Environmental Modelling & Software 99 (2018) 111–125

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Deriving life cycle assessment coefficients for application in integrated assessment modelling

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ARTICLE INFO

Article history:
Received 25 July 2016
Received in revised form
31 July 2017
Accepted 29 September 2017

Keywords:
Life cycle assessment (LCA)
Integrated assessment model (IAM)
THEMIS
Climate change mitigation
Transformation pathways
Sustainability assessment

ABSTRACT

The fields of life cycle assessment (LCA) and integrated assessment (IA) modelling today have similar interests in assessing macro-level transformation pathways with a broad view of environmental concerns. Prevailing IA models lack a life cycle perspective, while LCA has traditionally been static- and micro-oriented. We develop a general method for deriving coefficients from detailed, bottom-up LCA suitable for application in IA models, thus allowing IA analysts to explore the life cycle impacts of technology and scenario alternatives. The method decomposes LCA coefficients into life cycle phases and energy carrier use by industries, thus facilitating attribution of life cycle effects to appropriate years, and consistent and comprehensive use of IA model-specific scenario data when the LCA coefficients are applied in IA scenario modelling. We demonstrate the application of the method for global electricity supply to 2050 and provide numerical results (as supplementary material) for future use by IA analysts.

1. Introduction

1.1. Motivation and aims

Curbing greenhouse gas (GHG) emissions is a necessary requirement for achieving the international policy objectives of avoiding dangerous interferences with the climate system (UNFCCC, 1992). Life cycle assessment (LCA) and integrated assessment models (IAMs) are two complementary tools for assessing the GHG emission reduction potential of technologies (Edenhofer et al., 2014; Hertwich et al., 2016a). LCA offers a systematic, bottom-up framework and process for attributing environmental impacts that occur in complex international supply chains to one product. LCA strives to achieve extensive coverage of supply chain activities associated with production, use and waste handling of products. It also strives to achieve extensive coverage of types of environmental impacts, including toxic effects on humans and ecosystems, and natural resource use or depletion (Hauschild et al., 2013; Hauschild and Huijbregts, 2015; Hellweg and Milà i Canals, 2014). IAMs are widely used to explore potential strategies to mitigate future climate change (Krey, 2014; O'Neill et al., 2014; Schwanitz, 2013).[1] Under the principal assumption that different combinations of primary energy resources and energy transfers and transformations can provide substitutable energy services, the models select (and substitute) resource and technology alternatives so that costs are minimized or welfare is maximized, subject to constraints (e.g., on emissions allowances, resource availability or technology availability). Important reports targeted to policy makers and the public devote significant attention to scenarios produced by IAMs (Edenhofer et al., 2014; IEA, 2014; Johansson et al., 2012).

[1] In this work, by IAMs we refer broadly to models that are used to explore transformation pathways and to evaluate climate mitigation policies (Clarke et al., 2014; Riahi et al., 2012), as distinct from aggregated models that monetize climate change impacts in order to perform cost-benefit analysis of climate policy. AIM, GCAM, IMAGE, MESSAGE and REMIND are examples of models that fall into the former category (Edmonds et al., 2012). In addition, we are concerned with models that carry explicit representations of individual energy technologies, as distinct from models lacking technology-level detail.

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https://doi.org/10.1016/j.envsoft.2017.09.010

Existing LCA literature is for the most part concerned with assessing environmental impacts associated with one (small) reference unit (e.g., 1 kWh of electricity) in a static framework. While such assessments can offer useful insights, they carry no notion of absolute magnitude or timing of effects at regional or global levels. Hence, they provide limited basis for assessing long-term technology transformation pathways, especially under scenarios of rapid and large-scale deployment of new technologies (Arvesen and Hertwich, 2011; Dale and Benson, 2013). Also, while any LCA attributes effects occurring in various supply chains to a specific product, most LCAs do not capture other types of consequences of products that one may infer considering broader economic or policy contexts, such as indirect land use change emissions induced by bioenergy products.[2] IAMs, on the other hand, put their focus on representing the dynamics that shape natural and human systems over long time-scales and under large-scale changes in the economic setting. However, IAMs have more narrow boundaries in terms of environmental impacts and do not represent life cycle effects of products, or represent such effects only partially and/or only implicitly via interactions between energy system and macro-economy modules (Pauliuk et al., 2017).

We see two principal ways in which LCA can be useful for IA modelling. One is to integrate LCA results in IA modelling so that indirect emissions of technology and scenario alternatives can be explored, and potentially taken into account in the decision-making routines of the IAMs. Technology selection in state-of-the-art IAMs typically considers some types of indirect emissions, such as methane leakages from fossil fuel production and land use change-related emissions from biomass production, while not considering many other indirect emissions (e.g., emissions from producing metals for power plants). More fully considering indirect emissions of technology alternatives can yield more consistent evaluations, and thus potentially affect optimal technology selection or overall effectiveness of mitigation strategies in IAMs. The relative importance of indirect emissions may increase over time and increasingly stringent emission reduction targets, as technologies with zero or low direct emissions (e.g., electric vehicles, fossil fuel combustion with carbon capture) gradually replace those using fossil fuels. The second way LCA can be useful is to improve environmental impact assessment or broaden the range of environmental concerns addressed in IAMs. Most state-of-the art IAMs have an explicit description of non-CO_2 greenhouse gas emissions and air pollution (e.g, Strefler et al. (2014), Gernaat et al. (2015), Rao et al. (2017)), and recently have also considered water demands (e.g., Mouratiadou et al. (2016)), but lack many other crucial environmental impact dimensions. LCA routinely supports assessment of the effects of hundreds of pollutants, resource flows and land, incorporating environmental mechanisms (e.g., toxic effects on ecosystems or humans) not currently addressed by IAMs (Masanet et al., 2013). When we refer to impact indicator results in this article, we refer broadly to any indices of environmental impacts or natural resource requirements computed using impact assessment methods from LCA (Frischknecht et al., 2016).

The aims of this article are the following:

i) To develop a general method for deriving energy and impact indicator results from detailed, bottom-up LCA such that the results are suitable for application by IA modellers.

ii) To apply the method to calculate energy and impact indicator results for the global electricity system to 2050, for future use by IA practitioners.

The method allows for capturing technology variations and changes between geographical regions and over time. It enables consistent use of IAM-specific scenario data (e.g., emission factors, lifetime, load factors) in combination with LCA coefficients. This is achieved mainly by a separate treatment of main life cycle stages with a unit conversion adapted to the stage and technology in question, and by a decomposition of coefficients into individual energy carriers, industries and energy service types. IA modellers may combine the energy results derived from LCA with IAM-specific emission factors so as to determine emissions related to combustion of energy fuels on a life cycle basis. They may use the impact indicator results derived from LCA to address types of impact other than those commonly associated with combustion, such as toxic effects of pollution loads.

1.2. Existing literature

A few attempts have been made in literature to combine LCA and IAM perspectives for the purpose of long-term and large-scale assessment. A notable study by Daly et al. (2015) couples a national United Kingdom energy system optimization model with a multi-regional economic input-output model in order to investigate the significance of indirect emissions for national energy system transformations, explicitly accounting for domestic and nondomestic indirect emissions associated with energy supply. Their results indicate that domestic indirect emissions have little significance, while nondomestic indirect emissions appear significant and would, if included in an ambitious domestic emission reduction target and in absence of commensurate non-domestic mitigation, double the marginal abatement cost of meeting the target. The study assumes non-domestic emission intensities follow baseline trends, i.e. that no climate policies are implemented outside the United Kingdom. An accompanying study by the same authors identifies that the optimization model selects increased electrification and use of nuclear power as a cost-optimal strategy to mitigate the nondomestic indirect emissions (Scott et al., 2016). Dandres et al. (2011) use a computable general equilibrium model together with LCA in order to address economy-wide consequences of bioenergy policy. The authors report the finding that bioenergy policy increases environmental impacts owing to effects of price changes, while also underlining that "more work is needed to evaluate" the approach used.

The aforementioned studies rely on economic input-output analysis (Daly et al., 2015; Scott et al., 2016) or a mapping between economic input-output sectors and detailed, bottom-up LCA activities (Dandres et al., 2011) to determine emission multipliers. All studies rely on price information to convert between monetary and mass units. Another study implements generic LCA-type indicators derived from theoretical considerations in a system dynamics model (Dale et al., 2012b). A general advantage of approaches that do not require detailed technology information is that, owing to relatively easy data compilation, extensive coverage of energy technology and fuel types can be achieved, as indeed is the case in the above-cited works. Another advantage of employing multiregional input-output (MRIO) analysis (Daly et al., 2015; Scott et al., 2016) is that international trade and geographical differences in production are generally better captured in MRIO than in LCA.

The current work adopts a different strategy, making use of physical, rather than monetary, accounting of product systems, and a bottom-up, rather than top-down, calculation technique for determining indirect energy use and environmental impact

[2] So-called consequential LCA (CLCA) is an exception (Zamagni et al., 2012). CLCA is much less frequently applied than conventional (sometimes termed attributional) LCA, but a significant number of CLCA studies do exist. Perhaps in particular, CLCA is used in literature to study bioenergy (Creutzig et al., 2015).