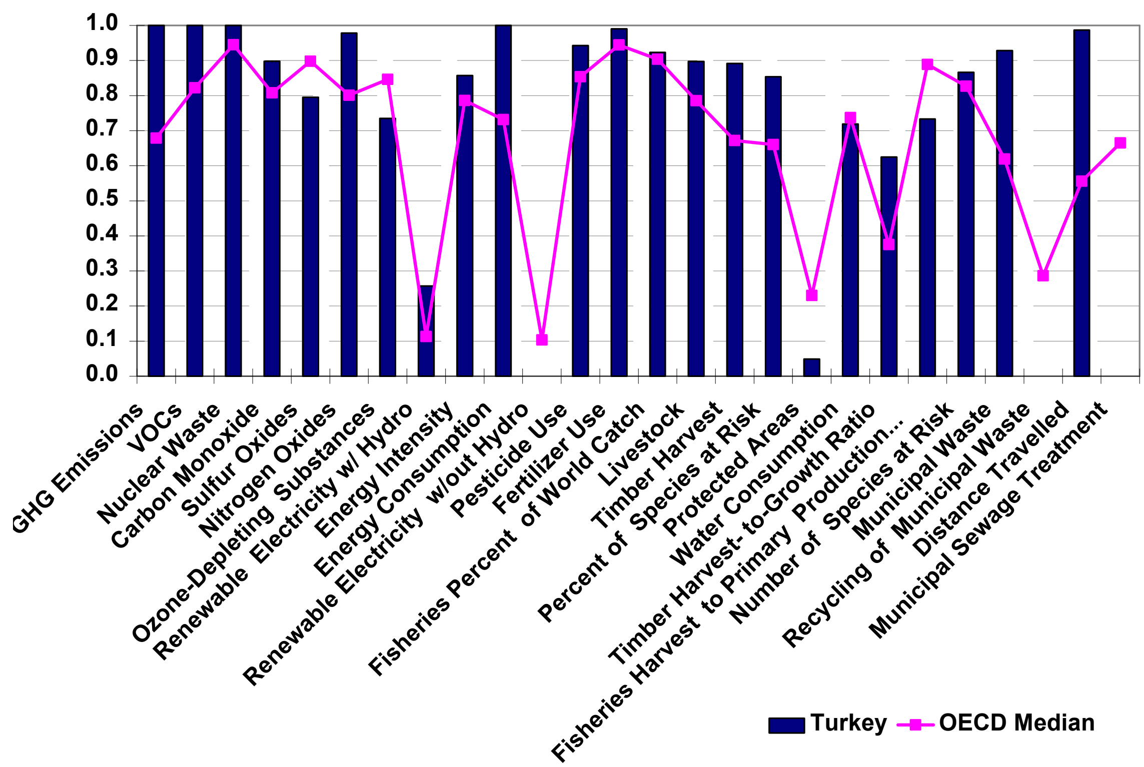
FACTOR	UNITS	OECD	TOP 3 AVG	SWITZERLAND
Climate	total degree days	3167.1	4998.3	**3555.9**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**192.54**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$27,376**
Technological Development	2002 dimensionless index	0.360	0.603	
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1069**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$972.20**
Environmental Governance	2002 dimensionless index	59.7	68.1	**67.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$438.02**

COUNTRY RESULTS FOR TURKEY

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

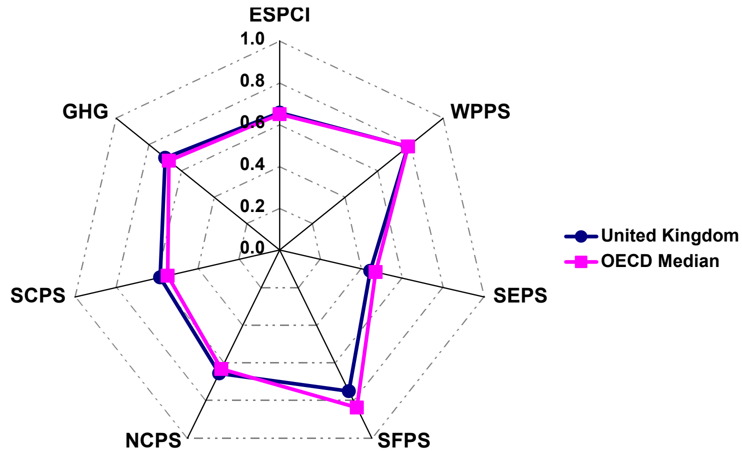


Country factors compared with OECD median and average of three highest countries

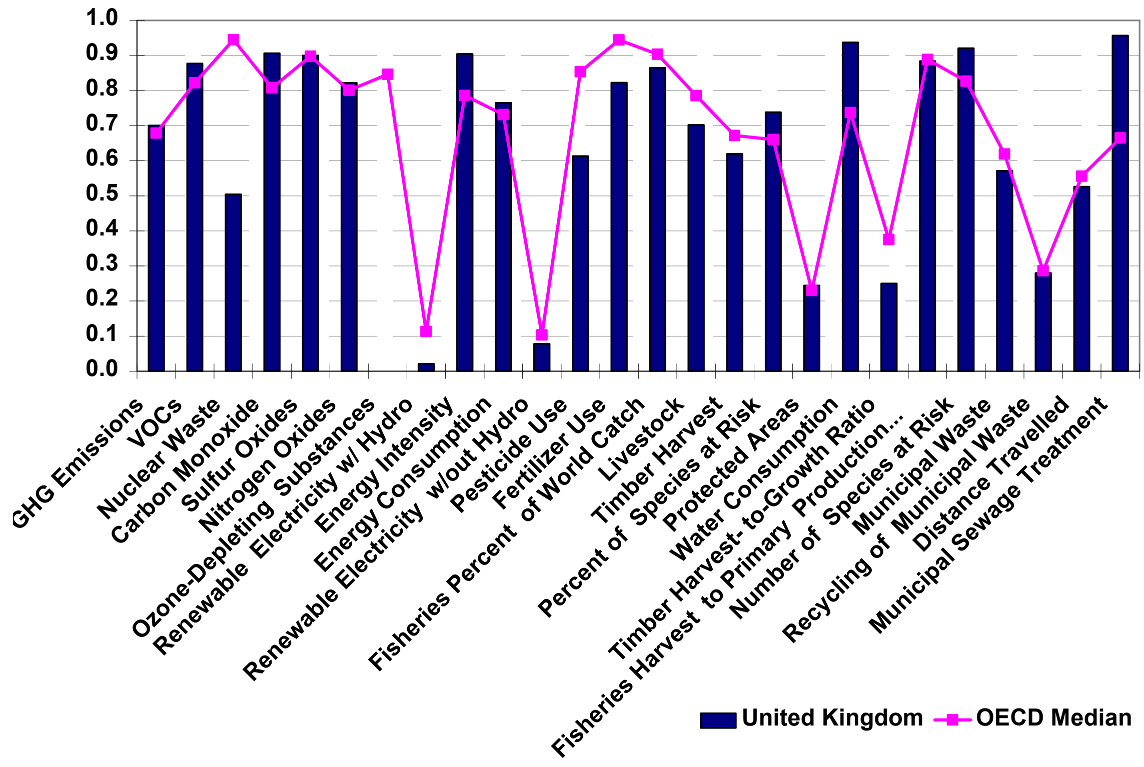
FACTOR	UNITS	OECD	TOP 3 AVG	TURKEY
Climate	total degree days	3167.1	4998.3	**2689.8**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**88.35**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$6,036**
Technological Development	2002 dimensionless index	0.360	0.603	**0.045**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$1,500.92**
Environmental Governance	2002 dimensionless index	59.7	68.1	**36.2**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$66.40**

COUNTRY RESULTS FOR UNITED KINGDOM

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median

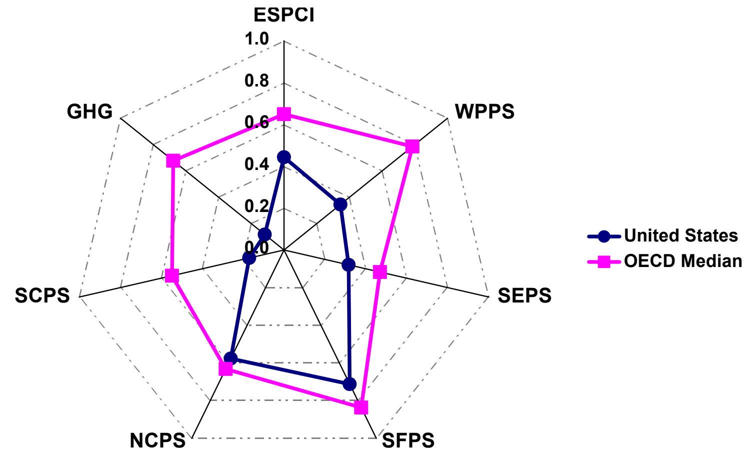


Country factors compared with OECD median and average of three highest countries

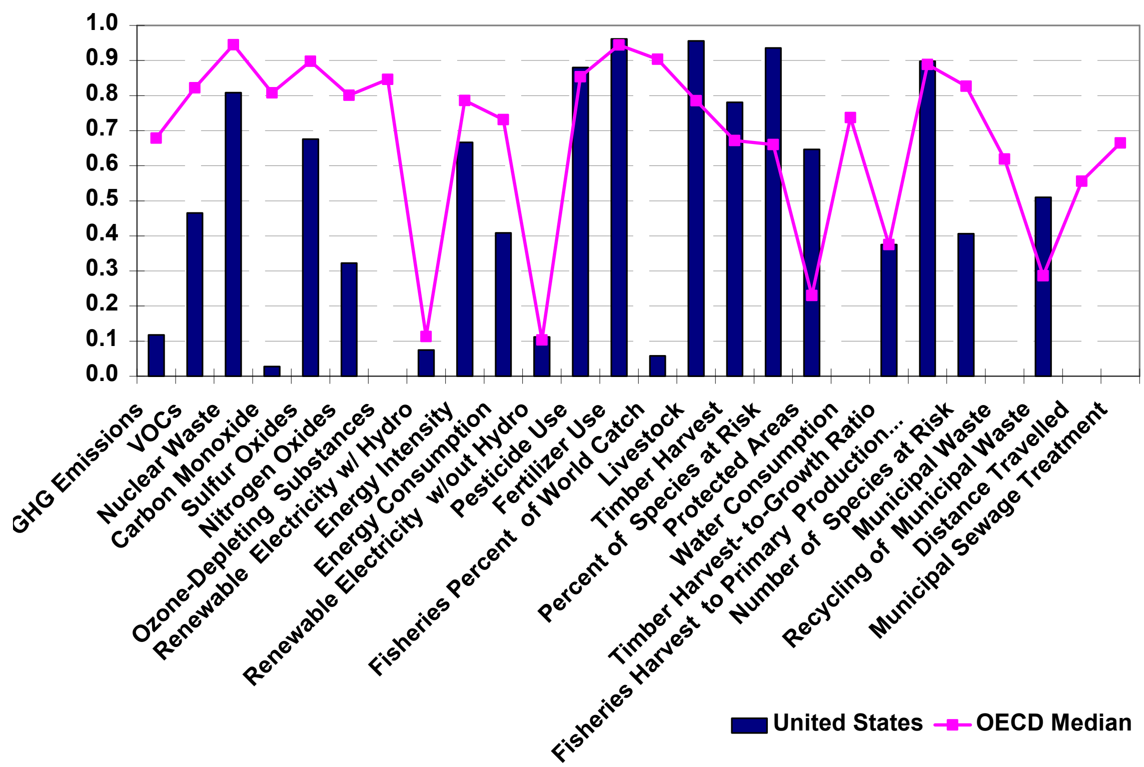
FACTOR	UNITS	OECD	TOP 3 AVG	U. K.
Climate	total degree days	3167.1	4998.3	**2876.5**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**266.31**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$21,888**
Technological Development	2002 dimensionless index	0.360	0.603	**0.453**
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.1017**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$880.76**
Environmental Governance	2002 dimensionless index	59.7	68.1	**60.0**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$153.22**

COUNTRY RESULTS FOR UNITED STATES

Country performance across policy subindices compared with OECD median



Country performance compared across individual indicators with OECD median



Country factors compared with OECD median and average of three highest countries

FACTOR	UNITS	OECD	TOP 3 AVG	U. S.
Climate	total degree days	3167.1	4998.3	**3041.3**
Population Density	2002 Inh./km² land area w/ >5 Inh.	106.54	392.15	**87.06**
Economic Output	2002 GDP/capita	$23,927	$35,201	**$32,086**
Technological Development	2002 dimensionless index	0.360	0.603	
Industrial Structure	2002 dimensionless index	0.1024	0.1638	**0.0905**
Energy Prices	2002 U.S.$/toe	$873.40	$1,274.94	**$506.10**
Environmental Governance	2002 dimensionless index	59.7	68.1	**56.7**
PAC Expenditures	2002 U.S.$/capita	$199.93	$534.54	**$513.37**

APPENDIX G:
DRIVERS OF GREENHOUSE GAS EMISSIONS

This appendix contains a discussion of the factors driving emissions of greenhouse gases (GHGs) that are emerging from the literature. The discussion centres on three different frameworks or perspectives:

- the Kaya identity,
- the results of decomposition analysis, and
- the IPAT identity.

Energy economists often use the Kaya identity to characterise the drivers of GHG emissions. Developed in the early 1990s by a Japanese energy economist, the Kaya identity combines four inputs to estimate total GHG emission levels: population, GDP per capita, energy use per unit of GDP, and carbon emissions per unit of energy consumed (Kaya and Yokobori 1993). A recent study uses this framework to analyse global and regional carbon dioxide emissions and determines that, since 2000, a reversal in what had been declining energy and carbon intensities, as well as continuing increases originating from population and economic growth, are driving growing global GHG emissions (Raupach et al. 2007). The Congressional Research Service add two factors—carbon intensity of electricity generation and carbon intensity of travel—to these four, in a study of the top twenty GHG emitters for 2000 (Blodgett and Parker 2008). Conducted for members of the U.S. Congress, this study explores how these factors interrelate to determine that intensity factors must decline substantially just to stabilise current GHG emission levels.

Several recent empirical studies examine various other drivers of GHG emissions. One method for explaining differences in environmental performance is to break the economy into subsectors and model the impact of changing key factors on each subsector by a series of production and output functions. Referred to as decomposition analysis, this methodology is data intensive, but a few studies have been able to use it to analyse differences in GHG emissions among countries. Bataille et al. (2007) conduct a recent decomposition analysis identifying the reasons for differences in GHG emissions among the G7 countries. The Bataille et al. study assesses the role of what are referred to as 'national circumstances[40]' in explaining differences among G7 GHG emissions. The study identifies five national circumstance factors: climate, industrial structure, population distribution, production of fossil fuels, and availability of electricity resources that are low-to-nil emitters of GHGs. The results for Canada, summarised in table G.1, show that overall these national circumstance factors explain about only 10% of the difference in GHG emissions between Canada and the G7 average. The reason for this happenstance is that two potentially adverse

[40] Recall from the discussion in chapter 4 that national circumstances are characteristics of a country that have a significant impact on environmental performance and that government may not easily mitigate with public policy.

factors—industrial structure and population distribution—have little affect and the other two adverse factors that have a considerable impact—climate and fossil fuel production—are largely offset by the favourable impact of Canada's access to low-polluting electricity sources, predominantly hydro.

Table G.1: Role of non-governable factors in explaining differences between Canada's GHG emissions and the G7 countries

	GHG EMISSIONS (t/cap)
G7 Average	9.93
Canada	23.32
NATIONAL CIRCUMSTANCE FACTORS	
Climate	+1.25
population Distribution	+0.17
Industrial Structure	+0.01
Fossil Fuel Production	+2.73
Low-GHG Electricity	-2.80
Net Impact	**+1.37**

Source: Bataille et al. (2007: 165)

Another approach utilises the IPAT identity to analyse GHG emissions drivers. Cole and Neumayer (2004) use this identity to examine links among population, demographic factors, and carbon dioxide emissions from 86 countries between 1975 and 1998 to discover that population growth, higher rates of urbanisation, and lower average household size tend to increase emissions. Meanwhile, York et al. (2003) employ a stochastic version of the IPAT identity, the STIRPAT model, to compare cross-national carbon dioxide emissions. These researchers find that population and economic growth both increase GHG emissions, while indicators of urbanisation and industrialisation tend to also be associated with higher emissions. Finally, with tropical nations producing lower emissions than non-tropical countries, climate appears to impact GHG emissions.

Another study using the STIRPAT model, investigates the impact of population, affluence, and technology on the total carbon dioxide emissions of countries at different income levels over the period 1975–2000 (Fan et al. 2006). Fan et al.'s findings demonstrate that economic growth has the greatest impact on global carbon dioxide emissions, and the proportion of the population between ages 15 and 64 has the least impact. An interesting secondary finding, whereby the impact arising from the proportion of the population between 15 and 64 is both adverse and favourable, depending on income level, suggests that differing patterns of behaviour can significantly influence environmental sustainability, supporting the notion of adding behaviour (B) to the IPAT identity, forming I = P*B*A*T (Schulze 2002).