Is Cumulative Fossil Energy Demand a Useful Indicator for the Environmental Performance of Products?

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The appropriateness of the fossil Cumulative Energy Demand (CED) as an indicator for the environmental performance of products and processes is explored with a regression analysis between the environmental life-cycle impacts and fossil CEDs of 1218 products, divided into the product categories "energy production", "material production", "transport", and "waste treatment". Our results show that, for all product groups but waste treatment, the fossil CED correlates well with most impact categories, such as global warming, resource depletion, acidification, eutrophication, tropospheric ozone formation, ozone depletion, and human toxicity (explained variance between 46% and 100%). We conclude that the use of fossil fuels is an important driver of several environmental impacts and thereby indicative for many environmental problems. It may therefore serve as a screening indicator for environmental performance. However, the usefulness of fossil CED as a stand-alone indicator for environmental impact is limited by the large uncertainty in the product-specific fossil CED-based impact scores (larger than a factor of 10 for the majority of the impact categories; 95% confidence interval). A major reason for this high uncertainty is nonfossil energy related emissions and land use, such as landfill leachates, radionuclide emissions, and land use in agriculture and forestry.

Introduction

Environmental assessment tools are used to support environmental decision-making, such as about industrial process optimization or the choice of environmentally friendly products. There are various such environmental assessment tools, the most comprehensive of which is life-cycle assessment (LCA). LCA is a tool for analyzing and comparing the potential environmental impact of products (and services) along their entire life cycle, that is, from the extraction of resources to manufacturing, use, and final disposal of products (*1*). LCA starts from a definition of the so-called functional unit of a product or service (e.g., the production of 1 MJ of electricity or the supply of 1 h of office light). In an inventory analysis, a table is compiled of all emissions and resource extractions that occur as a consequence of the production of one functional unit of product. A relatively large number of releases of pollutants and extractions of resources can be part of the inventory table (*2*). In a subsequent impact assessment, the additional impact of these emissions and extractions is quantified (*3*).

One of the difficulties of carrying out an LCA is that a relatively large amount of data is required. Although various software programs with inventory data are available (*4*−*6*), the data gathering for specific production processes is not without problems. This is due to the fact that process data are not (publicly) available or that they are not provided in a standardized format (*7*−*9*).

The applicability of LCAs would greatly improve, if less information with relatively high reliability could be used to compare or improve production processes (*10*−*12*). This is particularly the case for LCA studies focusing on early product development for which generally only little information is available on materials and processes. A potentially suitable option to simplify LCA is to apply the concept of Cumulative Energy Demand (CED) as a screening impact indicator (*13*−*19*). The CED represents the energy demand, valued as primary energy during the complete life cycle of a product (*20*, *21*). Particularly, from fossil energy demand it is well known that it is dominantly responsible for global warming and depletion of fossil resources (*22*−*24*). As compared to complete LCA studies, the calculation of CEDs requires substantially less information in the inventory analysis; that is, no emission estimates and impact assessment factors are required. Data to estimate energy requirements are in most cases readily available (*13*). Up to now, it has, however, not been thoroughly tested to what extent the CED-outcomes follow the results of the life-cycle impact assessment.

We studied the correlation between cumulative energy demand of fossil resources and a number of environmental impact categories (global warming, stratospheric ozone depletion, acidification, eutrophication, photochemical ozone formation, land use, resource depletion, and human toxicity). The study is based on LCA- and CED-data of 1218 product systems in the western economy. The potential usefulness and appropriateness of applying fossil CED as a screening indicator for environmental impact in LCA is discussed.

Methodology

Cumulative Energy Demand (CED). The Cumulative Energy Demand (CED) of a product represents the direct and indirect energy use throughout the life cycle, including the energy consumed during the extraction, manufacturing, and disposal of the raw and auxiliary materials (*20*). Different concepts for determining the primary energy requirement exist. For CED calculations, one may chose the lower or the upper heating value of primary energy resources where the latter includes the evaporation energy of the water present in the flue gas. Furthermore, one may distinguish between energy requirements of renewable and nonrenewable resources. A

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10.1021/es051689g CCC: $33.50

Published on Web 00/00/0000
PAGE EST: 7.4

TABLE 1. Upper Heating Values of Fossil Primary Energy Resources (*25*)

fossil energy resource	unit	value
hard coal	MJ kg^{-1}	19
lignite	MJ kg^{-1}	10
natural gas	MJ m^{-3}	40
crude oil	MJ kg^{-1}	46

TABLE 2. Selected Impact Indicators and Corresponding Characterization Factors on the Midpoint Level (*3*)

impact indicator	spatial scale	time span
global warming	global	100 years
stratospheric ozone depletion	global	infinite
acidification	Europe	infinite
eutrophication	global	infinite
photochemical ozone formation	Europe	5 days
land use	global	not specified
resource depletion	global	not specified
human toxicity	Europe	infinite

discussion on the pros and cons for the different valuation concepts can be found in Frischknecht et al. (*21*).

In this study, for every product, the fossil cumulative energy demand, that is, from hard coal, lignite, natural gas, and crude oil, has been derived from Frischknecht and Jungbluth (*25*). Table 1 shows the typical upper heating values for the fossil primary energy resources required in the fossil CED calculations.

Life-Cycle Impact Assessment. In LCA, one class of impact methods quantifies the potential impact of releases and extractions by way of so-called midpoint indicators. Indicators in this category are relatively close to environmental interventions (*3*). In the present study, we looked at a subset of commonly applied impact categories (Table 2). Ionizing radiation, for example, caused by high radioactive waste and radionuclide emissions from nuclear power plants, has not been included as an impact category, as this type of impact is better reflected by nuclear CED than by fossil CED (*25*).

The midpoint impact scores for a product p can be calculated by:

$$IS_{m,p} = \sum_x \sum_i M_{x,i,p} \cdot Q_{x,i,m} \qquad (1)$$

where $IS_{m,p}$ is the impact score of product p for midpoint indicator m (kg reference substance), $M_{x,i,p}$ is the intervention x (emission of substances or extraction of resources) in compartment i (e.g., air, soil, water) caused by the life cycle of product p (kg), and $Q_{x,i,m}$ is the characterization factor of intervention x in compartment i related to impact category m (kg reference substance kg^{-1}). Characterization factors are intervention-specific, quantitative representations of potential impacts per unit emission of a substance or unit extraction of resources. In the present study, we used the characterization factors reported by Guinée et al. (*3*) and implemented according to Frischknecht and Jungbluth (*25*).

Life-Cycle Inventory Database. The Ecoinvent database v1.2 (*4*), containing life-cycle information for many products consumed in the western economy, has been used to derive cumulative fossil energy demands and life-cycle impact scores. Table 3 provides an overview of the product groups and the corresponding number of products considered. Energy production includes both heat and electricity production processes by nonrenewable energy sources (oil, hard coal, lignite, natural gas, nuclear) and

TABLE 3. Product Groups Defined, Derived from Ecoinvent Centre (*4*)

product group	functional unit	number of products
energy production	1 MJ	226
material production	1 kg	750
transport	1 tkm	28
waste treatment	1 kg	214
total		1218

renewable energy sources (hydropower, photovoltaic, wood, wind). Material production comprises many different product types, including plastics, chemicals, metals, agricultural products, and building materials. Transport includes transport of products by road, ship, train, airplane, and pipelines. Finally, waste treatment represents various types of landfill and incineration. We confined the analysis to products (and services) reported in equal units to avoid distortions in the regression analysis due to largely different (and arbitrary) sizes of the functional units. To minimize the interdependency between the production processes, we limited the energy production dataset to production of heat and electricity at the operation unit only. Further aggregated unit processes, such as electricity mixes in the various European countries, were excluded from the dataset. Furthermore, for cogeneration energy processes allocation based on energy content is applied only, excluding results for the same process, but based on another allocation rule, such as exergy.

Linear Regression. Linear regression analysis was performed to relate the environmental impact scores with cumulative fossil energy demands. The data in all subgroups were log-transformed to account for their skewed distributions:

$$IS_p = 10^b \cdot \mathrm{CED}_p^{\,a} \qquad (2)$$

where IS_p is the environmental impact score for product p and CED_p represents the cumulative energy demand (fossil or renewable) of product p. The regression equations were optimized using a linear least-squares fit to find appropriate values for the slope (a) and intercept (b) of the regressions. Apart from the regression parameters a and b, the correlation coefficient (r^2) and the residual standard error (SE) were derived. Linear regression plots with 95% confidence intervals of the expected IS-values are also provided. The Supporting Information gives detailed information on the calculation of SE and the 95% confidence intervals.

Additionally, the uncertainty attached to using the CED as an indicator for environmental impact is summarized with an uncertainty factor k derived from the SE:

$$k = \frac{97.5p}{2.5p} = (10^{1.96 \cdot SE})^2 \qquad (3)$$

The uncertainty factor k is defined such that 95% of the values of a stochastic variable are within a factor k, assuming a log-normal distribution.

Results

Figures 1−4 show the regression results of the eight impact categories included for the respective product categories energy production, material production, transport, and waste treatment. The results show that particularly for global warming and resource depletion, the explained variance (r^2) of the regression analysis is high (>93%), except for global warming related to waste treatment processes. In contrast, the explained variance of fossil CED concerning land use is low for all product categories (<57%). For stratospheric ozone

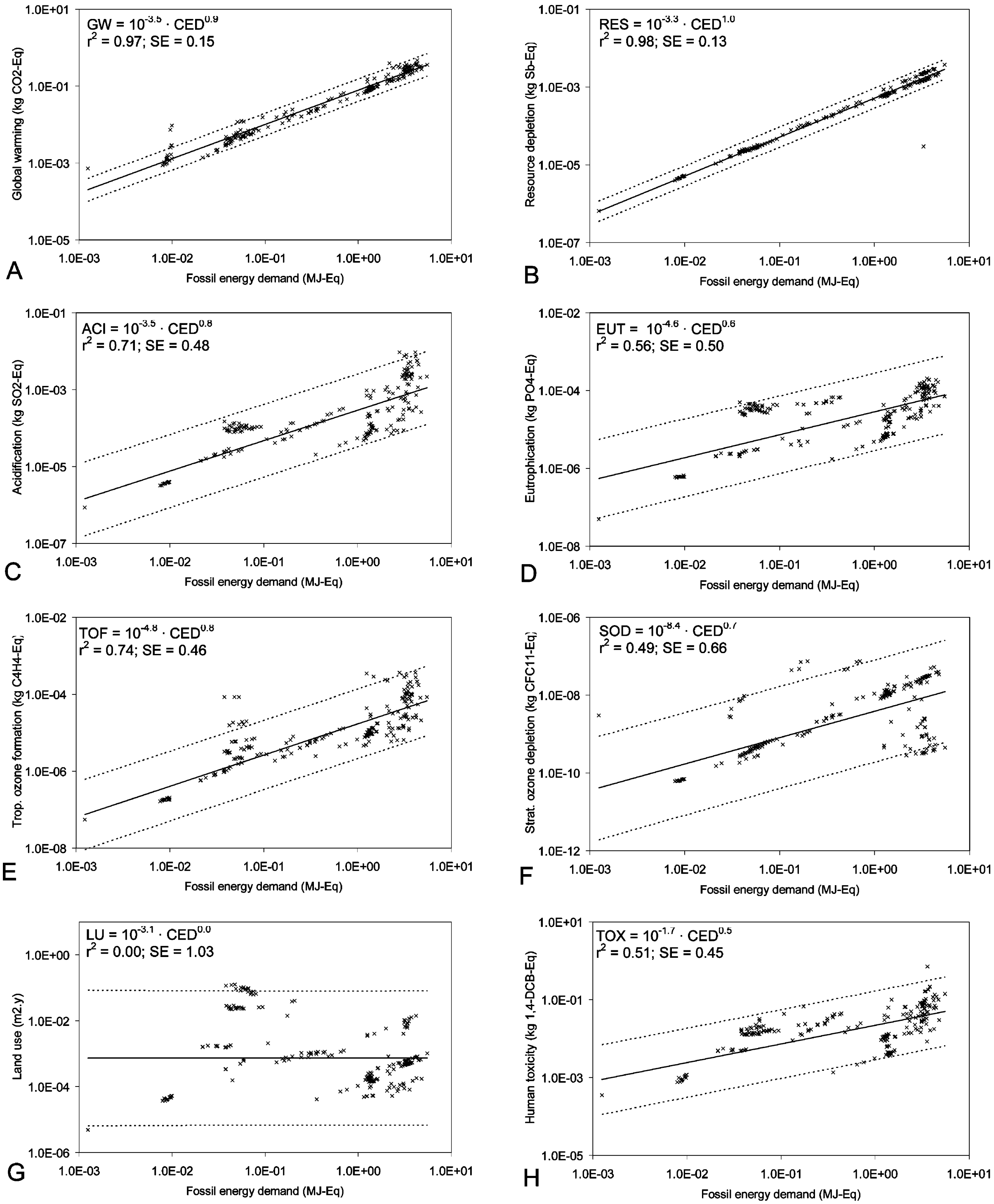

FIGURE 1. Linear regression plots with 95% confidence intervals (dotted lines), based on 226 energy production processes in MJ, for fossil cumulative energy demand (CED) and, respectively, global warming (A), resource depletion (B), acidification (C), eutrophication (D), photochemical ozone formation (E), stratospheric ozone depletion (F), land use (G), and human toxicity (H).

depletion, the explained variance is between 49% and 55% for energy production, material production, and transport, but higher than 90% for waste treatment.

For acidification, eutrophication, photochemical ozone formation, and human toxicity, the explained variance of the fossil CED is always higher for material production and transport systems than for energy production and waste treatment. Generally, the explained variance of the regression equations for these impact categories is always higher than 50%, reaching up to 86% in some cases. However, exceptions are the regression equations for human toxicity and eutrophication caused by waste treatment processes that showed a distinctly low explained variance (<20%).

It can be seen from Figures 1−4 and Table 4 that the 95% confidence intervals of the regression equations generally span 1−4 orders of magnitude. The exceptions are abiotic depletion and global warming, except for waste treatment, with confidence intervals ranging from 0.1 to 1 order of magnitude and land use with confidence intervals ranging from 2 to 4.6 orders of magnitude. The regression equations for stratospheric ozone depletion caused by material production and global warming and human toxicity caused by

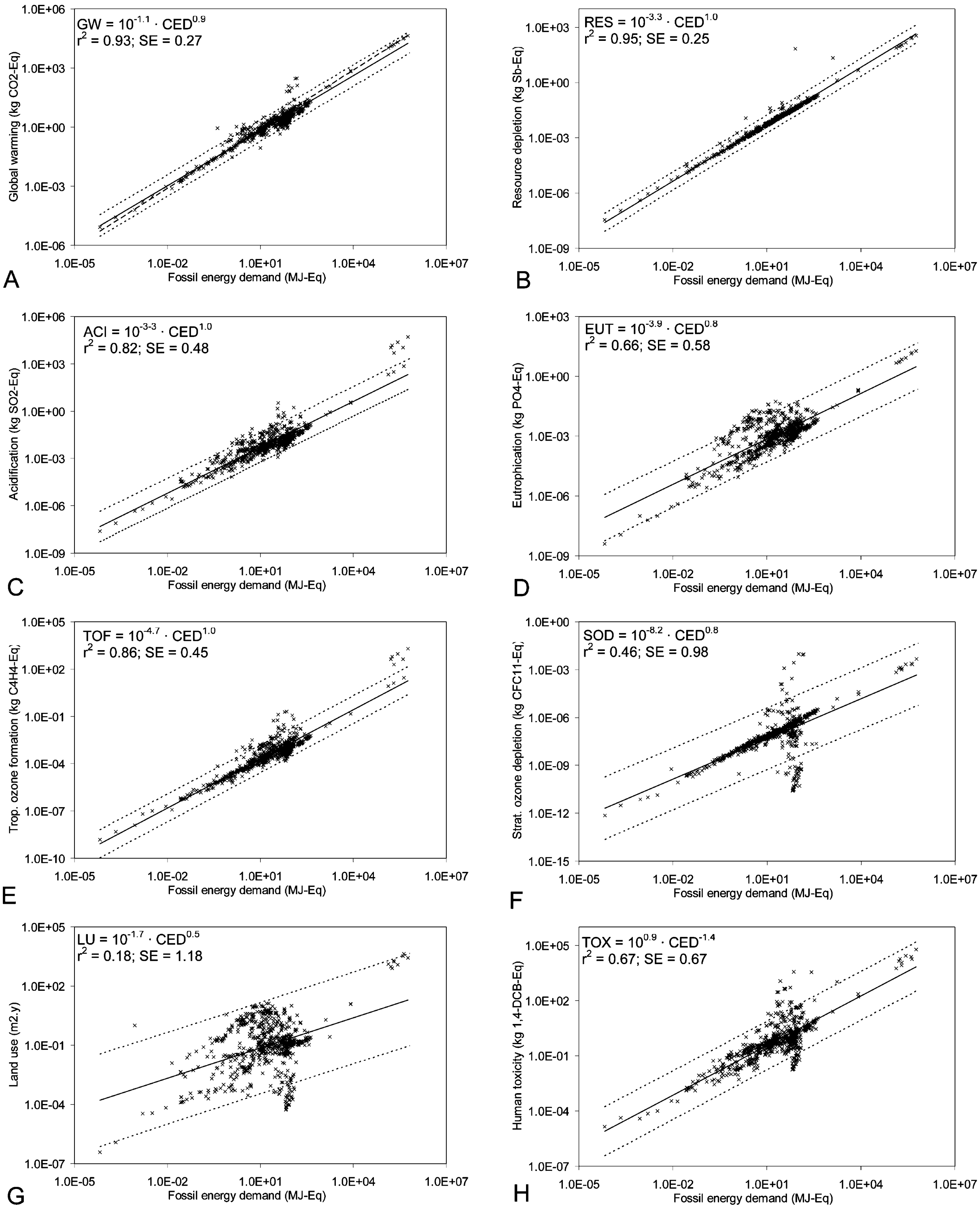

FIGURE 2. Linear regression plots with 95% confidence intervals (dotted lines), based on 750 material production processes in kg, for fossil cumulative energy demand (CED) and, respectively, global warming (A), resource depletion (B), acidification (C), eutrophication (D), photochemical ozone formation (E), stratospheric ozone depletion (F), land use (G), and human toxicity (H). (A) also includes the global warming regression plot for the full dataset without log-transformation (dashed line): GW = 0.077·CED, r^2 = 1.00.

waste treatment processes also have 95% confidence intervals larger than 3 orders of magnitude.

Note that for 102 products the Ecoinvent database reports a net negative value for CO_2 emissions, resulting in negative impact scores for the midpoint indicator "global warming". The reason for such negative values is, for instance, the use of renewable materials (e.g., wood) as primary material, and therefore the sequestration of carbon and extraction of CO_2 from the atmosphere. As the regression method on log-transformed data is not suitable to estimate negative impact scores, the datasets of these products were not included in the global warming regression analysis based on the log-transformed data. To check the influence of the removal of negative global warming scores on the outcome, the global warming regression analysis was also performed with the full dataset without log-transformation. Figure 2A shows that the global warming regression lines with and without log-transformation are virtually the same.

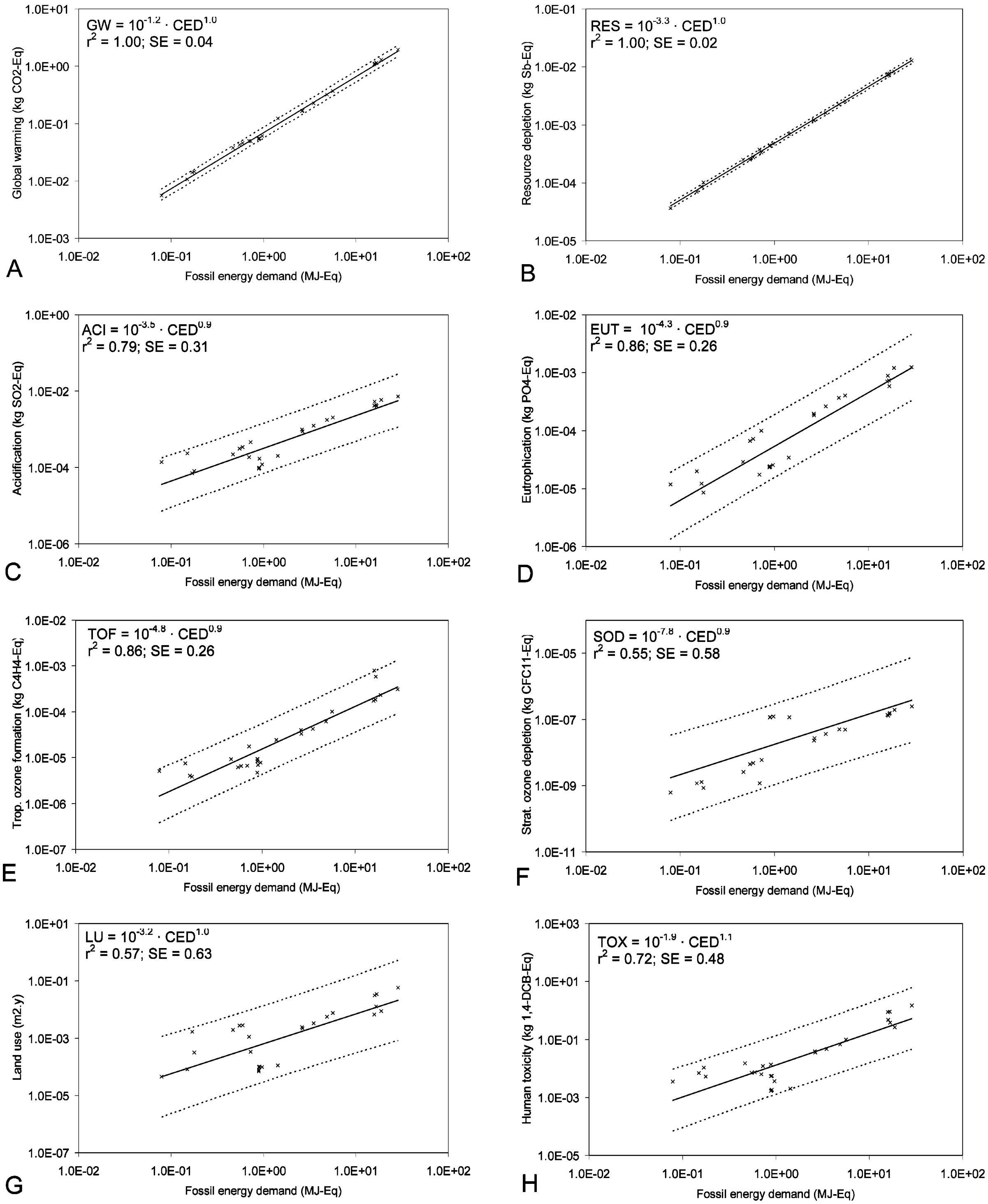

FIGURE 3. Linear regression plots with 95% confidence intervals (dotted lines), based on 28 transportation processes in tkm, for fossil cumulative energy demand (CED) and, respectively, global warming (A), resource depletion (B), acidification (C), eutrophication (D), photochemical ozone formation (E), stratospheric ozone depletion (F), land use (G), and human toxicity (H).

Discussion

What do the results tell us about the usefulness of cumulative energy demand as predictor of environmental impacts in LCA case studies? It seems that fossil cumulative energy demand explains a significant part of the variation in a variety of environmental impacts between products. This finding confirms the results of other studies, which indicate that the burning of fossil fuels is a major contributor to a number of environmental problems, such as global warming, acidification, eutrophication, and photochemical ozone formation (e.g., *22*−*24*, *26*, *27*). Furthermore, depletion of abiotic resources is commonly caused by the use of the fossil fuels oil, coal, and natural gas (*28*), clarifying the high explained variance of the CED regression line for the category resource depletion. Our findings also suggest that efforts to save fossil energy demand are in many cases justified from an environmental point of view. However, it does not automatically imply to substitute nuclear power for fossil power, because fossil CED evidently does not reflect the impacts of nuclear power. In contrast to the emission-related impact categories, land use and fossil CED show a relatively low explained

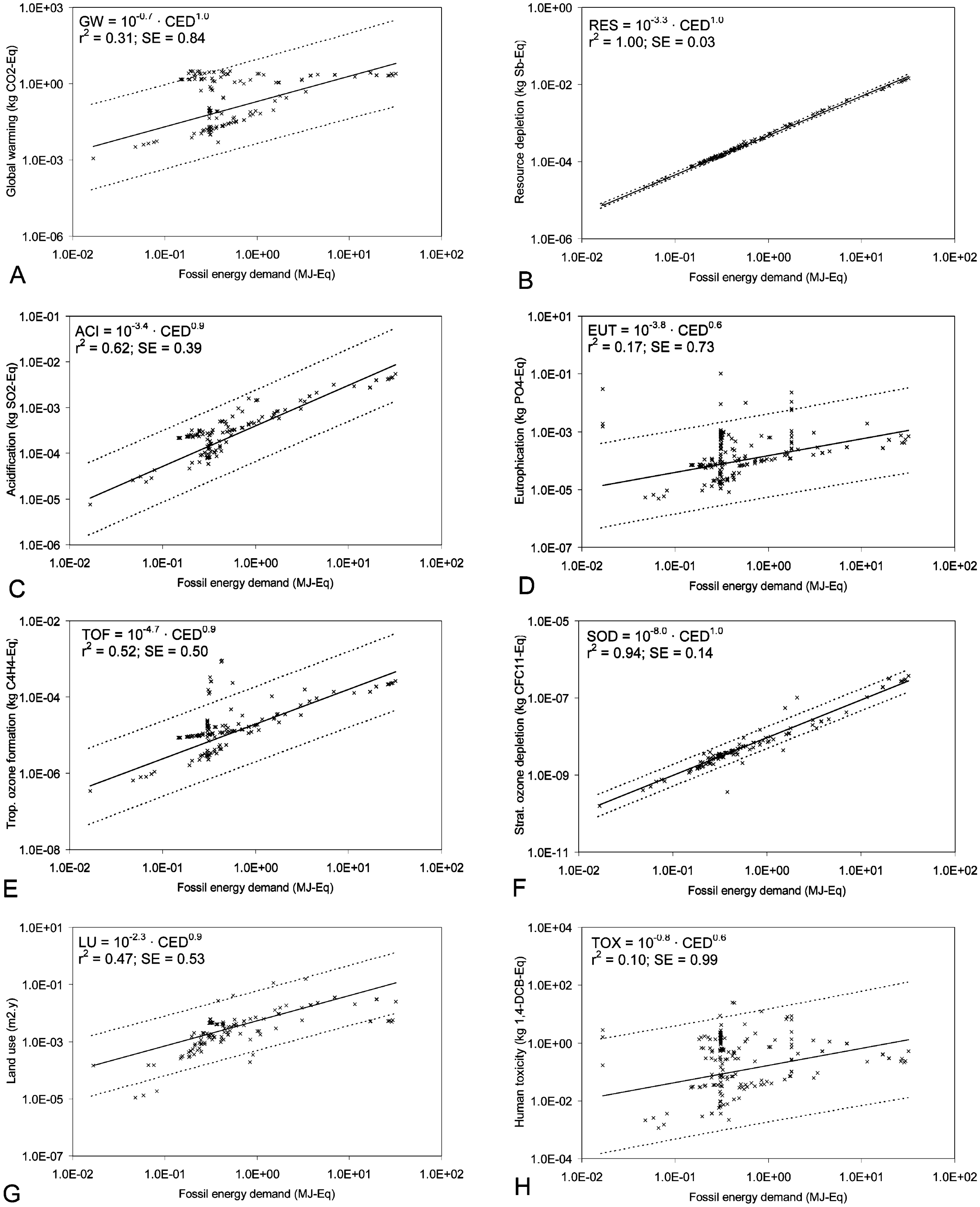

FIGURE 4. Linear regression plots with 95% confidence intervals (dotted lines), based on 214 waste treatment processes in kg, for fossil cumulative energy demand (CED) and, respectively, global warming (A), resource depletion (B), acidification (C), eutrophication (D), photochemical ozone formation (E), stratospheric ozone depletion (F), land use (G), and human toxicity (H).

variance. Land use plays an important role in relation to the production of renewable energy carriers and less for fossil fuel extraction (*29*, *30*). Therefore, land use should be used as a separate indicator for environmental performance, next to fossil CED.

The high explained variance between the majority of impact categories considered and the fossil CED may be seen as an argument for the application of sustainable development indicators based on fossil energy demand and land use, such as the ecological footprint methodology (*31*, *32*), in place of complex methods such as LCA. However, for most product group−impact category combinations, except for abiotic depletion, the linear regression equations resulted in uncertainties of 1−4 orders of magnitude (Table 4) (95% confidence interval). As compared to the uncertainty within life-cycle impact scores for various product comparisons (*33*−*35*), the residual variation in the regression equations is substantial. Apparently, the impacts of products are not only related to fossil CED, but also to process-specific emissions. For instance, in agricultural production processes,

TABLE 4. Uncertainty Factors *k* (eq 5, Two Significant Digits)

impact category	product group energy	materials	transport	waste
global warming	3.9	11	1.4	2000
resource depletion	3.2	9.5	1.2	1.3
acidification	76	76	16	34
eutrophication	91	190	11	730
tropospheric ozone formation	64	58	11	91
stratospheric ozone depletion	390	6900[a]	190	3.5
land use	11 000	42 000	300	120
human toxicity	58	420	76	7600

[a] Without chemicals and plastics, the uncertainty factor would be substantially reduced to a value of 6.7.

part of the category "material production", nonenergy related nitrogen emissions via fertilizers and manure application to agricultural land are the main contributor to eutrophication (*36*). Another example is the production of plastics and chemicals in which process-specific emissions of halogenated hydrocarbons play a relatively important role with regard to stratospheric ozone depletion (*37*). Furthermore, waste treatment processes show a relatively high uncertainty for global warming and toxicity. This is caused by nonenergy related emissions, such as methane air emissions and long-term heavy metal leaching from land fills (*38*).

Apart from process-specific emissions, the use of end-of-pipe technologies will also reduce the correlation between fossil energy use and environmental impacts, because these technologies reduce emissions to the environment at the expense of energy use. In fact, end-of-pipe technologies applied in energy production and waste treatment processes are one explanation for the systematically lower explained variance of fossil CED for acidification, eutrophication, photochemical ozone formation, and human toxicity for these product categories, as compared to the product categories material production and transport.

Another shortcoming to consider is that in the current study we evaluated the fossil CED with the environmental impacts assessed according to the LCA methodology, but not with observed environmental impact. This implies that in the current work, impacts missing in LCA have not been tested with regard to the CED either. For instance, some environmental problems such as scarcity of clean drinking water, salination, endocrine disruption, and indoor exposure to chemicals are usually neglected in LCA (and in the present paper). We do not expect that these impacts will have a good correlation with the fossil CED.

It should also be noted that the correlation analysis is based on cradle-to-gate and waste treatment data only. For a complete cradle-to-grave assessment, we would additionally need data on intermediate steps, such as product manufacturing and use. This information is for most products not readily available. Further research is required to unravel the correlation between fossil CED and environmental impacts on a cradle-to-grave basis.

Nevertheless, the overall picture suggests that fossil energy demand is indicative for many environmental problems. Fossil CED can therefore be used as a screening indicator for environmental performance instead of performing a full LCA, for instance, in the absence of sufficient data. However, care should be taken in case the environmental performance of individual product systems is to be assessed and compared. It was shown that environmental impacts could not be fully explained by fossil energy use for many products, implying that detailed LCA studies are still required for most product groups and impact categories.

Supporting Information Available

Additional information on the calculation of the confidence interval of the predicted values. This material is available free of charge via the Internet at http://pubs.acs.org.

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Received for review August 25, 2005. Revised manuscript received November 30, 2005. Accepted November 30, 2005.

ES051689G