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Analysis

# Sustainability ranking and improvement of countries

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ABSTRACT

Human society is on a collision course with nature, thus its sustainability is seriously questioned nowadays. To understand this problem better it is essential to define and measure sustainability. In this paper a model that uses fuzzy logic, called SAFE, is used to measure sustainability. The sustainability of a country is based on a multitude of basic indicators. In all 75 indicators for 128 countries are used. This work extends SAFE as follows: (a) The model is amended by an imputation procedure to fill in missing data, (b) the rule bases of SAFE are compiled algebraically, and (c) sustainability thresholds are defined so as to reflect expert opinion and international agreements and norms. Countries are ranked according to their sustainability index. Switzerland and Sweden take the first two places and Mauritania and Sudan the two last ones. A sensitivity analysis pinpoints those basic indicators that affect sustainability the most. Decision makers may focus on these indicators to improve sustainability.



## 1. Introduction

Society nowadays faces a host of often intractable problems ranging from climate change, species extinction, and pollution to economic collapse and re-emergence of deadly diseases. Such problems question the viability of our society in the long run. Put differently, one asks how sustainable countries are given their present course. The question then becomes one of defining and measuring sustainability.

There is no universally accepted definition or assessment technique of sustainability. This is due to the nature of sustainability. In addition to its scientific challenges, it is loaded politically. The recent Copenhagen summit showed in no uncertain terms that values and political and economic interests play a central role in the sustainability debate. From the scientific point of view, however, certain approaches of defining and assessing sustainability show promise in, at least, providing comparison tools among countries that record a path towards sustainability progress.

The history of sustainability definition and assessment is short but the effort towards capturing its essence quite intense. Several approaches have been proposed to test the sustainability of a region. Examples are: Pressure-State-Response model, Ecological Footprint, Barometer of Sustainability, Environmental Sustainability Index, etc. An exposition to some such approaches can be found in Phillis et al. (2010).

An outline of these approaches follows:

a) Pressure-State-Response (PSR): This model was developed by the Organization for Economic Co-operation and Development (OECD, 1991) and is based on the fact that humans exert pressures on the ecosystem and the society which alter their state and call for certain responses. Its primary focus is on ecological aspects although socio-economic indicators are also of interest.
b) Ecological Footprint: It was introduced in Rees (1992) and calculates the equivalent land needed to produce certain basic resources and absorb certain wastes associated with a given population. In short, the ecological footprint is the productive land that a population uses. It is biased towards the ecological side and computes a land area, not a sustainability score.
c) Barometer of Sustainability: This model was introduced by the International Union for the Conservation of Nature (IUCN) (Prescott-Allen, 2001) and is a visual tool of sustainability assessment. The sustainability of a country has two fundamental components, Ecosystem Well-Being and Human Well-Being. All indicators are scaled in [0, 100], where 0 is the worst performance and 100 the best performance of an indicator. Then scores are computed by a straightforward aggregation.
d) Environmental Sustainability Index (ESI): ESI (Esty et al., 2005) computes an environmental sustainability index for a country based on 21 indicators, which in turn are assessed from 76 data sets. The ESI index is computed as a weighted average of indicators with equal weights. Countries are ranked accordingly.
e) Sustainability Assessment by Fuzzy Evaluation (SAFE): This model was introduced in Phillis and Andriantiatsaholiniaina (2001) and developed further in Andriantiatsaholiniaina et al. (2004), Kouloumpis et al. (2008), and Phillis and Kouikoglou (2009). SAFE is a hierarchical fuzzy inference system. It uses knowledge encoded into "if-then" rules and fuzzy logic to combine 75 inputs, called basic indicators, into more composite variables describing various environmental and societal aspects and, finally, provides an overall sustainability index in [0, 1].

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f) Multiple Criteria and Fuzzy Logic: A model similar to ESI using 74 indicators and multiple-criteria decision-making (MCDM) in conjunction with a fuzzy inference scheme similar to SAFE was introduced in Liu (2007). It computes an aggregate sustainability index through sequential fuzzy reasoning while MCDM has three steps, decomposition, weighting, and synthesis.
g) Sustainable Society Index (SSI): The SSI (Van de Kerk and Manuel, 2008) is based on 22 environmental and societal indicators that are aggregated into 5 main categories using equal weights. The 5 categories are then aggregated into SSI using unequal weights. In all 150 countries are ranked accordingly.

SAFE, which is the subject of this paper, will be compared to the previous models in the conclusion. The model has the following features:

- It uses fuzzy logic which can coherently handle quantitative, qualitative or mixed information regarding the basic indicators, such as for example "the pesticide consumption of country A is *about* 6 kg per hectare" or "country B has a *very high* level of corruption."
- It takes into account past performance via exponential smoothing.
- It is amenable to a straightforward sensitivity analysis that pinpoints those basic inputs that affect sustainability the most. Decision makers should pay attention to the improvement of these inputs so that OSUS is also improved.

The SAFE model compared to the aforementioned approaches appears to be quite holistic in that it uses a balanced representation of environmental and social aspects. Most other approaches focus on a rather narrow suite of environmental and social indicators.

Methodologically SAFE needs several improvements. Almost all countries provide insufficient data for a number of indicators. This is the first question this paper addresses in detail. Next, the sustainable and unsustainable regions for each indicator should be defined in a systematic way. This question is addressed using expert knowledge in conjunction with international norms and agreements. Another improvement has to do with the system inputs and the concomitant rule bases. SAFE is flexible and admits any number of inputs. The number of fuzzy rules associated with these inputs grows geometrically with their number. An algebraic method is devised whereby the number of rules is in check and the whole model remains computationally tractable. Finally, a rationale should be provided for the metric used in the sensitivity analysis. In summary, the contribution of this work is:

1. Data imputation and validation
2. A systematic and compact representation of rule bases
3. Explanation of the rationale of the sensitivity procedures
4. Up-to-date ranking and sensitivity of countries based on:
   - Sustainability thresholds derived from experts' opinion
   - Latest data
   - Imputed data.

Accordingly, the objectives of the paper are:

1. To implement the SAFE model efficiently so that sustainability is assessed based on currently available information.
2. Provide a ranking of countries for which data exist.
3. Pinpoint those basic indicators that affect sustainability the most. Policies should be devised to improve the performance of these indicators.

The remainder of this paper is organized as follows. Section 2 presents an overview of the SAFE model and its improvements that answer several important open questions about missing data, the structure of rule bases, and the sensitivity analysis procedure. Section 3 applies the model to 128 countries and provides sustainability assessments, ranking, and critical basic indicators. Finally, Section 4 gives an overview of the strengths and shortcomings of the model and a brief comparison with other approaches.

## 2. Model

### 2.1. Brief Overview of the SAFE Model

The structure of the SAFE model is shown in Fig. 1. The overall sustainability (OSUS) of a country is a combination of two primary components: ecological sustainability (ECOS) and societal or human sustainability (HUMS). The ecological input comprises four secondary components: water quality (WATER), land integrity (LAND), air quality (AIR), and biodiversity (BIOD). The components of the human dimension of sustainability are political aspects (POLIC), economic welfare (WEALTH), health (HEALTH), and education (KNOW). Each secondary component is assessed using the Pressure-State-Response approach of the Organization for Economic Cooperation and Development (OECD, 1991), which assumes that humans exert pressures on the environment which alter its conditions (state) and call for certain responses by the society. In the SAFE model, tertiary indicators Pressure (PR), State (ST), and Response (RE) are obtained by combining certain basic indicators. For example, the indicator PR(BIOD) measures the pressure on biodiversity using six basic indicators which give the percentage of all threatened (endangered, vulnerable) species: mammals, birds, plants, fishes, reptiles and amphibians.

The sequence of data processing is the following:

- Collection of available data
- Normalization in [0, 1]
- Exponential smoothing
- Data imputation
- Fuzzy assessment of sustainability
- Sensitivity analysis-decision making.

To cover all aspects of sustainability, a total of 75 basic indicators are used for 128 countries. The data base of basic indicators goes as far back as 1990 and reaches the most recent data. There are 192 UN member states but they were not all included in the sustainability study because their areas or populations were considered small. States with population at least 100,000 people or area above 5000 $km^2$ are examined. These thresholds conform with those of Esty et al. (2005). Countries with population or area smaller than these numbers rely too much on others and resemble cities, thus, they cannot be compared to larger ones. However, some countries that were above limits didn't provide sufficient data to make reliable assessments and were excluded.

Table 1 shows the indicators used in the SAFE model and the corresponding thresholds of sustainable and unsustainable values. Definitions of indicators are given in Kouloumpis et al. (2008) and Phillis and Kouikoglou (2009).

It is clear that correlations between indicators might exist. However, a statistical approach that would exclude indicators with high correlations was not adopted for the following reasons:

1. Correlation does not always imply causality.
2. All models use overlapping indicators because of the nature of national statistics. There is no mechanism to separate overlaps. For example, Urban $NO_2$, $SO_2$, and TSP concentrations are related to mortality from poor air quality, but they also have additional effects (e.g., $NO_2$ and $SO_2$ concentrations contribute to acid rain).
3. Quite often, correlated indicators provide complementary information. For example, the indicators "public expenditure on education," "public expenditure on research and development," and "public expenditure on information and communication" are complementary measures of the national education policy.

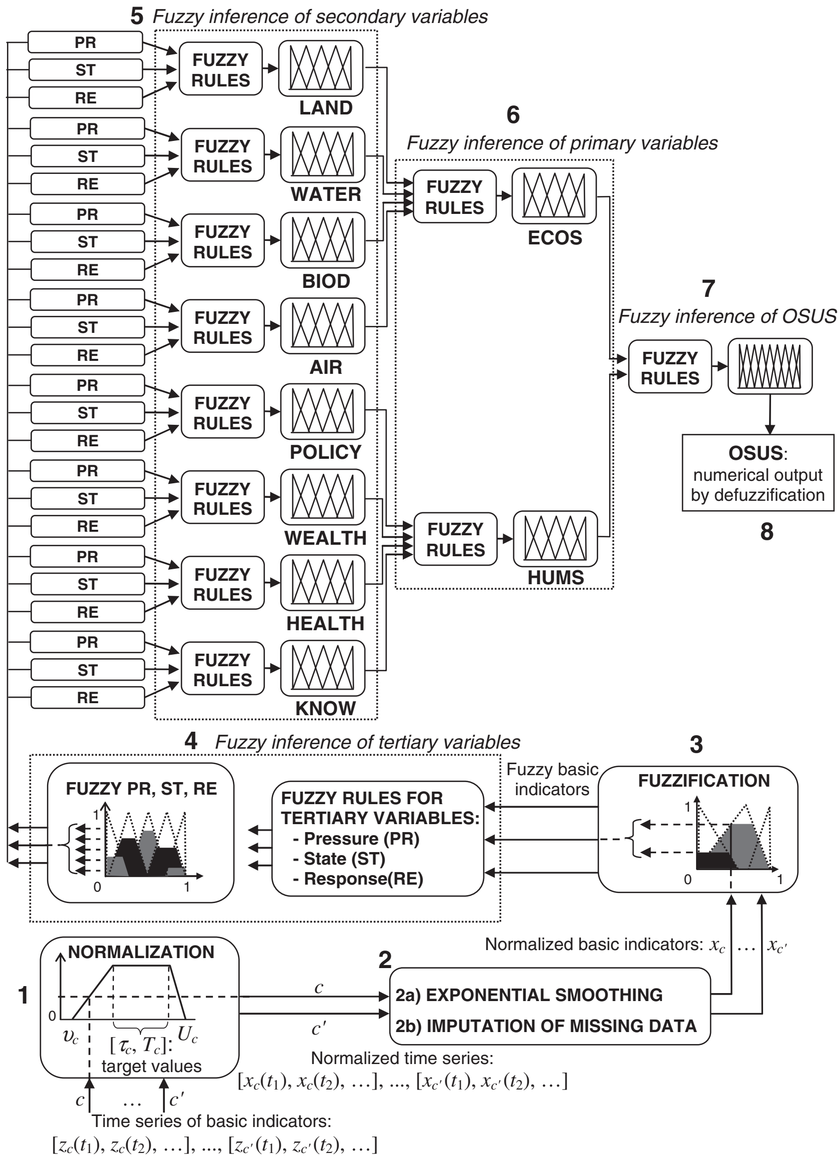


**Fig. 1.** Hierarchical structure of the SAFE model: (1–3) normalization, exponential smoothing, imputation, and fuzzification of basic indicators; (4–7) fuzzy inference of composite indicators and overall sustainability; (8) defuzzification. (Modified from Fig. 1 of Kouloumpis et al. (2008). © 2008 by IEEE. Used with permission.)

4. As will be explained later, the redundancy that exists among interrelated indicators can be exploited to impute missing data.

One more comment is in order here to explain the importance of certain indicators. There are indicators that appear to be more important than others. However, it is very hard if not impossible to quantify this importance. One reason is that such indicators lack consistency across countries. For example, expenditures for health are necessary but not sufficient conditions for improving public health. As reported in Bortz (2010), in 2003 the US spent 15.3% of its GDP for health and its life expectancy was 78 years. In Cuba on the other hand the corresponding numbers were 7.1% and 78 years. Also two countries with excellent public health systems, Sweden and Japan spent 7.9% of GDP and had life expectancies 81 and 83 years respectively.

SAFE uses time series of basic indicators as inputs. The basic indicators are normalized in [0, 1]. This is done by linear interpolation between sustainable and unsustainable indicator values specified by international agreements and norms, laws and regulations, and expert opinion. In particular, environmentalists, economists, and social scientists were consulted in order to provide expert opinion.

Certain sustainable indicator regions are adopted from international agreements. For example RE(AIR), which is renewable energy production as percentage of total primary energy supply, is chosen completely sustainable above 20% and completely unsustainable at 0%. The value 20% is the target of the European Union (EU) for the year 2020. One could question such a choice on various grounds. Renewables are not completely clean and sometimes have negative environmental effects. However, this is a thermodynamic consequence of any type of consumption. What is important here is the relative benefit of renewables as compared to the benefit of fossil fuel or nuclear fuel consumption.

Wind turbines alter to some extent the natural landscape and kill birds. But landscapes will be altered, arguably to a greater extent, and many species will become extinct because of global warming. The European Space Agency has estimated that about 35% of the land of Greece has a very high risk of desertification in the 21st century, and one of the main causes of desertification is climate change.

**Table 1**
Basic indicators used in the SAFE model.

| Component | Basic Indicator | Type[a] | Thresholds[b,c] |
|---|---|---|---|
| PR(LAND) | Municipal waste (kg per capita per year) | SB | $T=300$, $U=760$ |
| PR(LAND) | Nuclear waste (tons per capita per year) | SB | $T=0$, $U=0.05926$ |
| PR(LAND) | Hazardous waste (tons per capita per year) | SB | $T=0$, $U=1.08810$ |
| PR(LAND) | Population growth (rate of natural increase) | SB | $T=0$, $U=1.2$ |
| PR(LAND) | Pesticide consumption (kg per hectare) | SB | $T=3.22$, $U=8.0$ |
| PR(LAND) | Fertilizer consumption (kg per hectare) | SB | $T=221.2$, $U=494.984$ |
| ST(LAND) | Desertification of land (percent of dryland area) | SB | $T=0$, $U=100$ |
| ST(LAND) | Forest area (percent of what existed in 2000) | LB | $\upsilon=76.768$, $\tau=100$ |
| RE(LAND) | Forest change (percentage) | LB | $\upsilon=-4.5$, $\tau=6.9$ |
| RE(LAND) | Protected area (ratio to surface area) | LB | $\upsilon=0.003$, $\tau=0.63$ |
| RE(LAND) | Glass recycling (percent of apparent consumption) | LB | $\upsilon=0$, $\tau=100$ |
| RE(LAND) | Paper recycling | LB | $\upsilon=0$, $\tau=100$ |
| PR(WATER) | Pesticide consumption (kg per hectare) | SB | $T=3.22$, $U=8.0$ |
| PR(WATER) | Fertilizer consumption (kg per hectare) | SB | $T=221.2$, $U=494.984$ |
| PR(WATER) | Water withdrawals (percent) | SB | $T=13.15$, $U=63.24$ |
| ST(WATER) | BOD emissions (kg per capita per day) | SB | $T=7.367$, $U=18.824$ |
| ST(WATER) | Phosphorous concentration (mg per liter of water) | SB | $T=0.18$, $U=0.67$ |
| ST(WATER) | Metals concentration (micro-Siemens per centimeter) | SB | $T=439$, $U=2.247$ |
| RE(WATER) | Public wastewater treatment plants (percent of population connected) | LB | $\upsilon=0$, $\tau=78.96$ |
| PR(BIOD) | Threatened mammals (percentage) | SB | $T=0$, $U=35.5$ |
| PR(BIOD) | Threatened birds (percentage) | SB | $T=0$, $U=33.16$ |
| PR(BIOD) | Threatened plants (percentage) | SB | $T=0$, $U=8.45$ |
| PR(BIOD) | Threatened fishes (percentage) | SB | $T=0$, $U=55.1$ |
| PR(BIOD) | Threatened amphibians (percentage) | SB | $T=0$, $U=20.72$ |
| PR(BIOD) | Threatened reptiles (percentage) | SB | $T=0$, $U=20.75$ |
| ST(BIOD) | Desertification of land (percent of dryland area) | SB | $T=0$, $U=100$ |
| ST(BIOD) | Forest area (percent of what existed in 2000) | LB | $\upsilon=76.768$, $\tau=100$ |
| RE(BIOD) | Forest change (percentage) | LB | $\upsilon=-4.5$, $\tau=6.9$ |
| RE(LAND) | Protected area (ratio to surface area) | LB | $\upsilon=0.003$, $\tau=0.63$ |
| PR(AIR) | Ozone depleting substances (metric tons per capita) | SB | $T=0$, $U=1.1475$ |
| PR(AIR) | Greenhouse gas emissions (tons of $CO_2$ equivalent per capita) | SB | $T=0.0057$, $U=0.0368$ |
| ST(AIR) | Mortality from poor air quality (deaths per 100,000 population) | SB | $T=12.785$, $U=1,805.216$ |
| ST(AIR) | Urban $NO_2$ concentration (μg/$m^3$ of air) | SB | $T=18.20$, $U=109.16$ |
| ST(AIR) | Urban $SO_2$ concentration (μg/$m^3$ of air) | SB | $T=1.33$, $U=97.07$ |
| ST(AIR) | Urban TSP concentration (μg/$m^3$ of air) | SB | $T=18.92$, $U=320$ |
| RE(AIR) | Renewable energy production (percent of total primary energy supply) | LB | $\upsilon=0$, $\tau=20$ |
| PR(POLIC) | Military spending (percent of GDP) | SB | $T=1.75$, $U=12.48$ |
| PR(POLIC) | Refugees per capita | SB | $T=0$, $U=0+$ |
| PR(POLIC) | Poverty (percent of population below national poverty line) | SB | $T=0$, $U=30.15$ |
| ST(POLICY) | Political rights (values in [1, 7]) | SB | $T=1$, $U=3$ |
| ST(POLICY) | Civil liberties (values in [1, 7]) | SB | $T=1$, $U=3$ |
| ST(POLICY) | Gini index | SB | $T=25.79$, $U=50$ |
| ST(POLICY) | Corruption Perceptions Index (values in [0, 10]) | LB | $\upsilon=3$, $\tau=8$ |
| RE(POLICY) | Environmental governance (values in [0, 1]) | LB | $\upsilon=0.1774$, $\tau=0.5974$ |
| RE(POLICY) | Tax revenue (percent of GDP) | LB | $\upsilon=11.55$, $\tau=22.11$ |
| PR(WEALTH) | GDP implicit deflator (percent) | SB | $T=2.78$, $U=5.43$ |
| PR(WEALTH) | Imports (percent of GDP) | SB | $T=32.05$, $U=63.38$ |
| PR(WEALTH) | Unemployment (percent of total labor force) | NB | $\upsilon=1.3$, $\tau=4$, $T=7$, $U=12$ |
| PR(WEALTH) | Unemployment gender gap (percent) | SB | $T=0$, $U=5.2$ |
| ST(WEALTH) | Poverty (percent of population below national poverty line) | SB | $T=0$, $U=30.15$ |
| ST(WEALTH) | Central government debt (percent of GDP) | SB | $T=62.08$, $U=164$ |
| ST(WEALTH) | GNI per capita PPP | LB | $\upsilon=17,710$, $\tau=26,635$ |
| RE(WEALTH) | Exports (percent of GDP) | LB | $\upsilon=6.83$, $\tau=43.20$ |
| RE(WEALTH) | Foreign direct investment (percent of GDP) | LB | $\upsilon=-0.8227$, $\tau=3.3787$ |
| PR(HEALTH) | Mortality from poor air quality (deaths per 100,000 population) | SB | $T=12.785$, $U=1,805.216$ |
| PR(HEALTH) | Infant mortality rate (deaths per thousand) | SB | $T=3.53$, $U=129$ |
| PR(HEALTH) | Maternal mortality rate (deaths per 100,000 births) | SB | $T=7.67$, $U=1,200$ |
| PR(HEALTH) | HIV/AIDS prevalence rate (percent of population aged 15–49) | SB | $T=0$, $U=1.8$ |
| PR(HEALTH) | Tuberculosis prevalence rate (per 100,000 population) | SB | $T=0$, $U=697$ |
| PR(HEALTH) | Malaria cases (per thousand people) | SB | $T=0$, $U=0.1$ |
| ST(HEALTH) | Life expectancy (years) | LB | $\upsilon=36.48$, $\tau=78.77$ |
| ST(HEALTH) | Immunization against measles (percent of population) | LB | $\upsilon=75$, $\tau=100$ |
| ST(HEALTH) | Immunization against DPT (percent of population) | LB | $\upsilon=84$, $\tau=100$ |
| ST(HEALTH) | Daily per capita calorie supply | LB | $\upsilon=1,599$, $\tau=3,505$ |
| RE(HEALTH) | Number of doctors (per thousand people) | LB | $\upsilon=0.0113$, $\tau=3.4216$ |
| RE(HEALTH) | Hospital beds (per thousand people) | LB | $\upsilon=0.1167$, $\tau=7.5667$ |
| RE(HEALTH) | Public health expenditure | LB | $\upsilon=0.6450$, $\tau=7.7196$ |
| RE(HEALTH) | Access to improved water sources (percent of population) | LB | $\upsilon=40$, $\tau=100$ |
| RE(HEALTH) | Access to improved sanitation (percent of population) | LB | $\upsilon=7$, $\tau=100$ |
| PR(KNOW) | Primary education ratio of students to teaching staff | SB | $T=14$, $U=70$ |
| PR(KNOW) | Secondary education ratio of students to teaching staff | SB | $T=12$, $U=47$ |
| PR(KNOW) | Tertiary education ratio of students to teaching staff | SB | $T=14.88$, $U=45.50$ |
| ST(KNOW) | Male expected years of schooling | LB | $\upsilon=0$, $\tau=12$ |
| ST(KNOW) | Female expected years of schooling | LB | $\upsilon=0$, $\tau=12$ |
| ST(KNOW) | Primary net school enrollment (percent of children) | LB | $\upsilon=34.56$, $\tau=97.42$ |
| ST(KNOW) | Secondary net school enrollment (percent of children) | LB | $\upsilon=5.06$, $\tau=90.96$ |

(*continued on next page*)

**Table 1** (*continued*)

| Component | Basic Indicator | Type[a] | Thresholds[b,c] |
|---|---|---|---|
| ST(KNOW) | Literacy rate | LB | $\upsilon=12.8$, $\tau=100$ |
| ST(KNOW) | Knowledge Economy Index (KEI; values in [0, 10]) | LB | $\upsilon=4.07$, $\tau=8.61$ |
| RE(KNOW) | Public expenditure on research and development (percent of GDP) | LB | $\upsilon=0$, $\tau=2.02$ |
| RE(KNOW) | Public expenditure on education (percent of GDP) | LB | $\upsilon=0.9$, $\tau=5.46$ |
| RE(KNOW) | Personal computers (per thousand people) | LB | $\upsilon=0$, $\tau=406.11$ |
| RE(KNOW) | Internet users (per thousand people) | LB | $\upsilon=0.06$, $\tau=418.20$ |
| RE(KNOW) | Expenditure on information and communication (percent of GDP) | LB | $\upsilon=0$, $\tau=5.74$ |

[a] SB = smaller is better; LB = larger is better; NB = nominal is best.
[b] $\upsilon$, $\tau$, $T$, and $U$ are thresholds of target (sustainable) and unsustainable values. Values in the interval $[\tau, T]$ are assigned the sustainability index 1. Values $\leq \upsilon$ or $\geq U$ indicate poor performance and are assigned the sustainability index 0. Values in $(\upsilon, \tau)$ or $(T, U)$ are scaled in (0, 1) by linear interpolation.
[c] Sources of indicator data:
CIA, 2008. The World Factbook, Central Intelligence Agency, Washington, DC.
Esty et al. (2005).
Food and Agricultural Organization (http://www.fao.org).
Human Development Report (http://hdr.undp.org).
OECD, 2005. OECD Environmental Indicators: Environment at a Glance, OECD Publications, Paris.
OECD, 2005. OECD Factbook 2005, OECD Publications, Paris.
Population Reference Bureau (World Population Data Sheets; http://www.prb.org).
UNESCO (http://stats.uis.unesco.org/unesco/ReportFolders/ReportFolders.aspx).
United Nations — MDG Indicators (http://mdgs.un.org/unsd/mdg/Data.aspx).
United Nations Data Retrieval System (http://data.un.org/Default.aspx).
United Nations Environment Programme (http://geodata.grid.unep.ch).
United Nations Statistics Division (http://unstats.un.org/unsd/environment/Questionnaires/country_snapshots.htm).
World Bank, 2007. *World Development Indicators* (book and CD-ROM) (The World Bank, Washington, DC).
World Health Organization (http://www.who.int/whosis/database/core/core_select.cfm).

Another point worth mentioning is that all national statistics include biofuels in their renewables. It is well known that biofuels have several detrimental environmental and economic effects. However, there is no mechanism to separate biofuels from renewables for 128 countries. A lot of research is devoted nowadays to improving the environmental performance of biofuels. Governments are promoting biofuels from non-food feedstocks because of environmental concerns. Most notable is cellulosic ethanol production. Thus incorporating biofuels into renewable could be viewed as a future promise for overall improvement of fuels.

Finally, accepting norms and goals of authoritative international bodies, such as the EU or the UN, is a safer bet than arbitrary choices unless convincing arguments are provided to the opposite.

Table 1 gives upper and lower thresholds, $U_c$ and $\upsilon_c$, of unsustainable values and an interval $[\tau_c, T_c]$ representing the range of sustainable or target values for each basic indicator $c$. For a given country, let $z_c(t)$ be the value of indicator $c$ in year $t$. The corresponding normalized value is calculated from

$$x_c(t) = \begin{cases} 0, & z_c(t) \leq \upsilon_c \\ \dfrac{z_c(t)-\upsilon_c}{\tau_c-\upsilon_c}, & \upsilon_c < z_c(t) < \tau_c \\ 1, & \tau_c \leq z_c(t) \leq T_c \\ \dfrac{U_c-z_c(t)}{U_c-T_c}, & T_c < z_c(t) < U_c \\ 0, & U_c \leq z_c(t). \end{cases}$$

Normalization allows for combinations of different indicators by assigning the value 1 to best performance and 0 to the worst.

Annual indicator data are often unavailable or imprecise. Moreover, past environmental pressures have significant cumulative effects. To deal with these issues, present and past indicator data are combined into a single value using exponentially weighted sums. Suppose that $K$ measurements of indicator $c$ are available for some country. Let $x_c(t_1)$, $x_c(t_2)$, ..., $x_c(t_K)$ be the normalized values in years $t_1, t_2, \ldots, t_K$. These years need not be consecutive due to missing data. An aggregate value $x_c$ for indicator $c$ is computed by exponential smoothing, using the a weighted average

$$x_c = \frac{x_c(t_K) + x_c(t_{K-1})\beta^{t_K-t_{K-1}} + \ldots + x_c(t_1)\beta^{t_K-t_1}}{1+\beta^{t_K-t_{K-1}} + \ldots + \beta^{t_K-t_1}},$$

in which older observations are assigned geometrically decreasing weights with parameter $\beta \in [0, 1]$. The smoothing parameter $\beta$ is chosen so as to minimize the mean squared error

$$[x_c(t_1) - \hat{x}_c(t_1)]^2 + \ldots + [x_c(t_K) - \hat{x}_c(t_K)]^2.$$

The quantity $\hat{x}_c(t_k)$ is the weighted average of indicator data *prior to* year $t_k$, and is given by

$$\hat{x}_c(t_1) = 0 \text{ and } \hat{x}_c(t_{k+1}) = \frac{x_c(t_k) + x_c(t_{k-1})\beta^{t_k-t_{k-1}} + \ldots + x_c(t_1)\beta^{t_k-t_1}}{1+\beta^{t_k-t_{k-1}} + \ldots + \beta^{t_k-t_1}}, k = 1, \ldots, K-1.$$

It should be noted that the weights $\beta$ differ among countries as well as among indicators. If no indicator data are available for some country, a value $x_c$ is imputed using an approach to described in a separate section.

The normalized basic indicators are grouped by type and combined into more composite ones using a hierarchical fuzzy system. Sustainability is measured via fuzzy logic, because this method is very effective in handling vague and complex concepts. The basic indicators and components of sustainability are represented as fuzzy sets, and their contribution to overall sustainability (OSUS) is assessed using a multistage inference process. The sequence of aggregations is represented schematically by the steps 4–7 shown in Fig. 1. Each inference stage uses various indicators as inputs and computes a composite indicator, which is then passed to another inference stage, and so forth.

The normalized basic indicators are fuzzified using three fuzzy sets with linguistic values *Weak* (W), *Medium* (M), and *Strong* (S). For composite indicators (primary, secondary, and tertiary components) five linguistic values are used: *Very Bad* (VB), *Bad* (B), *Average* (A), *Good* (G), and *Very Good* (VG). The overall sustainability is measured using nine fuzzy sets: *Extremely Low* (EL), *Very Low* (VL), *Low* (L), *Fairly Low* (FL), *Intermediate* (I), *Fairly High* (FH), *High* (H), *Very High* (VH), and *Extremely High* (EH).

Each indicator value $x$ belongs to one or more fuzzy sets with certain membership grades. For simplicity, triangular membership functions $\mu(x)$ are used, as shown in Fig. 2, but the model admits any polygonal function. For example, in 2002, 13.7% of the mammal species in Greece were endangered. The target value for this indicator is $T=\tau=0\%$ and the upper threshold of unsustainable values is $U=35.5\%$ (maximum of all countries). Thus, the normalized value for this indicator is $x=(13.7-35.5)/(0-35.5)=0.614$. As shown in Fig. 2a, this value belongs to the fuzzy set Medium with membership grade $\mu_M(0.614)=0.965$ and to the fuzzy set Strong with grade $\mu_S(0.614)=0.035$.

The inference engines combine indicators into composite ones. Each inference engine is equipped with "if–then" linguistic rules which relate input indicators to a composite indicator. A rule has the form "if *premise* (inputs) then *consequence* (output)." Examples of "if–then" rules used in the model are:

*if* 'Threatened Mammals' is Medium *and* 'Threatened Birds' is Strong *and* 'Threatened Plants' is Medium *and* 'Threatened Fishes' is Weak *and* 'Threatened Reptiles' is Strong *and* 'Threatened Amphibians' is Strong, *then* PR(BIOD) is Bad;
*if* ECOS is Bad *and* HUMS is Good, *then* OSUS is Intermediate.

The inference engine combines rules of its rule base and membership grades of its input variables using product–sum algebra, and computes the membership grades of its output to the corresponding fuzzy sets shown in Fig. 2b or c. Products and sums correspond to the logical operations of conjunction ("and") and disjunction ("or"). The former is involved in the rule premises and the latter corresponds to the operation that aggregates all rules. Product-sum inference is described below by means of an example.

Each rule is assigned a *firing strength* which measures the degree to which the rule matches the inputs. Suppose, for example, that ECOS is A (Average) with membership grade 0.4 and G (Good) with grade 0.6, and HUMS is A with membership grade 0.9 and G with grade 0.1. Consider four rules of the rule base for OSUS:

R1: *if* ECOS is A *and* HUMS is A, *then* OSUS is I (Intermediate)
R2: *if* ECOS is A *and* HUMS is G, *then* OSUS is FH (Fairly High)
R3: *if* ECOS is G *and* HUMS is A, *then* OSUS is FH (Fairly High)
R4: *if* ECOS is G *and* HUMS is G, *then* OSUS is H (High).

The firing strength of a rule is given by the product of the input membership grades, and this value is passed to the membership grade of the output to the corresponding fuzzy set. Thus,

firing strength of $R_1=0.4\times0.9=0.36=$ membership grade of OSUS to the fuzzy set I
firing strength of $R_2=0.4\times0.1=0.04=$ membership grade of OSUS to the fuzzy set FH
firing strength of $R_3=0.6\times0.9=0.54=$ membership grade of OSUS to the fuzzy set FH
firing strength of $R_4=0.6\times0.1=0.06=$ membership grade of OSUS to the fuzzy set H.

If several rules assign the same fuzzy set to the output variable (here we have a disjunction or union of rules), then the overall membership grade of the output is the sum of the individual firing strengths. In the above example, both rules $R_2$ and $R_3$ assign the fuzzy FH to OSUS. Thus, the output of the inference engine is

$$\mu_I(\text{OSUS}) = 0.36, \mu_{FH}(\text{OSUS}) = 0.04 + 0.54 = 0.58, \mu_H(\text{OSUS}) = 0.06.$$

Finally, a crisp value for a composite indicator, here OSUS (step 8 in Fig. 1), is computed via the height method of defuzzification,

$$\text{OSUS} = \frac{\sum_{\substack{\text{all fuzzy sets } L\\ \text{of OSUS}}} y_L\,\mu_L(\text{OSUS})}{\sum_{\substack{\text{all fuzzy sets} L\\ \text{of OSUS}}} \mu_L(\text{OSUS})},$$

where $y_L$ is the peak value of the fuzzy set $L$—a value of OSUS for which the membership function of $L$ is maximized. For the example given above, only I, FH, and H are involved in the defuzzification. It is seen in Fig. 2c that $y_I=0.5$, $y_{FH}=0.625$, and $y_H=0.75$. Therefore, the overall sustainability is given by

$$\text{OSUS} = \frac{0.5\times0.36+0.625\times0.58+0.75\times0.06}{0.36+0.58+0.06} = 0.5875.$$

An important feature of the SAFE model is monotonicity. Whenever a basic indicator of sustainability is improved, the components of sustainability that depend on this indicator as well as OSUS increase or at least do not decrease. The use of product–sum algebra in all inference engines ensures that the hierarchical fuzzy system is monotonic (Kouikoglou and Phillis, 2009).

### 2.2. Rule Bases

The rules used in each inference step express linguistically the dependence of a composite indicator on other, more elementary indicators. This section describes a compact representation of the rule bases, which avoids storing all rules in the computer memory. This is done in three steps outlined below.

1) The fuzzy sets of Fig. 2 are assigned integer values 0, 1, 2, …, where 0 corresponds to the fuzzy sets with the lowest sustainability. The fuzzy set Weak in Fig. 2a is assigned the value 0, Medium is assigned the value 1, and Strong is assigned the value 2. The corresponding weights for the composite indicators of Fig. 2b are Very Bad → 0, Bad → 1, Average → 2, Good → 3, and Very Good → 4, and for OSUS (Fig. 2c) Extremely Low → 0, Very Low → 1, …, Extremely High → 8. Moreover, each indicator used as input to an inference engine is also assigned a positive weight, which measures its relative importance against the other inputs. Currently, all inputs of the SAFE inference engines are assigned the weight 1.

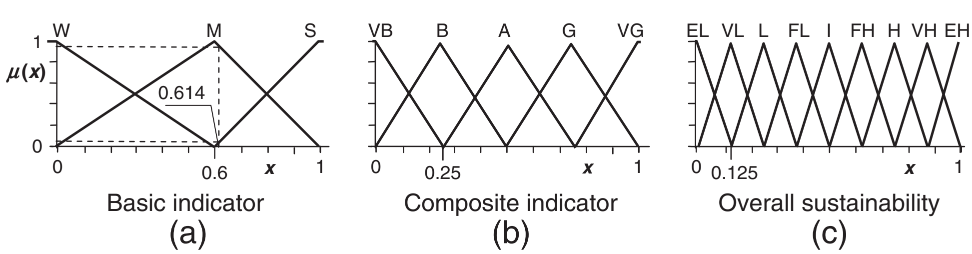


**Fig. 2.** Fuzzy sets and corresponding membership functions $\mu(x)$.

2) For each rule, a weighted sum of inputs is computed and assigned to the output variable. For example, consider the rule
*if* 'Threatened Mammals' is Medium *and* 'Threatened Birds' is Strong *and* 'Threatened Plants' is Medium *and* 'Threatened Fishes' is Weak *and* 'Threatened Reptiles' is Strong *and* 'Threatened Amphibians' is Strong, *then* PR(BIOD) is Bad;
The weighted sum of its inputs is

$$\text{weight of PR(BIOD)} = 1 + 2 + 1 + 0 + 2 + 2 = 8.$$

3) The resulting weight is assigned to some fuzzy set. The larger the weight the larger or better the fuzzy set of the output. For example, the rule base for the composite indicator PR(BIOD) comprises 729 rules ($3^6$ six-tuples of the fuzzy sets W, M, and S). It is represented compactly as follows

$$\text{fuzzy set of PR(BIOD)} = \begin{cases} \text{VB}, & \text{if weight} \le 7 \\ \text{B}, & \text{weight} = 8 \\ \text{A}, & \text{weight} = 9 \\ \text{G}, & \text{weight} = 10 \\ \text{VG}, & \text{weight} = 11,12 \end{cases}.$$

The same rule base is used for PR(LAND), which has also six inputs as shown in Table 1. The rule bases used to assess other composite indicators are given in Appendix A.

As mentioned previously, equal weights are assigned to the input indicators of each rule base. This choice, albeit subjective to some extent, is made in most of the existing aggregation methods and in certain cases it is supported by expert opinion. For example, a principal components analysis of ESI (Esty et al., 2005, pp. 88–91 and Table A.18) reveals that the ESI indicators have almost equal weights. The same was concluded in Liu (2007) with the aid of expert opinion about the components of environmental sustainability.

### *2.3. Data Imputation*

The problem of data availability is crucial, although it is common in sustainability studies (see, e.g., Esty et al., 2005). SAFE needs 75 basic indicators per country as inputs to assess all aspects of sustainability. For the 128 countries considered, a total of $128 \times 75 = 9600$ normalized inputs are required. However, because only few counties provide data for all indicators, 284 values (approximately 3% of the data) are missing. No model, irrespectively of its value, can provide useful assessments if based on unreliable or insufficient data. Moreover, simple approaches (e.g., listwise deletion and mean substitution) are not able to sufficiently handle the missing data problem.

To ameliorate this situation a data imputation procedure is performed. Unknown values are imputed from other countries for which data are available by taking averages. Data donor countries must meet certain criteria which are presented below.

Groups of highly similar and moderately similar countries are formed according to geographic and economic criteria. These similarities are shown schematically in Fig. 3. Mathematically they

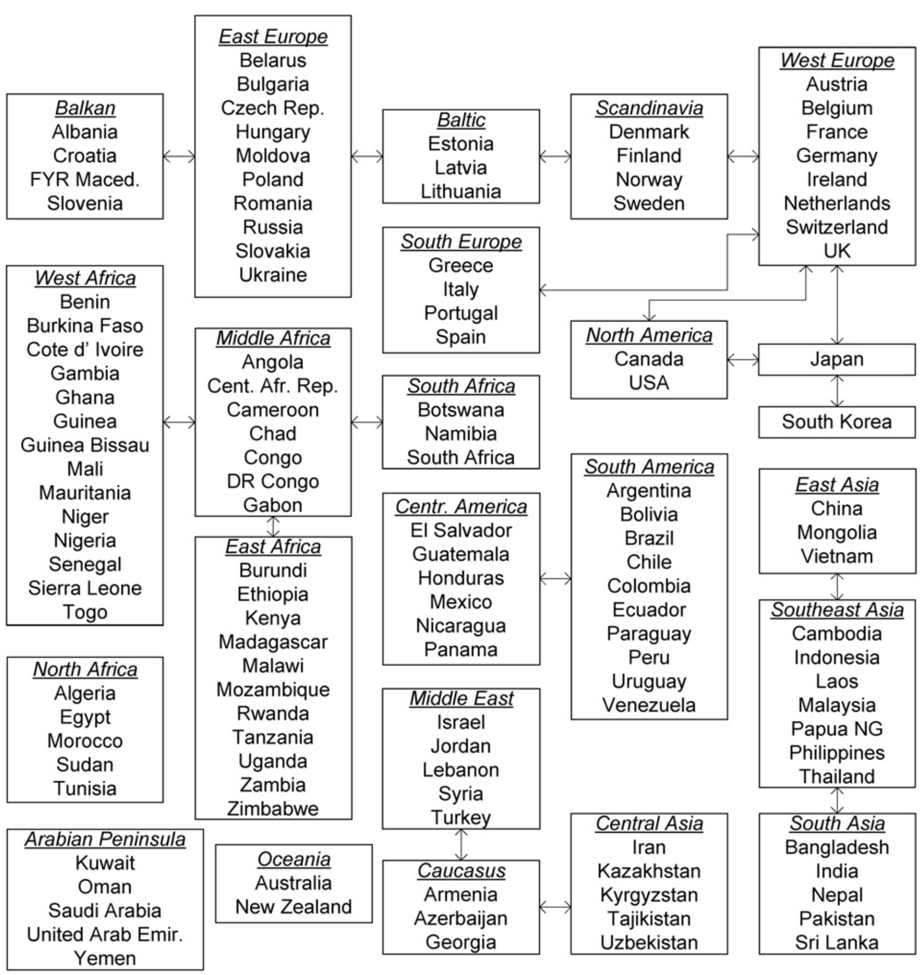


**Fig. 3.** Countries with high similarity (boxes) and moderate similarity (arrows).

are modeled by a square matrix $S$ with elements $s_{ij}$ that quantify the degree of similarity between country $i$ and country $j$, for all $i$, $j=1, 2, \ldots, 128$. The elements $s_{ij}$ take three possible values: 0 for no similarity, 1 for moderate similarity, and 2 for high similarity.

The assessment of similarity degrees among countries is based on the following procedure:

1. Country groups are formed according to geography as given by the United Nations Statistics Division (2010).
2. These groups are refined, taking into account economic criteria. Such country groupings are also given by the United Nations Statistics Division (2010) and the World Bank (2010). For example:
   a. The group of Baltic countries is separated from the group of Scandinavian countries, since the latter forms a group of high-income OECD countries, although they all belong to the geographic area of North Europe.
   b. UK and Ireland are grouped together with other Western European countries, although they are located in North Europe in order to form a homogenous group of OECD countries and high-income developed economies.
   The resulting groups consist of highly similar countries ($s_{ij}=2$), as shown by the rectangular boxes of Fig. 3.
3. Pairs of groups with moderate similarity are found using geographical and economic criteria. For example:
   a. Western European countries are moderately similar to other OECD members which belong to the groups of North America, Scandinavia, South Europe, and Japan.
   b. The group of South America consists of middle-income countries which are moderately similar to Central American countries, but not to the high-income OECD countries in North America. The result of this step is presented by the arrows of Fig. 3, which correspond to moderately similar (groups of) countries ($s_{ij}=1$).

It should be noted that moderate similarity ($s_{ij}=1$) is not necessarily transitive. For example, Albania and Belarus are fairly similar as seen in Fig. 3, and so are Belarus and Estonia. Yet, Albania is not similar to Estonia.

Some groups (e.g., North Africa, Oceania, Arabian Peninsula) have no similarity with other countries ($s_{ij}=0$) since they do not satisfy economic and geographic criteria.

As already mentioned, the basic indicators fall within 8 groups: LAND, WATER, BIOD, AIR, POLICY, WEALTH, HEALTH, and KNOW. Suppose that some basic input from indicator group $g$ is not available for country $i$. Let $j$ be an index of countries similar to $i$, i.e., $s_{ij}=1$ or 2. For each pair $(i, j)$, the Euclidean distance $d_{ijg}$ is computed using those normalized indicators of group $g$ for which data are available for both $i$ and $j$. The Euclidean distance is given by the square root of the average of squared indicator differences:

$$d_{ijg} = \sqrt{\frac{\sum\limits_{\substack{\text{available indicators}\\ c \text{ of group } g}} \left(x_{ic}-x_{jc}\right)^2}{\text{number of group } g \text{ indicators available for both } i \text{ and } j}},$$

where $x_{ic}$ is the normalized value of indicator $c$ for country $i$, which is obtained by exponential smoothing (step 2a of Fig. 1). When no group $g$ indicator is available for both countries $i$ and $j$ the corresponding Euclidean distance is assumed to be infinite, i.e., $d_{ijg}=\infty$.

If a given country misses a basic indicator, a set of countries with maximum similarity and minimum Euclidean distance is formed. The missing value equals the average value of this indicator for all countries that satisfy the above criteria. Specifically, suppose that an indicator of group $g$ is not available for country $i$. The following algorithm is used to find countries that meet the similarity and distance criteria. Index $j$ runs exclusively over those countries for which the indicator to be imputed is available.

1. Compute $d_{ijg}$ for each country $j$ in the same group as $i$ ($s_{ij}=2$). Find those countries for which $d_{ijg}\leq 0.1$ (10% of the maximum value of a normalized indicator). If no countries are found, then go to step 2.
2. Compute $d_{ijg}$ for all moderately similar countries ($s_{ij}=1$). Choose those countries for which $d_{ijg}\leq 0.1$. If no country satisfies this, then go to step 3.
3. Find countries in the same group as $i$ ($s_{ij}=2$) for which $d_{ijg}\leq 0.2$ (20% of the maximum value of a normalized indicator). If no countries are found, then go to step 4.
4. Find moderately similar countries ($s_{ij}=1$) for which $d_{ijg}\leq 0.2$. If no countries are found, then go to step 5.
5. Compute $d_{ijg}$ for each unrelated country $j$ ($s_{ij}=0$) and select those with the minimum distance.

All missing inputs were imputed using only steps 1–4 of the above algorithm, and a complete data base is formed for 128 countries and 75 indicators per country. Step 5 is introduced to ensure that the data imputation method will give a result even in the extreme case when only one group $g$ indicator is available. On average, 1.86 or about two countries are chosen to impute each of the 284 missing inputs. The average value of distances $d_{ijg}$ is 0.105, with an average range of 0.012.

The previous procedure is similar to a hot deck imputation approach, which is an intuitively simple and popular method of handling missing data. Data imputation is able to avoid under- or overestimation of sustainability results. As we shall see, the numerical results indicate that this method is quite efficient.

### 2.4. Use of SAFE for Sustainability Improvement

Sensitivity analysis can provide quantitative information to policy makers about the most important aspects of sustainable development for a given country. Gradient information of the overall sustainability index with respect to each basic input can be used to find those indicators that affect sustainability critically and then focus on their improvement so as to improve overall sustainability.

Consider a country with normalized values of basic indicators $x_c$, $c=1, \ldots, 75$. Its overall sustainability, OSUS$(x_1, \ldots, x_c, \ldots)$, is assessed using the procedure described previously. If certain measures were to be taken to improve indicator $c$ to the value $x_c+\delta$, $\delta>0$, and all the other indicators are unaltered, then the new sustainability score, OSUS$(x_1, \ldots, x_c+\delta, \ldots)$, would be higher or at least as high as the previous one. This follows from the monotonicity property of the SAFE system. The divided difference

$$\Delta_c = \frac{\text{OSUS}(x_1,\ldots,x_c+\delta,\ldots)-\text{OSUS}(x_1,\ldots,x_c,\ldots)}{\delta}$$

gives the rate of improvement of OSUS with respect to each indicator $c$. Ranking the indicators by the magnitude of their divided differences (the larger the $\Delta_c$ the higher the ranking) reveals crucial directions and efficient practices towards a sustainability progress.

This approach is biased towards indicators which belong to small groups (Kouloumpis et al., 2008). For example, the tertiary component State of Biodiversity, ST(BIOD), depends only on forest area (see Table 1). Therefore, an increase in the latter directly affects the former. PR(BIOD), on the other hand, depends on six basic indicators, which describe the extinction rates of animal and plant species. An improvement of one of these indicators will result in a small improvement of PR(BIOD).

To resolve this problem, basic indicators are ranked according to the product

$$\Delta_c(1-x_c),$$

where $1-x_c$ is the distance of indicator $c$ from the sustainable value. Thus those indicators that affect OSUS the most and are farther in the unsustainable region are considered most crucial in formulating policies for sustainable development. The following discussion provides a rationale for the choice of index $\Delta_c(1-x_c)$ used to rank the indicators. This discussion albeit not rigorous, illustrates the point of our choice.

Suppose there is a fixed capital $K$ (or "total effort") available for implementing policies for sustainable development in a given country. Let $K_c(x_c)$ be the cost of maintaining indicator $c$ at a sustainability level $x_c$, $x_c \in [0, 1]$. The cost functions $K_c$, $c=1, \ldots, 75$, are increasing or, in other words, sustainability costs. Consider the problem of maximizing the overall sustainability of the country:

$$\text{maximize OSUS}(x_1, \ldots, x_c, \ldots) \text{ subject to the constraint } K = \sum_{c=1}^{75} K_c(x_c).$$

The above is equivalent to the unconstrained problem

$$\text{maximize OSUS}(x_1, \ldots, x_c, \ldots) + \lambda\left[K - \sum_{c=1}^{75} K_c(x_c)\right],$$

where $\lambda$ is a Lagrange multiplier. The necessary conditions for a maximum are

$$\frac{\partial \text{OSUS}}{\partial x_c} - \lambda \frac{dK_c(x_c)}{dx_c} = 0$$

for $c=1, \ldots, 75$. To maximize OSUS, $x_c$ must be such that all quantities

$$D_c = \frac{\partial \text{OSUS}}{\partial x_c}\left[\frac{dK_c(x_c)}{dx_c}\right]^{-1}$$

equal $\lambda$. Therefore, an "optimal" development policy must decrease those $D_c$-values that are currently large and increase the small ones. This is the basic rule for policy making.

The ranking index $D_c$ defined above is compared with the index $\Delta_c(1-x_c)$. The partial derivative of OSUS involved in $D_c$ is approximated by the divided difference $\Delta_c$. Therefore, the two ranking indices can be considered similar if the cost functions satisfy

$$\left[\frac{dK_c(x_c)}{dx_c}\right]^{-1} \approx 1 - x_c$$

or, equivalently, $K_c(x_c) \approx A - \ln(1-x_c)$, where $A$ is a constant term. We provide some evidence to support the validity of this approximation ignoring the constant term. For $x_c=0$, one has that $-\ln(1-x_c)=0$ and also $K_c(0)=0$ since a country does not have to spend any resources to keep its indicator unsustainable. The function $-\ln(1-x_c)$ is increasing and convex. The function $K_c$ is also increasing and convex. That is, an improvement of sustainability involves a necessary cost and this additional cost or *cost rate* $dK_c/dx_c$ grows with $x_c$. The latter property agrees with the fact that it is usually easier or less costly to improve an index with low sustainability than one with high sustainability by the same magnitude.

## 3. Results and Discussion

### 3.1. Sustainability of Countries

Table 2 gives the overall, ecological, and human sustainability assessments for 128 countries. The basic indicators cover a period of sixteen years (1990–2005). The ten highest-ranking countries are European: Switzerland, Sweden, Finland, Denmark, Norway, Austria, France, Netherlands, Germany, and Belgium.

The results of Table 2 reveal the following:

1. European countries, Japan, New Zealand, Australia, and North America occupy the top places of the ranking. The bottom places are occupied by African countries, whereas the middle is taken by Central and South America and some Asian countries.
2. The top 32 places belong to OECD members, together with Croatia, Uruguay, and the Baltic countries.
3. The results of the SAFE model are similar to those of the 2005 ESI index (Esty et al., 2005) if only the ecological (ECOS) component is considered. Overall, however, the inclusion of the human component in SAFE changes the two rankings considerably.
4. Economic development seems to play an important role in the overall sustainability ranking mainly because it is related to the human sustainability of countries (e.g., the correlation coefficient between log(GNI per capita) and OSUS is 0.812 and between log (GNI per capita) and HUMS is 0.899). Interestingly, ecological and human sustainability are not correlated.

It should be noted that the results derived herein differ from those of Kouloumpis et al. (2008) although the input data were almost identical. This is due to the introduction of the imputation procedure and a better computation of sustainable indicator regions in the present work. To derive proper sustainability thresholds for each indicator a lot of effort was committed to consulting with experts and taking into account international agreements and norms.

### 3.2. Sensitivity Analysis

The quantities $\Delta_c(1-x_c)$ for all basic indicators are calculated and ranked by magnitude. To compute $\Delta_c$, each indicator is increased by 1% or $\delta=0.01$. Table 3 shows the most important indicators for selected countries. In general, the critical factors for developed countries are mainly ecological. For less developed countries the most important factors are ecological as well as human.

The following are observed:

1. The most critical factors for the US are ecological. The US is a developed country with a very strong human component. Development, however, is accompanied by environmental problems such as $CO_2$ emissions. The SAFE model captures such aspects readily.
2. Similar arguments also hold for Germany. This country, however, due to the turmoil following unification as well as the fact that tax revenue as percentage of GDP is low compared to other EU-14 members, exhibits some critical human aspects as well.
3. Spain's critical factors are exclusively ecological. Indeed, deforestation, desertification, and municipal waste generation are among the most prominent problems of the country.
4. Greece's problems are primarily economic, a fact that has made the headlines lately. Again SAFE captures this fact.
5. Ecuador and India are developing countries and their problems are both ecological and human, hence the factors of Table 3.

### 3.3. Validation of the Data Imputation Procedure

The data imputation approach is validated through an experimental procedure. For a given group of indicators 10% of the available data are randomly removed. Then, the data imputation algorithm is applied and deviations between actual and imputed values are computed. This procedure is repeated 100 times for each indicator group, in all $8 \times 100 = 800$ times. The imputed values within each group have a mean absolute deviation 0.073 and a mean squared error 0.016. The squared coefficient of correlation between actual and imputed values (coefficient of determination) is $R^2 = 0.863$. Therefore, the proposed data imputation approach accounts for about 86% of the variability in the removed data and appears to be quite efficient.

**Table 2**
Sustainability ranking of 128 countries (data for 1990–2005).

| | Country | OSUS | ECOS | HUMS |
|---|---|---|---|---|
| 1 | Switzerland | 0.884 | 0.769 | 0.998 |
| 2 | Sweden | 0.877 | 0.755 | 1.000 |
| 3 | Finland | 0.876 | 0.751 | 1.000 |
| 4 | Denmark | 0.875 | 0.750 | 1.000 |
| 5 | Norway | 0.868 | 0.752 | 0.984 |
| 6 | Austria | 0.865 | 0.792 | 0.938 |
| 7 | France | 0.825 | 0.716 | 0.935 |
| 8 | Netherlands | 0.808 | 0.626 | 0.989 |
| 9 | Germany | 0.786 | 0.744 | 0.829 |
| 10 | Belgium | 0.783 | 0.647 | 0.920 |
| 11 | Canada | 0.765 | 0.744 | 0.786 |
| 12 | New Zealand | 0.759 | 0.647 | 0.870 |
| 13 | Latvia | 0.750 | 0.750 | 0.750 |
| 14 | Estonia | 0.750 | 0.750 | 0.750 |
| 15 | Lithuania | 0.750 | 0.750 | 0.749 |
| 16 | Italy | 0.747 | 0.743 | 0.750 |
| 17 | Slovakia | 0.745 | 0.743 | 0.747 |
| 18 | Czech Rep. | 0.740 | 0.730 | 0.750 |
| 19 | Australia | 0.740 | 0.582 | 0.897 |
| 20 | Portugal | 0.734 | 0.719 | 0.750 |
| 21 | Croatia | 0.731 | 0.726 | 0.736 |
| 22 | UK | 0.710 | 0.599 | 0.822 |
| 23 | Poland | 0.706 | 0.749 | 0.663 |
| 24 | Hungary | 0.704 | 0.659 | 0.750 |
| 25 | Greece | 0.704 | 0.735 | 0.673 |
| 26 | Spain | 0.691 | 0.634 | 0.748 |
| 27 | Japan | 0.685 | 0.621 | 0.750 |
| 28 | Ireland | 0.671 | 0.560 | 0.782 |
| 29 | USA | 0.645 | 0.541 | 0.750 |
| 30 | Slovenia | 0.644 | 0.517 | 0.771 |
| 31 | Uruguay | 0.633 | 0.747 | 0.520 |
| 32 | Chile | 0.629 | 0.594 | 0.664 |
| 33 | Bulgaria | 0.628 | 0.527 | 0.729 |
| 34 | Georgia | 0.625 | 0.749 | 0.500 |
| 35 | Israel | 0.624 | 0.499 | 0.750 |
| 36 | South Korea | 0.624 | 0.500 | 0.748 |
| 37 | Panama | 0.621 | 0.745 | 0.496 |
| 38 | Malaysia | 0.619 | 0.498 | 0.740 |
| 39 | Belarus | 0.619 | 0.737 | 0.500 |
| 40 | Albania | 0.617 | 0.750 | 0.484 |
| 41 | Bolivia | 0.611 | 0.743 | 0.479 |
| 42 | Tunisia | 0.610 | 0.594 | 0.627 |
| 43 | Thailand | 0.610 | 0.675 | 0.545 |
| 44 | Venezuela | 0.605 | 0.725 | 0.484 |
| 45 | Romania | 0.605 | 0.649 | 0.560 |
| 46 | Paraguay | 0.601 | 0.746 | 0.455 |
| 47 | Ukraine | 0.594 | 0.673 | 0.514 |
| 48 | FYR Maced. | 0.589 | 0.678 | 0.501 |
| 49 | Peru | 0.584 | 0.695 | 0.473 |
| 50 | El Salvador | 0.580 | 0.714 | 0.447 |
| 51 | Brazil | 0.579 | 0.655 | 0.503 |
| 52 | Moldova | 0.577 | 0.653 | 0.500 |
| 53 | Nicaragua | 0.568 | 0.745 | 0.391 |
| 54 | Kazakhstan | 0.559 | 0.617 | 0.500 |
| 55 | Argentina | 0.556 | 0.601 | 0.510 |
| 56 | Kyrgyzstan | 0.546 | 0.600 | 0.493 |
| 57 | Ecuador | 0.540 | 0.675 | 0.404 |
| 58 | Armenia | 0.536 | 0.574 | 0.498 |
| 59 | Azerbaijan | 0.528 | 0.557 | 0.499 |
| 60 | Russia | 0.525 | 0.545 | 0.505 |
| 61 | Vietnam | 0.524 | 0.554 | 0.494 |
| 62 | Jordan | 0.524 | 0.514 | 0.533 |
| 63 | Mongolia | 0.520 | 0.500 | 0.540 |
| 64 | Mexico | 0.519 | 0.536 | 0.501 |
| 65 | China | 0.516 | 0.514 | 0.518 |
| 66 | Syria | 0.514 | 0.554 | 0.474 |
| 67 | Kuwait | 0.510 | 0.493 | 0.526 |
| 68 | Turkey | 0.507 | 0.537 | 0.476 |
| 69 | Saudi Arabia | 0.502 | 0.501 | 0.503 |
| 70 | Botswana | 0.502 | 0.749 | 0.254 |
| 71 | Algeria | 0.501 | 0.502 | 0.501 |
| 72 | Morocco | 0.500 | 0.500 | 0.501 |
| 73 | Uzbekistan | 0.500 | 0.500 | 0.501 |
| 74 | Gambia | 0.500 | 0.750 | 0.250 |
| 75 | Congo | 0.500 | 0.749 | 0.250 |
| 76 | Gabon | 0.499 | 0.749 | 0.248 |
| 77 | Colombia | 0.498 | 0.545 | 0.452 |
| 78 | Lebanon | 0.498 | 0.497 | 0.500 |
| 79 | Egypt | 0.495 | 0.492 | 0.498 |
| 80 | Zimbabwe | 0.494 | 0.740 | 0.249 |
| 81 | Senegal | 0.494 | 0.739 | 0.249 |
| 82 | Namibia | 0.492 | 0.705 | 0.279 |
| 83 | Zambia | 0.490 | 0.748 | 0.232 |
| 84 | Malawi | 0.489 | 0.738 | 0.239 |
| 85 | Papua NG | 0.488 | 0.720 | 0.257 |
| 86 | Oman | 0.485 | 0.490 | 0.481 |
| 87 | Ghana | 0.485 | 0.718 | 0.252 |
| 88 | Honduras | 0.484 | 0.607 | 0.361 |
| 89 | Sri Lanka | 0.483 | 0.531 | 0.435 |
| 90 | Kenya | 0.482 | 0.728 | 0.236 |
| 91 | Cambodia | 0.479 | 0.712 | 0.246 |
| 92 | Angola | 0.479 | 0.708 | 0.250 |
| 93 | Cote d'Ivoire | 0.479 | 0.728 | 0.229 |
| 94 | Bangladesh | 0.477 | 0.704 | 0.250 |
| 95 | Benin | 0.473 | 0.706 | 0.241 |
| 96 | Laos | 0.472 | 0.694 | 0.249 |
| 97 | Guatemala | 0.467 | 0.677 | 0.258 |
| 98 | South Africa | 0.464 | 0.498 | 0.431 |
| 99 | Philippines | 0.464 | 0.507 | 0.421 |
| 100 | Chad | 0.463 | 0.714 | 0.211 |
| 101 | United Arab E | 0.459 | 0.254 | 0.664 |
| 102 | Niger | 0.454 | 0.677 | 0.231 |
| 103 | Tanzania | 0.453 | 0.664 | 0.243 |
| 104 | Uganda | 0.453 | 0.657 | 0.249 |
| 105 | Nigeria | 0.451 | 0.676 | 0.226 |
| 106 | Togo | 0.451 | 0.693 | 0.208 |
| 107 | Tajikistan | 0.447 | 0.542 | 0.352 |
| 108 | Indonesia | 0.446 | 0.576 | 0.315 |
| 109 | Guinea Bissau | 0.445 | 0.748 | 0.141 |
| 110 | Centr. Afr. R | 0.441 | 0.749 | 0.132 |
| 111 | Mozambique | 0.433 | 0.743 | 0.122 |
| 112 | Rwanda | 0.429 | 0.744 | 0.113 |
| 113 | Madagascar | 0.424 | 0.623 | 0.225 |
| 114 | Burkina Faso | 0.420 | 0.734 | 0.107 |
| 115 | Cameroon | 0.420 | 0.648 | 0.192 |
| 116 | Nepal | 0.419 | 0.682 | 0.155 |
| 117 | Mali | 0.418 | 0.617 | 0.220 |
| 118 | Iran | 0.412 | 0.387 | 0.437 |
| 119 | Guinea | 0.407 | 0.741 | 0.073 |
| 120 | DR Congo | 0.398 | 0.720 | 0.077 |
| 121 | India | 0.398 | 0.547 | 0.250 |
| 122 | Yemen | 0.374 | 0.500 | 0.248 |
| 123 | Ethiopia | 0.372 | 0.709 | 0.035 |
| 124 | Pakistan | 0.369 | 0.501 | 0.238 |
| 125 | Sierra Leone | 0.352 | 0.682 | 0.022 |
| 126 | Burundi | 0.351 | 0.668 | 0.035 |
| 127 | Mauritania | 0.350 | 0.511 | 0.188 |
| 128 | Sudan | 0.349 | 0.573 | 0.125 |

Other data imputation methods (Little and Rubin, 1987) are less efficient or model-based and do not fit our fuzzy reasoning model.

## 4. Conclusions

A model called SAFE was presented that assesses the sustainability of countries. SAFE is based on statistical analysis and fuzzy multistage reasoning and serves as a definition and measurement scheme for sustainability. The model defines and measures sustainability globally from the ecological and societal points of view. It is adaptive in that it admits modifications of inputs, outputs, rule bases and membership functions as new knowledge about the environment and the society amass. For example, global warming is a lot more important today than twenty years ago.

In this paper a number of important open questions concerning SAFE have been answered. First, if data are missing, an imputation procedure generates them. Second, the problem of rule explosion in rule bases having several inputs is eliminated using an algebraic

**Table 3**
Most important basic indicators to improve sustainability for selected countries.

| COUNTRY: Indicators | COUNTRY: Indicators | COUNTRY: Indicators |
|---|---|---|
| USA: Renewable energy production, Ozone-depleting substances, Municipal waste generation, Protected area, Greenhouse gas emissions | SPAIN: Protected area, Municipal waste generation, Forest change, Glass recycling, Water withdrawals, Paper recycling | ECUADOR: Poverty, Tax revenue, Environmental laws and enforcement, Refugees per capita, Forest change |
| GERMANY: Tax revenue, Foreign direct investments, Exports, Renewable energy production, Protected area, Forest change | GREECE: Unemployment gender gap, GNI per capita, Public wastewater treatment, Foreign direct investments, Exports, Poverty | INDIA: Public wastewater treatment, Population growth rate, Metals concentration, Protected area, Water withdrawals |

approach. Third, sustainability thresholds are fine-tuned using extensive discussion with experts as well as norms derived from international bodies. The past is taken into account via an exponential smoothing equation. The model provides a ranking of all countries for which data are available together with the most important environmental and societal indicators that affect sustainability the most. Improvement of these indicators results into the greatest improvement of sustainability.

The model can be viewed as both a definition and an assessment tool of sustainability. In other words, sustainability is defined as an aggregate index of two and then eight inputs.

SAFE has similarities and differences when compared to other sustainability models such as those outlined in the introduction. It uses the pressure-state-response (PSR) approach, primarily because of reasons of computational convenience. When one of the 8 components LAND, WATER, BIOD, AIR, POLICY, WEALTH, HEALTH, KNOW has too many inputs, the number of possible rules explodes geometrically. The number of rules is $F^I$, where $F$ is the number of fuzzy sets and $I$ is the number of inputs. For $F=3$ and $I=8$ the number of rules is $3^8=6561$ which is enormous. However, when these 8 inputs are grouped into PR, ST, and RE, the number of rules goes down dramatically.

SAFE, however, goes beyond PSR by computing a sustainability index and then going backwards by performing a sensitivity analysis.

The ecological footprint is an interesting index because it does the reverse of all sustainability models. Instead of taking a given piece of land and computing a sustainability index, it takes a given population at a prescribed consumption level and computes the land needed to support it. As such, of all models the ecological footprint has the least similarity with SAFE.

Multicriteria Decision Analysis (MCDA) is an interesting alternative for measuring sustainability, particularly when a clear policy framework exists. In such situations it is possible to extract decision-maker's (DM) preferences (e.g., weights of sustainability indicators) and develop policies that improve sustainability. For example, sustainability is assessed on a city-level (Munda, 2006), where the mayor or the city council play the role of the DM. However, decision-making problems on a global scale would in principle require global consensus, as for example happened when ozone depleting substances were banned or restricted. Global decision-making is a rarity, despite international goodwill. Global warming is a case in point.

An analytical review of MCDA is presented in Munda (2005) in the context of sustainability. It is suggested that linear aggregation models be avoided, since there are phenomena of synergy or conflict among the different sustainability indicators. Thus, non-compensatory MCDA approaches seem more suitable for this problem, such as ELECTRE (Figueira et al., 2005), PROMETHEE (Brans and Mareschal, 2005), and NAIDE (Munda, 1995).

In principle SAFE computes a sustainability index as do the barometer of sustainability, ESI, or SSI.

SAFE and the barometer of sustainability seem to be the most balanced models in their use of societal and environmental indicators. SAFE uses fuzzy logic which does not require an explicit mathematical model between indicators and it can process quantitative as well as qualitative information. Fuzzy logic avoids the use of weights which are often arbitrary or cannot be easily extracted from a DM. Moreover, SAFE is a rather simple model that respects the non-compensability property, while it is the only approach that evaluates sustainability taking into account the time dimension.

On the other hand SAFE has certain shortcomings that are found in other models as well:

a) It is subjective to an extend and it doesn't possess a mechanism whereby the number of inputs is limited to the absolutely necessary ones. A certain overlap among indicators exists. For example, the number of hospital beds overlaps with public health expenditure or urban total particulates and urban $NO_2$ concentration overlaps with mortality from respiratory diseases. However, it is next to impossible to find causal models connecting such indicators.
b) The rule bases and the membership functions reflect the values, knowledge and biases of those who devise them. The rule bases of SAFE put equal weights of importance to the input variables, as is done in other aggregation methods after consulting with experts. Given that sustainability is not a concept amenable to a rigorous definition, subjectivity in its modeling is not surprising. This is the case with all other models of sustainability.
c) More work remains to be done to refine the weights and membership functions of certain indicators such as $CO_2$ emissions, nuclear and hazardous waste, loss of biodiversity, central government debt, etc., in order to capture emerging sustainability issues as reality changes.

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## Appendix A. Compact Representation of Rule Bases

Tertiary components with only one input have the same fuzzy sets and membership grades as their inputs. RE(WATER) depends solely on the basic indicator “Public wastewater treatment plants (percent of population connected)” and RE(AIR) depends on “Renewable energy production (percent of total primary energy supply).” Contrary to the other basic indicators which are mapped on three fuzzy sets, these two indicators are fuzzified using the five fuzzy sets VB, B, A, G, and VG and the resulting membership grades are passed on to RE(WATER) and RE(AIR).

Tertiary components with two inputs:

$$\left\{\begin{array}{c}\mathrm{ST(LAND)}\\ \mathrm{PR(BIOD)}\\ \mathrm{ST(BIOD)}\\ \mathrm{PR(AIR)}\\ \mathrm{RE(POLICY)}\\ \mathrm{RE(WEALTH)}\end{array}\right\} = \left\{\begin{array}{rl}\mathrm{VB}, & \text{if weight} = 0\\ \mathrm{B}, & \text{weight} = 1\\ \mathrm{A}, & \text{weight} = 2\\ \mathrm{G}, & \text{weight} = 3\\ \mathrm{VG}, & \text{weight} = 4\end{array}\right. .$$

Tertiary components with three inputs:

$$\mathrm{PR(WATER)} = \begin{cases} \mathrm{VB}, & \text{if weight} = 0, 1, 2 \\ \mathrm{B}, & \text{weight} = 3 \\ \mathrm{A}, & \text{weight} = 4 \\ \mathrm{G}, & \text{weight} = 5 \\ \mathrm{VG}, & \text{weight} = 6 \end{cases} \quad \left\{ \begin{matrix} \mathrm{ST(WATER)} \\ \mathrm{PR(POLICY)} \\ \mathrm{ST(WEALTH)} \\ \mathrm{PR(KNOW)} \end{matrix} \right\} = \begin{cases} \mathrm{VB}, & \text{if weight} = 0 \text{ or } 1 \\ \mathrm{B}, & \text{weight} = 2 \\ \mathrm{A}, & \text{weight} = 3 \\ \mathrm{G}, & \text{weight} = 4 \\ \mathrm{VG}, & \text{weight} = 5 \text{ or } 6 \end{cases}.$$

Freshwater availability and quality have become an increasingly crucial concern for many countries. The rule base of PR(WATER) is more pessimistic than those of the other tertiary components. Indeed, out of the seven possible weights (0–6) of PR(WATER), the four smallest ones or 60% correspond to the fuzzy sets VB and B. This is in agreement with widely accepted practices for the assessment of environmental pressures. For example OECD (2004) considers water stress to be high when the annual water withdrawals are at least 40% of the total renewable water resources. Equivalently, 60% of values are VB or B. The same reasoning is followed in the rule bases of pressure indicators PR(LAND) and PR(BIOD) which have six inputs.

Tertiary components with four inputs:

$$\left\{ \begin{matrix} \mathrm{RE(LAND)} \\ \mathrm{ST(AIR)} \\ \mathrm{PR(WEALTH)} \\ \mathrm{ST(HEALTH)} \end{matrix} \right\} = \begin{cases} \mathrm{VB}, & \text{if weight} = 0, 1, 2 \\ \mathrm{B}, & \text{weight} = 3 \\ \mathrm{A}, & \text{weight} = 4 \\ \mathrm{G}, & \text{weight} = 5 \\ \mathrm{VG}, & \text{weight} = 6, 7, 8 \end{cases} \quad \mathrm{ST(POLICY)} = \begin{cases} \mathrm{VB}, & \text{if weight} \leq 3 \\ \mathrm{B}, & \text{weight} = 4 \text{ or } 5 \\ \mathrm{A}, & \text{weight} = 6 \\ \mathrm{G}, & \text{weight} = 7 \\ \mathrm{VG}, & \text{weight} = 8 \end{cases}.$$

ST(POLICY) gives the state of human rights and is assessed using more strict criteria than the other components.

Tertiary components with five inputs:

$$\left\{ \begin{matrix} \mathrm{RE(HEALTH)} \\ \mathrm{RE(KNOW)} \end{matrix} \right\} = \begin{cases} \mathrm{VB}, & \text{if weight} \leq 3 \\ \mathrm{B}, & \text{weight} = 4 \\ \mathrm{A}, & \text{weight} = 5 \\ \mathrm{G}, & \text{weight} = 6 \\ \mathrm{VG}, & \text{weight} \geq 7 \end{cases}.$$

Tertiary components with six inputs:

$$\left\{ \begin{matrix} \mathrm{PR(LAND)} \\ \mathrm{PR(BIOD)} \end{matrix} \right\} = \begin{cases} \mathrm{VB}, & \text{if weight} \leq 7 \\ \mathrm{B}, & \text{weight} = 8 \\ \mathrm{A}, & \text{weight} = 9 \\ \mathrm{G}, & \text{weight} = 10 \\ \mathrm{VG}, & \text{weight} = 11 \text{ or } 12 \end{cases} \quad \left\{ \begin{matrix} \mathrm{PR(HEALTH)} \\ \mathrm{ST(KNOW)} \end{matrix} \right\} = \begin{cases} \mathrm{VB}, & \text{if weight} \leq 4 \\ \mathrm{B}, & \text{weight} = 5 \\ \mathrm{A}, & \text{weight} = 6 \\ \mathrm{G}, & \text{weight} = 7 \\ \mathrm{VG}, & \text{weight} \geq 8 \end{cases}.$$

Environmental pressures are judged using stricter rules, as discussed previously.

Secondary components with three inputs (PR, ST, RE):

$$\left\{ \begin{matrix} \mathrm{LAND} \\ \mathrm{WATER} \\ \mathrm{BIOD} \\ \mathrm{AIR} \\ \mathrm{POLICY} \\ \mathrm{WEALTH} \\ \mathrm{HEALTH} \\ \mathrm{KNOW} \end{matrix} \right\} = \begin{cases} \mathrm{VB}, & \text{if weight} = 0 \text{ or } 1 \\ \mathrm{B}, & \text{weight} = 2, 3, 4 \\ \mathrm{A}, & \text{weight} = 5, 6, 7 \\ \mathrm{G}, & \text{weight} = 8, 9, 10 \\ \mathrm{VG}, & \text{weight} = 11 \text{ or } 12 \end{cases}.$$

Finally, the rule bases of the primary components of sustainability and the overall sustainability index are

$$\left\{ \begin{matrix} \mathrm{ECOS} \\ \mathrm{HUMS} \end{matrix} \right\} = \begin{cases} \mathrm{VB}, & \text{if weight} = 0, 1, 2 \\ \mathrm{B}, & \text{weight} = 3, 4, 5, 6 \\ \mathrm{A}, & \text{weight} = 7, 8, 9, 10 \\ \mathrm{G}, & \text{weight} = 11, 12, 13, 14 \\ \mathrm{VG}, & \text{weight} = 15 \text{ or } 16 \end{cases} \quad \mathrm{OSUS} = \begin{cases} \mathrm{EL}, & \text{if weight} = 0 \\ \mathrm{VL}, & \text{weight} = 1 \\ \mathrm{L}, & \text{weight} = 2 \\ \mathrm{FL}, & \text{weight} = 3 \\ \mathrm{I}, & \text{weight} = 4 \\ \mathrm{FH}, & \text{weight} = 5 \\ \mathrm{H}, & \text{weight} = 6 \\ \mathrm{VH}, & \text{weight} = 7 \\ \mathrm{EH}, & \text{weight} = 8 \end{cases}.$$

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