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BUILDINGS AND BUILDING MATERIALS

Dynamic life cycle assessment: framework and application to an institutional building

William O. Collinge · Amy E. Landis · Alex K. Jones · Laura A. Schaefer · Melissa M. Bilec

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Abstract
Purpose This paper uses a dynamic life cycle assessment (DLCA) approach and illustrates the potential importance of the method using a simplified case study of an institutional building. Previous life cycle assessment (LCA) studies have consistently found that energy consumption in the use phase of a building is dominant in most environmental impact categories. Due to the long life span of buildings and potential for changes in usage patterns over time, a shift toward DLCA has been suggested.
Methods We define DLCA as *an approach to LCA which explicitly incorporates dynamic process modeling in the context of temporal and spatial variations in the surrounding industrial and environmental systems*. A simplified mathematical model is used to incorporate dynamic information from the case study building, temporally explicit sources of life cycle inventory data and temporally explicit life cycle impact assessment characterization factors, where available. The DLCA model was evaluated for the historical and projected future environmental impacts of an existing institutional building, with additional scenario development for sensitivity and uncertainty analysis of future impacts.
Results and discussion Results showed that overall life cycle impacts varied greatly in some categories when compared to static LCA results, generated from the temporal perspective of either the building's initial construction or its recent renovation. From the initial construction perspective, impacts in categories related to criteria air pollutants were reduced by more than 50 % when compared to a static LCA, even though nonrenewable energy use increased by 15 %. Pollution controls were a major reason for these reductions. In the future scenario analysis, the baseline DLCA scenario showed a decrease in all impact categories compared with the static LCA. The outer bounds of the sensitivity analysis varied from slightly higher to strongly lower than the static results, indicating the general robustness of the decline across the scenarios.
Conclusions These findings support the use of dynamic modeling in life cycle assessment to increase the relevance of results. In some cases, decision making related to building design and operations may be affected by considering the interaction of temporally explicit information in multiple steps of the LCA. The DLCA results suggest that in some cases, changes during a building's lifetime can influence the LCA results to a greater degree than the material and construction phases. Adapting LCA to a more dynamic approach may increase the usefulness of the method in assessing the performance of buildings and other complex systems in the built environment.

Keywords Building energy use · Dynamic life cycle assessment · Environmental life cycle assessment · Scenario analysis

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W. O. Collinge · M. M. Bilec (✉)
Department of Civil and Environmental Engineering,
University of Pittsburgh, 3700 O'Hara Street,
Pittsburgh, PA 15260, USA
e-mail: mbilec@pitt.edu

A. E. Landis
School of Sustainable Engineering and the Built Environment,
Arizona State University, P.O. Box 875306, Tempe,
AZ 85287-5306, USA

A. K. Jones
Department of Electrical and Computer Engineering,
University of Pittsburgh, Pittsburgh, PA, USA

L. A. Schaefer
Department of Mechanical Engineering and Materials Science,
University of Pittsburgh, Pittsburgh, PA, USA

1 Introduction

The construction and operation of commercial and institutional buildings consume a large amount of energy and materials, both of which contribute to known environmental impacts such as global climate change, human health, ecosystem services, and resource depletion (USDOE 2009; Young and Sachs 1994). Life cycle assessment (LCA) can aid in quantifying the environmental impacts of whole buildings by evaluating materials, construction, operation, and end of life stages, with the goal of identifying areas of potential improvement (Junnila et al. 2006; Scheuer et al. 2003; Kofoworola and Gheewala 2008; Wu et al. 2011). Accurate whole-building LCA is limited by the standard practice of applying static factors throughout the life cycle inventory (LCI) and life cycle impact assessment (LCIA) stages. Since buildings have long useful lifetimes, and the use phase can have large environmental impacts, variations within the use phase can sometimes be greater than the total impacts of materials, construction, or end-of-life phases (Aktas and Bilec 2011; Junnila et al. 2006; Scheuer et al. 2003). The ability to accurately model future scenarios is critical for improved building sustainability (Scheuer et al. 2003). Additionally, individual buildings are operated within changing industrial and environmental systems; the simultaneous evaluation of these dynamic interactions during product or building lifetimes is recognized as a key need in LCA (Reap et al. 2008).

1.1 Time in LCA

Time-related issues affect LCA in numerous ways; broadly, they can be categorized into (1) industrial and environmental dynamics and (2) time horizons and discounting of future emissions (Reap et al. 2008). Temporal variations can be accounted for independently of any discounting of future emissions, using the physical models underlying the inventory data and impact assessment methods (Hellweg and Frischknecht 2004; Hellweg et al. 2003). For industrial and environmental dynamics, one approach is to consider temporal and spatial variability as components of parameter uncertainty in LCA and use probabilistic scenario analysis as a technique for overcoming this uncertainty (Huijbregts 1998; Huijbregts et al. 2001). This approach aggregates temporal and spatial variability with other sources of uncertainty, such as different technologies in use at different industrial facilities, or inaccurate emission measurements. Another approach is to link explicit modeling of the primary systems of study (e.g., a building or an industrial process) with traditional aggregated LCA datasets and use additional probabilistic analysis to characterize uncertainty in upstream or downstream material flows or emissions (Udo de Haes et al. 2004; Reap et al. 2003; Ries 2003). Another approach is to shift the focus away from a single product or functional unit to the entire in-use suite of products to capture changes in technology or infrastructure over a given period of interest (Field et al. 2000; Levine et al. 2007; Stasinopoulos et al. 2011).

Recent research has approached different aspects of the time-LCA problem. These studies can be differentiated by whether dynamic methods are applied to the LCI or LCIA steps in the analysis. Several studies have used dynamic LCI data to assess renewable energy systems, considering past and potential technology improvements affecting production efficiencies (Pehnt 2006; Zhai and Williams 2010). For the LCIA step, studies have used atmospheric and other environmental models to calculate time-dependent characterization factors (CFs) on both multi-year scales (Struijs et al. 2010; Seppälä et al. 2006) and seasonal scales (Shah and Ries 2009). The time dependence of these CFs is a function of background pollutant concentrations or climatic factors. Other studies have investigated the relative impact of emission timing with respect to a fixed time horizon (e.g., 100-year global warming potential) in the case of land use change and biofuels (Kendall et al. 2009; Levasseur et al. 2010); vehicle regulations (Kendall and Price 2012); and the institutional building previously studied by Scheuer et al. (2003) (Kendall 2012). In these cases, emissions occurring farther in the future are effectively discounted by their proximity to the overall study time horizon. This effective discounting is distinct from economic discounting or pure time preference discounting. However, few studies so far combine dynamic scenario analysis with temporally explicit LCI data or any type of temporally explicit LCIA method.

1.2 Scope and functional unit of this study

The scope of this study was to establish a dynamic LCA (DLCA) approach and test this approach with a case study of an existing institutional building. These results were compared with LCA results from a static approach. The functional unit chosen for this study was an institutional building (Benedum Hall at the University of Pittsburgh) over its assumed lifetime of 75 years (until 2045). Benedum Hall is an existing building that opened in 1971. The system boundary for the study included primarily materials for construction and renovation and electricity/fuels for building operation. Two separate comparative static versus dynamic analyses were constructed: one for the entire lifetime of the building assuming a 1971 perspective and one for the remaining life of the building including an actual major renovation and addition, assuming a 2009 perspective. A scenario and sensitivity analysis was conducted for the 2009 dynamic perspective to elicit the effects of changing individual model parameters.

2 Methods

2.1 Modeling approach

Heijungs and Suh (2002) developed a general equation for the environmental impact of a product system for a process-based LCA approach. Mutel and Hellweg (2008) restated this equation as shown in Eq. (1):

$$h = \mathbf{C} \times \mathbf{B} \times \mathbf{A}^{-1} \times f \tag{1}$$

where h is a vector representing total environmental impacts of the studied system, in some number of impact categories determined by the selected LCIA method; f represents the quantities of outputs from the industrial supply chain (e.g., materials, fuels) required for a specified function of the studied system; **A** is the technosphere matrix representing each unit of output as a function of the inputs to the various processes needed to generate that output; **B** is the biosphere matrix representing the environmental interventions (emissions and resource consumption) required for each process in the supply chain; and **C** (originally **W** in Mutel and Hellweg; changed to **C** herein) is a matrix of CFs which represent the magnitude of the effect of each quantity of emission or other intervention in each impact category. **C** is given here as a matrix rather than a vector or diagonal matrix, to efficiently account for the effect of some emissions in multiple impact categories.

The static approach to LCA often assumes point values for all of the coefficients in the **C**, **B**, and **A** matrices and is usually structured such that the f vector represents a one-time output of the system (quantity x of product y at an arbitrary time). By contrast, a building is an example of a system whose input requirements vary with time and as a function of changes in its usage. Thus, the demand vector f becomes f_t at any point in time t, as a function of basic operating variables (e.g., occupancy schedules, thermostat set points), which are not normally captured in LCA. These operating variables may include material inputs during maintenance, various types of energy inputs required for routine operations based on building schedule and seasons, and replacement of materials and systems at periodic intervals.

Similarly, over the long life of a building, time-related changes may affect the other variables in Eq. (1). The technosphere matrix **A** may change over time due to product substitutions, efficiency improvements, or other changes in the structure of the industrial supply chain. The biosphere matrix **B** may also change over time for the above reasons or due to regulatory controls on emissions. Temporal changes in CFs in the **C** matrix are also possible as evidenced by previous studies, e.g., Kendall (2012), Shah and Ries (2009), Seppälä et al. (2006), and Struijs et al. (2010).

Given the potential for each term in Eq. (1) to change over time, a simplified model for DLCA is shown in Fig. 1 and represented mathematically by the following:

$$h_t = \sum_{t_0}^{t_e} \mathbf{C}_t \times \mathbf{B}_t \times \mathbf{A}_t^{-1} \times f_t \tag{2}$$

where the t represents a point in time at which the values in the various terms are known, and t_0 and t_e represent the beginning and ending time points of the analysis, usually the beginning and end of the product or system life cycle. The t subscript does not imply that these terms are direct mathematical functions of time; rather, they are functions of their underlying variables that can be represented as a time series. Particularly, the matrix of CFs, $\mathbf{C}_t$ could encompass variations in all the underlying variables (fate, exposure, and effect factors), which must be calculated for each point in time by the physical models applicable to each category. $\mathbf{C}_t$ could also encompass adjustments made to CFs for other reasons, such as proximity to the analysis time horizon, as in Kendall (2012). Separate types of changes to CFs could be explicitly documented by constructing several separate **C** matrices (e.g., $\mathbf{C}_{t,\ [\text{fate}]}$ or $\mathbf{C}_{t,\ [\text{time horizon}]}$) and combining these matrices by scalar multiplication (Hadamard product) at the time of analysis.

There are several considerations to this approach. First, this approach follows an attributional, rather than consequential LCA structure (Ekvall and Weidema 2004). In attributional

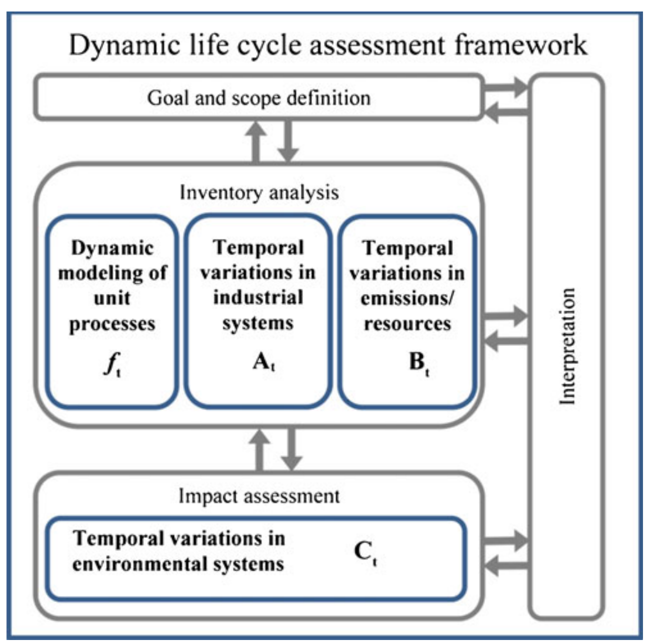

Fig. 1 Conceptual diagram of DLCA framework

LCA, the impact of an emission is considered to be the total impact of the product system normalized to a functional unit, whereas consequential LCA investigates the effects of marginal choices. In the attributional formulation of the DLCA model, the aggregation is performed at the time step level (variations at smaller scales are implicitly averaged). Thus, the terms in Eq. (2) are able to vary independently of each other. However, the use of dynamic modeling of system interactions introduces the possibility of feedback loops in which changes occurring in different parts of the system induce mutual changes in each other. The inclusion of feedback loops between variables in Eq. (2) (e.g., coefficient $\mathbf{A}_{i,j}$ relating process i to product j as a function of f_j, the quantity of product j required) would move the model toward a consequential structure. For the current study, feedbacks are hypothesized to be significant only within the systems captured by the building energy model that produces the f vector. These feedbacks are briefly discussed in Section 2.4.1.

Another consideration is the issue of lag time in the supply chain, where lag time is defined as the difference in timing of processes and emissions at multiple levels in the supply chain (Levine et al. 2007). Some examples are the time difference between the production of a building material and its installation at the construction site or the time difference between fuel extraction and combustion. For the simplified mathematical model in Eq. (2), supply chain functions must be assumed to occur simultaneously in order to invert the **A** matrix. A more complete formulation would involve specifying the lag time for each supply–demand linkage, which would require calculation using a tree structure rather than a matrix structure, as the number of inputs at different time lags would multiply with each step back through the supply chain. This approach could be implemented with an inventory or impact cutoff tolerance. However, data limitations prevented the inclusion of lag times in this study as discussed further in Section 3.4.

A prototype DLCA model was constructed using Microsoft Excel and Visual Basic for Applications (VBA). The model used Excel worksheets to store basic data such as process inputs and outputs, emission factors, and CFs, while VBA code was used to perform the matrix calculations. The key difference between the prototype model and most standard LCA applications was the use of time series tables to simulate dynamic variation in matrix coefficients representing modeled relationships. With the time series enabled, any coefficient c_i in a vector or $c_{i,j}$ in a matrix can become $c_{i,j,t}$, where i and j represent the coefficient's position in the matrix in question and t is the current model time step. The model explicitly considered four categories of time series in the LCA calculation, corresponding with the four variables of Eq. (2). These categories are outlined in Table 1, along with illustrative examples. Any variable without a time series available due to data limitations was assumed to have a constant value, as in a typical static LCA calculation.

2.2 Case study

An existing institutional building—Benedum Hall at UPitt—was selected as the case study for this project. Originally constructed in 1971 to house UPitt's engineering program, the Benedum Hall complex includes 12-story tower housing laboratories, offices, and classrooms; two below-grade floors with additional office and laboratory space; and a two-story auditorium. The two below-grade floors extend under the footprints of both the tower and the auditorium and support a first-floor level outdoor plaza. The complex underwent a major renovation beginning in 2006, including the construction of a new wing on the first, second, and third floors; major upgrade of all mechanical systems; replacement of all the windows and floor coverings; roof replacement including green roof spaces on both the auditorium and a portion of the plaza; and numerous interior space renovations. The additional wing and renovation of the second floor of the tower were completed in November 2009; roof and window replacement on the remaining structure and renovations of the below-grade floors, ground floors, and auditorium were completed by August 2010; and renovations of the 3rd–12th floors of the tower are scheduled to be completed by the end of 2012.

Since the original construction, steam for heating the building has been supplied by a district heating system used by the university and several nearby institutions. Until June 2009, steam was generated using a combination of coal-fired and natural gas-fired boilers at a single plant; in June 2009, a second plant was added and the existing plant was converted to 100 % natural gas-fired boilers. Cooling was originally provided by a stand-alone chiller plant on the building's roof, which was replaced by a connection to a new district chilled water plant in 2002.

2.3 Static and dynamic LCA comparisons

The DLCA model and a static LCA model were compared over two analysis time frames. The first time frame consisted of the entire lifetime of the building and used a 1971 perspective; while the second time frame consisted of the remaining life of the building using a 2009 perspective. We will refer to these as the "full lifetime" and "remaining lifetime" analyses hereafter. The system boundary for both static and dynamic analyses included building materials and operating fuels/electricity, as well as their respective upstream processes. The system boundary of the DLCA model, including the extent of dynamic processes included, is shown in Fig. 2. Material transportation, on-site construction activities, routine maintenance, and end-of-life disposition were excluded from the study. Due to the complexity of modeling the entire building, only major systems were selected from the initial construction, and a comparison was made to two previous studies to assess the degree of

Table 1 Categories of dynamic life cycle assessment (DLCA) parameters for buildings, examples, and data sources used in the case study

Category [with parameter from Eq. (1) in brackets]	Examples	Data used in case study with associated time interval
Building operations [f_t]—initial construction activities; additions, renovations, or major component replacements; changes in usage patterns or energy consumption	Material required for initial construction; material required for replacement of components or reconfiguration of interior spaces; changes in energy consumption	Benedum Hall original construction plans; 1971 (DRA 1965) Benedum Hall utility usage (steam, electric, and water); July 1992–December 2010 Benedum Hall construction plans for renovation and addition; 2006–2010 (Edge 2007, 2008) eQUEST model (projected); 2009–2045
Supply chain dynamics [$\mathbf{A}_t$]—changes to upstream processes independent of building management decisions	Changes in fuel mix and efficiency of the electricity grid; changes in origin of natural gas and petroleum supplies; changes in regional waste treatment practices	District heating plant fuel consumption and steam production; January 2000–December 2010 National annual and monthly electric power generation by fuel type; 1970–2008 (USDOE 2010b): (projected); 2009–2045 (USDOE 2010a)
Inventory dynamics [$\mathbf{B}_t$]—changes in resource use or pollutant emissions by processes due to technology, regulation, or other factors	Influence of environmental regulations on pollutant emissions; changes in efficiency of industrial processes	National GHG emissions from electric power generation by fuel type and other major GHG sources; 1990–2008 (USEPA 2010) National criteria air pollutant (CAP) and hazardous air pollutant (HAP) emissions; 1970–2008 (USEPA 2009, 2011b): (projected); 2009–2016 (USEPA 2011a)
Environmental system dynamics [$\mathbf{C}_t$]—changes in background environmental systems affecting the fate, exposure, and effects	Changes in system sensitivity due to background concentrations or distribution of populations; changes in ambient conditions affecting emission fates; consideration of an analysis time horizon	Time-adjusted (global) warming potentials (TAWPs); 2009–2045 (Kendall 2012) Seasonal characterization factors for photochemical ozone; 2009–2045 (Shah and Ries 2009)

f_t vector of outputs from the industrial supply chain (e.g., materials, fuels), $\boldsymbol{A}_t$ matrix representing each unit of output as a function of the inputs to the various processes needed to generate that output, $\boldsymbol{B}_t$ matrix representing the environmental interventions (emissions and resource consumption) required for each process, $\boldsymbol{C}_t$ matrix of characterization factors representing the magnitude of the effect of each quantity of emission or other intervention in each impact category

completeness of the results (Junnila et al. 2006; Scheuer et al. 2003).

The full lifetime of Benedum Hall was assumed to be 75 years, consistent with its current status (recently renovated at 40 years old) and one previous study of an institutional building (Scheuer et al. 2003). It has been noted that arbitrary assumptions about building lifetime can significantly affect LCA results (Aktas and Bilec 2011). The full lifetime DLCA encompassed four distinct phases: (1) initial construction (1971); (2) initial operations (1971–2008); (3) renovation activities (2006–2012); and (4) future operations (2009–2045). The renovation activities were assumed to occur in 2009. Construction material quantities from the original construction, renovation, and addition were obtained from the construction drawings and specifications for each project (DRA 1965; Edge 2007, 2008). The full lifetime static LCA coupled the initial construction results with a projection of the initial year's operations over the 75-year assumed building lifetime and did not include the renovation/addition. The remaining lifetime DLCA and static LCA included the renovation and future operations phases. The remaining lifetime DLCA was used as the basis for the future scenario analysis (Section 2.5).

For this study, the DLCA model used a monthly time series for several reasons. Historical values for the building's utilities were available on a monthly basis, and fuel mixes for the electricity grid (USDOE 2010b) and heating plant were also available on a monthly basis (Section 2.4.2). Annual aggregation of these values would potentially have masked variation in the results due to the timing of variations in energy use and the fuel mix. Emission factors were typically annual values.

2.4 Data collection

2.4.1 Dynamic LCI—building-level data and modeling (f_t)

Historical and future values for the f vector were generated specifically for the case study building. Operating energy consumption was taken from utility meter data for Benedum Hall. Data availability varied depending on the individual

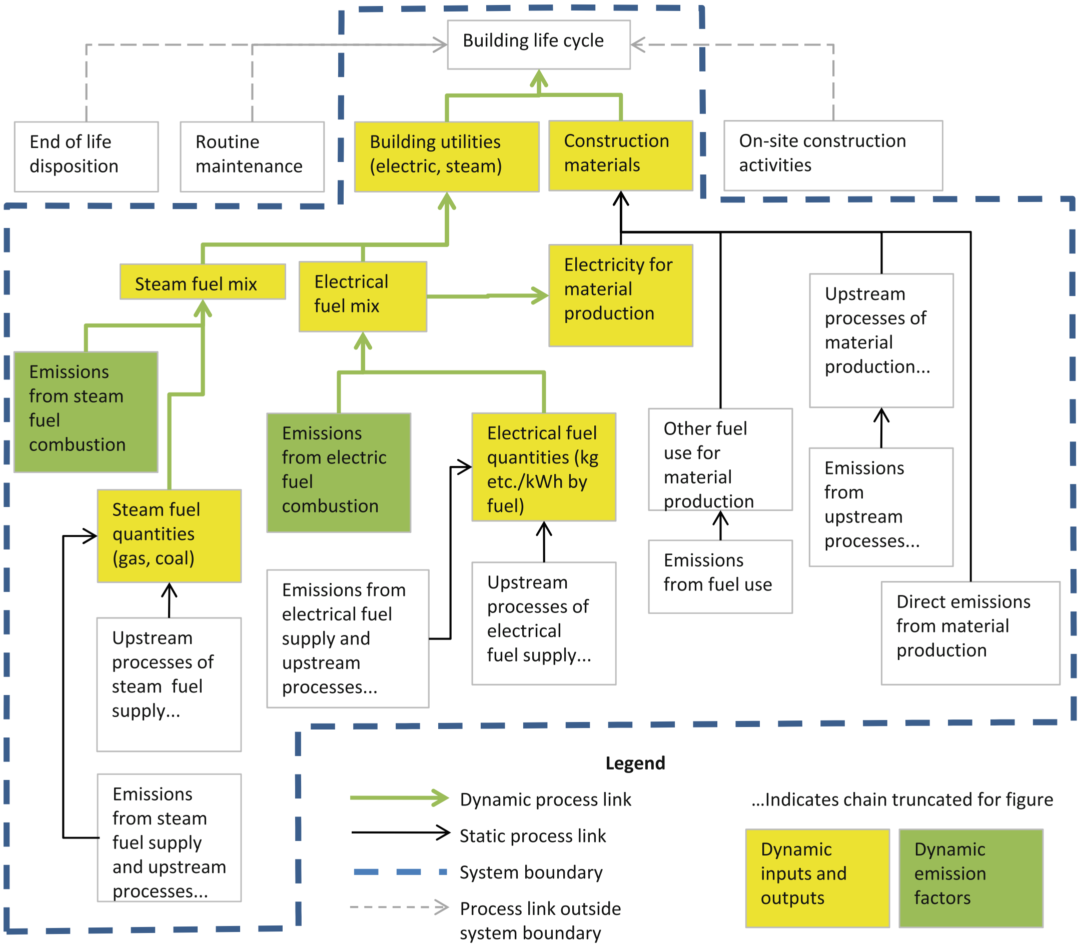

Fig. 2 System boundary and dynamic modeling

variables; a summary is provided in Table 1 and a complete list is given in Table SI-1 (Electronic Supplementary Material). For years prior to data availability, the average of the first three available years was used. Future energy consumption was estimated using the U.S. Department of Energy's (USDOE) eQUEST model (Hirsch 2010), adjusting model default parameters to reflect the specific conditions for Benedum Hall. A qualitative comparison of the eQUEST model results and both the extensive pre-renovation and limited post-renovation utility meter data was performed to verify the model's predictive capacity; results of this comparison are presented in Figs. SI-1 and SI-2 (Electronic Supplementary Material).

2.4.2 *Dynamic LCI—unit processes* ($\mathbf{A}_t$)

Temporally specific historical and projected future unit processes for the **A** matrix were constructed from U.S. Energy Information Agency (EIA) records and projections (USDOE 2010a; USDOE 2010b) for the national electricity generation mix; and meter data for the central campus steam plant (Table SI-1, Electronic Supplementary Material). Data sources for each process type are provided in Table 1. Upstream processes without dynamic data available were referred to (1) United States Life Cycle Inventory (USLCI) unit processes (NREL 2010), for energy and fuels, and (2) the ecoinvent v2.2 database (Frischknecht and Rebitzer 2005), for materials. Ecoinvent was chosen over USLCI for materials because some material processes in the USLCI database do not explicitly link to upstream processes, but rather aggregate emissions from all upstream processes into one list. Separation of upstream unit processes was necessary to enable the DLCA model to function properly. However, because ecoinvent consists of mainly European data and does not contain time series, several modifications were made: (1) process electricity requirements from materials in ecoinvent were referred back to the time series described above, and (2) other process energy (e.g., heat, equipment fuel use) were referred to the USLCI energy unit processes. Thus, the material processes used for the 1971 construction were the same as those used for the 2009 renovation/addition, with the exception of changing the fuel mix and emissions for the electricity generation required by these processes.

2.4.3 Dynamic LCI—emission factors ($\mathbf{B}_t$)

Temporally specific emission factors for the **B** matrix were constructed from available industry and environmental data (USEPA 2009; USEPA 2010, 2011b) and Allegheny County Health Department (ACHD) data for the central campus steam plant (ACHD 2011). For example, emission factors for criteria air pollutants (CAPs) from electric power generation were calculated by dividing U.S. Environmental Protection Agency (EPA) historical emission data (USEPA 2009, 2011b) by the U.S. EIA records of power generation by fuel type (USDOE 2010b). Data sources for each variable are provided in Table 1; time series of emission factor results in each LCIA category are presented in Fig. SI-3 (Electronic Supplementary Material). Where possible, these values were compared against the USLCI database (NREL 2010) for consistency within the time frames for which the USLCI database applies. Qualitative results of this comparison are also presented in Fig. SI-3 (Electronic Supplementary Material).

2.4.4 Dynamic LCIA—characterization factors ($\mathbf{C}_t$)

Temporally specific CFs are only available in a few LCIA categories. Therefore, for the baseline full lifetime and remaining lifetime DLCA calculations, static factors from the Tool for the Reduction and Assessment of Chemical and other environmental Impacts (TRACI) method were used (Bare et al. 2003). Temporally specific CFs available in the literature include monthly CFs for photochemical ozone in the USA (Shah and Ries 2009); annual global CFs for ozone depletion (Struijs et al. 2010), decadal-scale CFs for acidification, and eutrophication in Europe (Seppälä et al. 2006); time horizon-adjusted CFs for acidification in Europe (Van Zelm et al. 2007); and time horizon-adjusted CFs for global warming (e.g., Kendall 2012). The European acidification and eutrophication CFs are not adaptable to the USA due to the lack of a US-based database of ecosystem sensitivities (Norris 2003). The lack of any consistent set of temporally variable CFs for the USA across multiple impact categories led to the decision not to include them in the baseline analyses for this study. However, example calculations using two sets of dynamic CFs—photochemical ozone from Shah and Ries (2009) and global warming (Kendall 2012)—have been included in the future scenario analysis (Section 2.5). The compilation of a set of temporally variable CFs across multiple impact categories and time scales for the USA is planned as future work.

2.5 Future scenario analysis

A future scenario analysis was conducted to probe the sensitivity of the results to changes in assumptions about future trends, building on the remaining lifetime DLCA calculation (2009–2045). The individual and combined influence of end-use energy variations, fuel mixes, and emission controls was investigated by pairing different combinations of each variable in Eq. (1). For f_t, scenarios were generated using 10 % increases and decreases in electricity consumption and steam heat consumption separately. This range was anticipated to be within the capacity of adjustments to existing set points and operating schedules and thus allowed for some level of uncertainty in occupant usage and behavior. For $\mathbf{A}_t$, the EIA's 47 projected cases from the Annual Energy Outlook (AEO) were examined and the cases which resulted in the greatest variation in generation mixes from the baseline were added to the analysis (USDOE 2010b). For $\mathbf{B}_t$, a scenario without the EPA's currently proposed regulations was examined, in which emission factors remained constant at 2009 levels. The scenario pairing no increase or decrease in energy consumption with no new EPA rules was similar to the static LCA, except that even the EIA's baseline (reference case) includes expected changes in the future generation mix and is thus dynamic.

Finally, for $\mathbf{C}_t$, calculations were constructed in the global warming potential (GWP) category using time-adjusted warming potentials (TAWPs) from Kendall (2012) and in the photochemical ozone category using monthly factors for a typical year from Shah and Ries (2009). Shah and Ries developed CFs at the midpoint level for nitrogen oxides (NOx) and volatile organic compounds (VOCs) in terms of parts per billion $O_3 \times$square kilometers$\times$day per kilogram emission. To compare with the static TRACI CFs, which use a reference unit of kg NOx eq., the Shah and Ries CFs were normalized by dividing the monthly values for NOx and VOC by the annual average value for NOx from their own study.

3 Results and discussion

3.1 Static LCA validation

Total mass of the materials and embodied energy inputs of the static LCA for the original construction were compared with two previous studies of commercial and/or institutional buildings in the USA (Junnila et al. 2006; Scheuer et al. 2003) to validate LCA inputs. Scheuer et al. analyzed a six-story combination academic and hotel building in Michigan, and Junnila et al. analyzed a five-story office building in the midwest of USA. Results of the comparison are summarized in Table 2. A complete comparison of LCI results is given in Table SI-2 (Electronic Supplementary Material). Total normalized mass of Benedum Hall was estimated to be 1,670 kg/m^2 and total embodied energy to be 5,080 MJ/m^2, compared to 2,000 kg/m^2 and 6,250 MJ/m^2 for Scheuer et al. and 1,290 kg/m^2 and 11,900 MJ/m^2 for Junnila et al. Total annual operating energy was 3,920 MJ/m^2, compared to 4,100 MJ/m^2 for Scheuer et al. and 1,320 MJ/m^2 for Junnila et al.

Table 2 Mass and energy inputs for static LCA model of the building materials and initial energy consumption

Material and energy results	Case study: Benedum Hall		Scheuer et al. (2003)		Junnila et al. (2006)	
	Mass/area (kg/m^2)	Energy/area (MJ/m^2)	Mass/area (kg/m^2)	Energy/area (MJ/m^2)	Mass/area (kg/m^2)	Energy/area (MJ/m^2)
Total materials	1,670	5,080	2,000	6,250	1,360	11,920
Original construction materials	1,570	4,250	NG	NG	1,290	7,060
Renovation/addition materials	100	820	NG	NG	70	4,860
Annual operating energy—total	–	3,920	–	4,100	–	1,360
Annual operating energy—electricity	–	3,340	–	NG	–	700
Annual operating energy—heat	–	580	–	NG	–	660

Embodied energy was calculated as total nonrenewable energy. Results from two other LCA studies of commercial or institutional buildings in the USA are presented for comparison and validation

NG not given (results are presented graphically)

The results of this study agreed qualitatively with Scheuer et al. in most categories and with Junnila et al. in some categories. A significant degree of variation is expected even between comparable buildings, due to differences in construction details, selection of system boundaries, and the use of different LCI databases. The material systems included in this study for Benedum Hall represented 90 % of the results of the Scheuer et al. study by mass and 74 % by embodied energy. Mass results on a system-by-system basis were comparable to Scheuer et al. (more detail provided in Table SI-2, Electronic Supplementary Material); the differences in embodied energy can be attributed primarily to (1) the exclusion from this study of internal finish materials, such as carpet and ceiling tiles and (2) the value for embodied energy for steel from the LCI databases used. Finish materials such as carpet and ceiling tile have high embodied energy contents and frequent replacement intervals and account for a significant portion of the total embodied energy results in Scheuer et al. The amounts of such materials in Benedum Hall are minor by comparison with most buildings and were not considered in this study. Compared with Junnila et al., the lower embodied energy per unit mass can also be attributed in part to the exclusion of interior finishes from this study, since items such as structural steel and concrete had reasonably similar value for total embodied energy per unit area of the building. However, Junnila et al. also used a hybrid process-based and economic input–output-based LCA model, which may have contributed to the difference. From comparison with both studies, future work on the dynamic LCA model should include finish materials such as paint, carpet, and tile for the sake of full compatibility with other studies and to accommodate buildings with larger amounts of these materials than Benedum Hall.

3.2 DLCA and static LCA results for full lifetime analysis

The DLCA results were lower than static LCA results in most impact categories with the exception of nonrenewable energy use (NREU; +12 %), as shown in Fig. 3. The factors affecting the DLCA results in terms of Eq. (2) were: (1) the

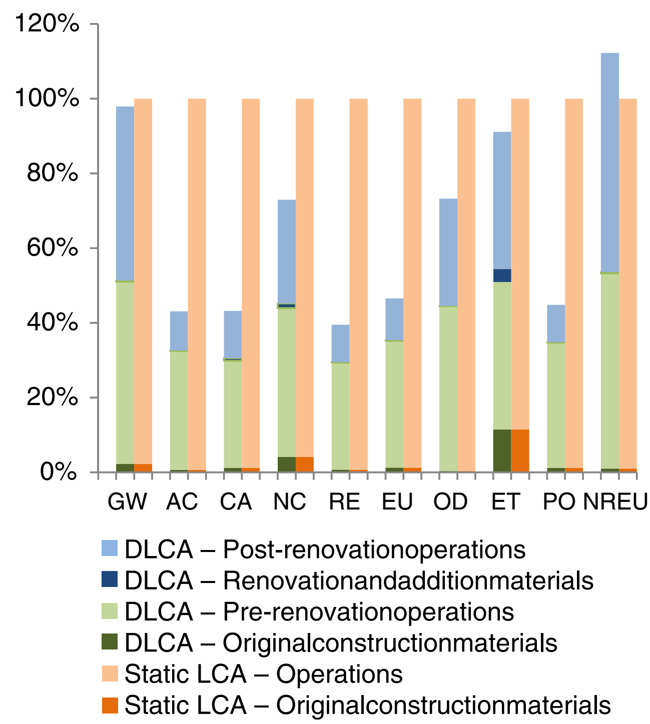

Fig. 3 Comparison of results from static and DLCA models, using the TRACI method. Results are normalized to the total static LCA results for each category. Static LCA results were calculated as the total of the initial construction and projection of the initial year's operating energy consumption for the 75-year life of the building. DLCA results are classified into four categories: original construction materials; pre-renovation operations (operating energy consumption through 2008); renovation and addition materials; and post-renovation operations (operating energy consumption 2009 through end of lifetime). *GW* global warming potential, *AC* acidification potential, *CA* human health cancer effects, *NC* human health noncancer effects, *RE* human health respiratory effects, *EU* eutrophication, *OD* ozone depletion potential, *ET* ecotoxicity, *PO* photochemical smog, *NREU* nonrenewable energy use

building's end-use energy consumption (included in f_t), (2) the electrical generation fuel mix (included in $\mathbf{A}_t$), (3) the steam generation mix (also included in $\mathbf{A}_t$), and (4) emission factors for the national electrical grid (included in $\mathbf{B}_t$). The results showed reductions of more than half in the categories of acidification (−57 %), human health respiratory effects (−61 %), photochemical ozone (−55 %), eutrophication (−53 %), and carcinogens (−57 %). Non-carcinogens and ecotoxicity were reduced by lesser amounts (−27 and −9 %, respectively). GWP decreased by 2 %.

The largest differences in the results were due to the lowering of emission factors for CAPs from 1970 to the present, documented by EPA's extensive historical estimation of CAP trends and continuing projected reduction in the near future through 2015 due to the EPA's proposed Transport and Toxics Rules. Data for hazardous air pollutants (HAPs) also exist in EPA's historical estimates and future projections, though coverage dates are generally more limited (1990–2008). No such national database for water pollution was found, though estimates are noted in the literature (Junnila et al. 2006; Bare 2011). Therefore, the water emissions estimated herein are primarily static values from the ecoinvent and USLCI databases. Additionally, water pollution-related categories such as eutrophication and ecotoxicity may be underrepresented because wastewater from the building was not included in the study.

The three toxic pollutant LCIA categories (human health cancer, human health noncancer, and ecotoxicity) are typically affected by both air and water emissions of hazardous metals and organic compounds. However, air emissions of metals from coal combustion dominated the results in the three toxic categories. In accordance with EPA modeling documentation, combustion-related air emissions of metals were projected proportionately to particulate matter <2.5 μm and organic compounds were projected proportionately to total VOCs (USEPA 2011a). Non-carcinogens and ecotoxicity were affected to a higher degree than carcinogens by water emissions, and thus do not show as much reduction from historical levels, due to the use of static data for water emissions. Material production processes for the construction and renovation had a proportionately greater impact in the non-carcinogens and ecotoxicity categories than the other categories; however, operating energy consumption still had the greatest impact. For ozone depletion, all processes considered in this LCA are minor sources, and thus neither the static nor dynamic results were considered to be significant.

Changes in emissions factors had the greatest influence on the LCIA results, but the remaining variables in Eq. (2) (f_t, $\mathbf{A}_t$) were also important, particularly in the GWP and NREU categories. Figure 4 shows the DLCA results as cumulative time series in each LCIA category, normalized to the cumulative totals in each category as of 2008. Impacts from construction and renovation are represented at a single point in time; realistically, these impacts occur over the span of several years. The time scale associated with these activities is shorter than that for building operations, even when operations are classified into phases between major renovations. Since the temporal changes incorporated into the current analysis are mainly gradual and on the order of decades, the treatment of material- and construction-related emissions as pulses were not expected to influence the overall results.

Electrical energy consumption increased gradually during the period of pre-renovation meter data availability, growing 10 % from 1993–1994 through 2007–2008. Steam consumption remained essentially constant during this same period. The cause of the increased electrical usage was not known, but it was assumed to be from increases in laboratory and office equipment demand, including computers. If electrical energy consumption was due to increased use of the overall building (e.g., extended hours, increased ventilation, etc.), it would be expected to result in an increase in steam use as well. For the renovated building, modeled energy consumption of both types increased. An increase in overall building footprint, coupled with increased heating, cooling, and fan usage demands from increased space ventilation requirements, was responsible for the increased energy consumption.

In the GWP category, the increasing trend in energy consumption was offset by a decreasing trend in greenhouse gas (GHG) emissions from the energy supply chain. While the electrical generation mix continues to rely heavily on coal-fired power plants, GWP for the electrical generation sector decreased 11 % from 0.72 kg CO_2 eq/kWh in 1970 to 0.64 kg CO_2 eq/kWh in 2008. GWP of the district steam production decreased 39 % from 2.3 to 1.4 kg CO_2 eq/kg steam, following the switch from mixed coal- and gas-fired generation to 100 % gas in June 2009. However, the modest decrease in GWP per kilowatt-hour from electrical generation was offset by the modest increase in electrical usage over the building's lifetime to date, and the larger decrease in GWP per kilogram steam was offset by the larger increase in projected steam usage following the renovation as noted above. Because the heating fuel switch and renovations occurred at nearly the same time, the slope of the NREU curve in Fig. 4 is higher post-renovation than pre-renovation, while the slope of the GWP curve in Fig. 4 remains the same. Because natural gas emits fewer CAPs and HAPs than coal, the heating fuel switch also affected the curves in Fig. 4, combining with the reduced emissions factors from electric power generation to reduce the slope of the future curves.

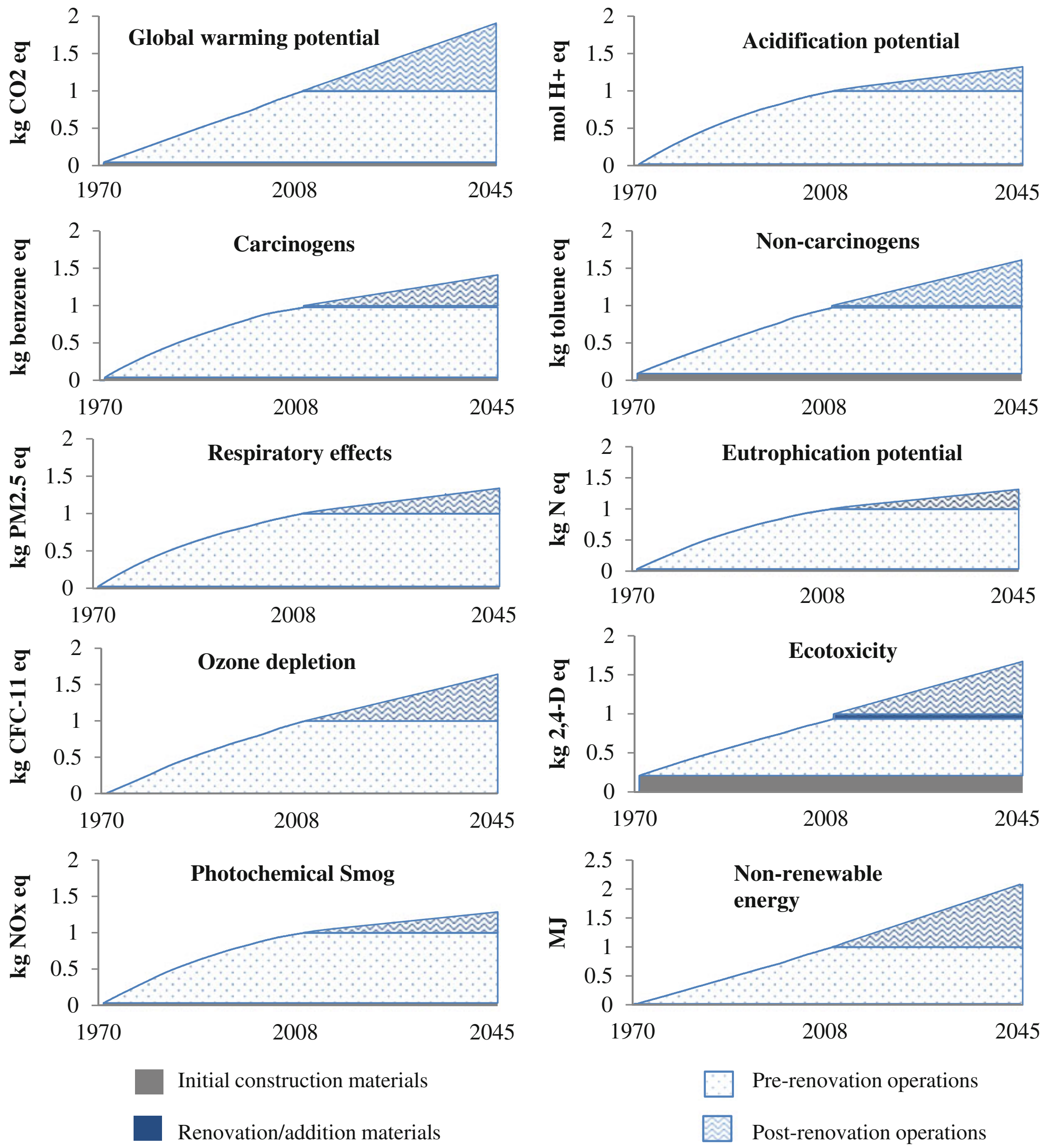

Fig. 4 Cumulative time series of dynamic LCA results for Benedum Hall construction, renovation and operations in TRACI impact categories and nonrenewable energy use. Cumulative totals are normalized to year 2008 totals (prior to renovation)

3.3 DLCA and static LCA results for remaining lifetime analysis

The DLCA results for the remaining lifetime analysis were lower than the static LCA results in every impact category shown in Fig. 5. As with the full lifetime analysis, the static LCA used energy mixes and emission factors from the year of analysis (2009) projected through the remaining lifetime. However, in contrast with the full lifetime analysis, the building's end-use energy consumption was the same for both static and dynamic analyses, since no actual energy data were available yet. Reductions in impacts from largest to smallest were: acidification (−17 %), photochemical ozone (−16 %), human health respiratory effects (−15 %), eutrophication (−14 %), carcinogens (−5 %), NREU (−4 %), non-carcinogens (−3 %), ecotoxicity (−3 %), and GWP (−2 %). As with the full lifetime analysis, the largest decreases were caused by a reduction in emission factors following environmental regulations (the proposed EPA Transport and Toxics Rules). The reductions in global warming potential and nonrenewable energy use were due to changes in the electrical fuel generation mix.

3.4 Future scenario analysis

The maximum variations from the baseline for the different DLCA scenarios are shown as error bars on the DLCA results in Fig. 5. For the baseline energy use case, the

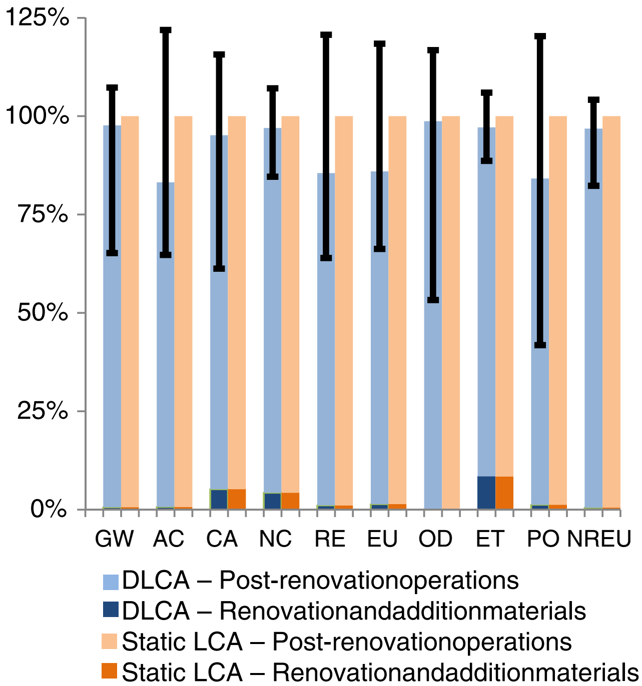

Fig. 5 Comparison of predicted results from static and DLCA models for the renovation and post-renovation operations. *Error bars* on the DLCA results indicate the minimum and maximum values obtained through the sensitivity analysis. For the *GW* and *PO* categories, the *error bars* include consideration of dynamic characterization factors at the impact assessment step. *Error bars* for all other categories include only variation in the life cycle inventory. *GW* global warming potential, *AC* acidification potential, *CA* human health cancer effects, *NC* human health noncancer effects, *RE* human health respiratory effects, *EU* eutrophication, *OD* ozone depletion potential, *ET* ecotoxicity, *PO* photochemical smog, *NREU* nonrenewable energy use

minimum and maximum variabilities from the static LCA due to combining variability in energy mixes and emissions factors were: acidification (+39 %/−18 %), photochemical ozone (+36 %/−15 %), human health respiratory effects (+35 %/−22 %), eutrophication (+32 %/−20 %), carcinogens (+20 %/−34 %), non-carcinogens (+10 %/−12 %), and ecotoxicity (+9 %/−9 %). The minimum and maximum variabilities for categories depending only on energy mixes were nonrenewable energy use (+7 %/−15 %) and global warming potential (+10 %/−17 %).

Figure 6 shows selected time series for the global warming and photochemical ozone impact categories, representing scenarios with different combinations of variation from the baseline, for each term in Eq. (2). The remaining series are presented in Fig. SI-6 (Electronic Supplementary Material). Of the variations in the *f* vector, the ±10 % electricity scenarios had greater influence than the ±10 % heat scenarios, due to (1) the larger overall energy use represented by electricity for this building, and (2) the larger impact in most categories per unit energy of electricity, due to the use of coal as a fuel. The variations in the *f* vector are a simple scaling of the baseline results, but are qualitatively illustrative of uncertainty in building use, such as hours of operation, user behavior, or HVAC system set points. They are also a point of reference in Fig. 6 for the relative changes in impact due to the scenarios representing variations of the **A**, **B**, and **C** matrices.

Of the 47 electricity grid mix scenarios drawn from the EIA AEO (represented in the **A** matrix), the greatest decrease in impact in most categories was the "GHG price economywide" scenario, representing a future in which coal use drops steeply due its greater CO_2 emissions than other fuels. The AEO scenario with the greatest increase in impacts was the "low shale resource" scenario, in which estimated unproven resources are assumed to be half those in the reference case. The low availability of shale gas in this scenario leads to a reduced use of gas and a corresponding increase in coal for electric power generation.

For any combination of *f* and **A** scenarios, eliminating the introduction of the new EPA regulations (represented in the **B** matrix) showed increased impact in most categories associated with CAPs (and some HAPs, such as metals from coal-fired power plants) compared to the baseline DLCA case. Scenarios eliminating the new EPA regulations combined with low gas resources—and hence increased coal use for power generation without significant new emission controls—showed increased impacts in these categories compared even to the static LCA.

The effect of including dynamic CFs is shown in the odd-numbered curves in Fig. 6 and is reflected in the error bars in the global warming and photochemical ozone categories in Fig. 5. In both cases, the addition of dynamic CFs reduced the total impacts compared to static CFs, though for different reasons. For global warming potential, the dynamic CFs, or TAWPs, reduced the cumulative impacts for any combination of other variables by approximately 13 % at the year 2045. This reduction represents the application of a fixed 100-year time horizon for integrating radiative forcing of GHGs, applied over the 36-year lifetime of the building. For example, CO_2 emissions in 2045 treated in this manner have a TAWP of 0.71, instead of 1. For more information on TAWPs, see Kendall (2012). Although the TAWPs for different GHGs vary differently with time, CO_2 was by far the dominant GHG in this analysis. Since the TAWP is calculated on an annual basis, any process with a total lag time of less than 1 year is accurately represented, which should capture the bulk of energy extraction and supply processes.

For photochemical ozone, the inclusion of dynamic CFs reduced the individual scenarios resulting from the combination of the other variables by 26 to 50 %. The reduction was lowest for low emission scenarios (e.g., scenario 16 in Fig. 6; 90 % electricity with AEO GHG price and new EPA rules) and highest for high emission scenarios (e.g., scenario 36; 110 % electricity with AEO low shale resources and no new EPA rules). The overall reductions are explained by the fact that higher emissions of ozone precursors—mainly NOx in this case—occurred during winter months, when the

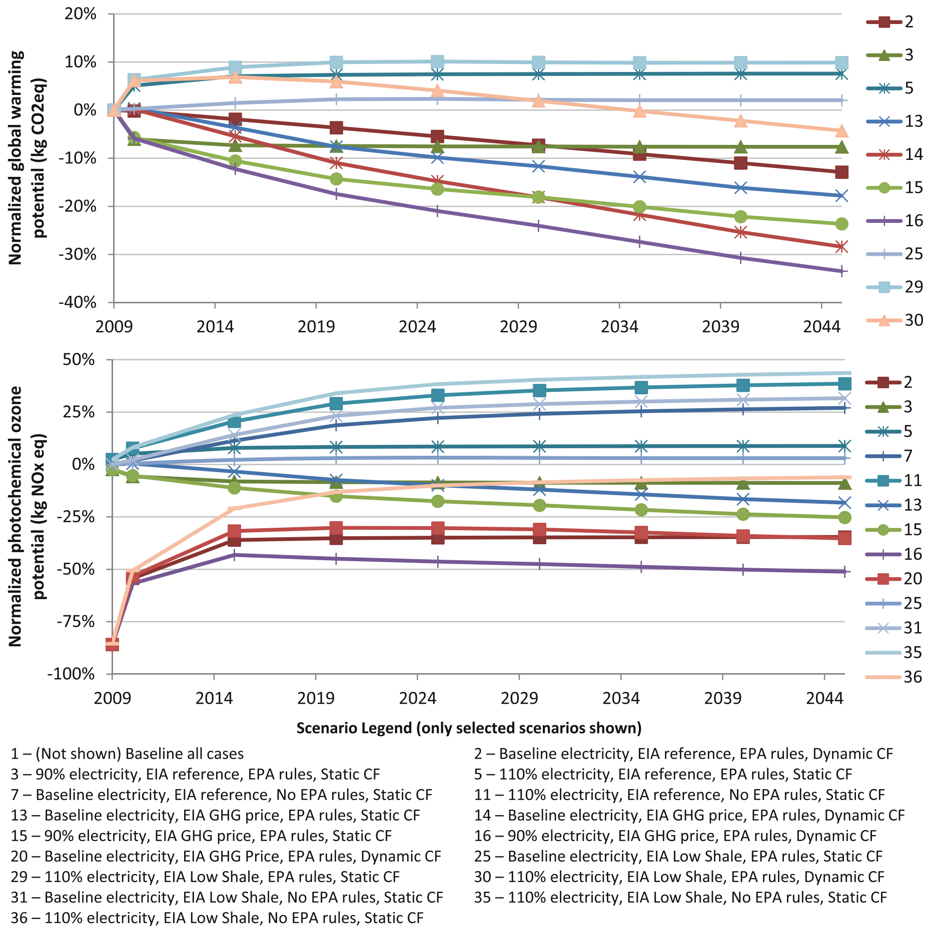

Fig. 6 Time series of DLCA results for the sensitivity analysis, shown as cumulative percent deviations from the baseline scenario for the global warming potential and photochemical smog categories. Time series plots of the deviations from baseline for the remaining TRACI impact categories are presented in Fig. SI-6 in the Supporting Information

dynamic CFs are lowest. This was due to (1) overall increased demand for energy in the winter, due to heating needs, and (2) relatively constant year-round electrical demand, but with a higher percentage of coal-fired power generation in winter months. Since the photochemical ozone CFs vary on a scale of months, it is possible that including lag times could affect this calculation. However, uncertainty in the supply chain required assuming an annual average CF for all upstream processes, while using the monthly CFs for combustion. This formulation implicitly resulted in a variable lag time of up to 1 year between upstream processes and combustion.

3.5 Limitations

3.5.1 Additional dynamic CFs

CF variations were not considered in most categories because no applicable source of temporally CFs was found in the literature. The lack of characterization methods incorporating both short-term and long-term temporal variability is a shortcoming of current LCA practice and could be remedied by additional LCIA method development. Temporally variable CFs need to take into account changes in background chemical concentrations, environmental systems, and the distributions of exposed populations, as well as time horizon relevance. The examples used in this study represent one instance of a time horizon-related CF (TAWP) and one instance of a physical system variation (photochemical ozone). In the case of the latter, additional investigation into the combination of daily, seasonal, and long-term factors is needed (Reap et al. 2008).

3.5.2 Data availability

Dynamic variation in industrial processes and emission factors is hampered by a lack of available data. In this case study, unit energy use for industrial processes and emission factors from fuel use other than in electrical power plants were not able to be modeled dynamically. This resulted in lower energy use and emissions associated with building material production for the initial construction. However, in LCIA categories that were highly influenced by energy use, these contributions were small relative to the impacts of operating energy. With respect to emission factors, it is noted that continued increases in data quality are expected to provide additional accuracy in results. Efforts to track and control toxic pollutants have historically lagged behind

CAPs, and thus, there is greater uncertainty in the temporal trends in toxic-related impact categories. With respect to lag times, the inclusion of supply chain lag times as an additional variable in LCI databases is critical for the accurate application of temporally varying CFs. However, the uncertainty related to upstream production functions may require annual averaging of most processes except those occurring in the building itself, which can be known with some detail, or those which are predictable based on system characteristics, such as energy and fuel supplies.

3.5.3 Spatial variability

Significant spatial uncertainty exists in LCA. The definition proposed herein for DLCA includes consideration of spatial variability, though it has not been directly addressed yet in this analysis. Noting that the term dynamic usually connotes temporal changes, it should be considered that spatial patterns of industrial activity and environmental impacts change over time; the NEI and other databases provide explicit spatial detail related to emissions, and LCIA methods with spatially explicit CFs are available. For North America, both TRACI and Impact (e.g., Impact North America, Humbert et al. 2009) models have some spatial resolution, though additional detail is needed in most categories. Related to spatial variation, it has been noted that there is extensive regional variation in the electrical generation mix. The national generation mix has been used herein, but regional or even sub-state-level mixes have been used in some studies. However, it has been shown that power trading between regions tends to drive the mix toward a national average (Weber et al. 2010); thus, the use of non-spatially explicit factors may be warranted in this case. More so than for electricity, the concentration of major producers in some industries (e.g., petroleum refineries, mining) in specific regions with CFs different from the national average may lead to a case for regionalization of LCA results even when the exact supply chain is uncertain.

3.5.4 Uncertainty of future scenarios

The outlook of this paper comprises both historical temporal variations and predicted future variations. However, it is likely that the primary use for LCA of buildings will continue to be predictive. Uncertainty in future scenarios depends on both building-level variables (e.g., occupancy levels, renovations) and external variables such as emission controls and environmental background conditions. Since Benedum Hall was recently renovated, projection of past building-level trends into the future was limited to assuming as-is operations of the building and district heating plants (since the building recently underwent a full renovation), with variation in energy usage of ±10 % to accommodate occupant behavior. However, exact knowledge of future occupant needs or renovation schedules will not usually be available to the LCA practitioner, even with DLCA modeling. There are also predictive assumptions built into the models used by EIA and EPA to forecast future energy mixes and emissions. Though uncertainty in prediction cannot be fully avoided, considering multiple future scenarios can illuminate possible environmental tradeoffs; for example, the often-cited tradeoff between embodied energy in construction materials and use-phase operating energy is changed somewhat when a DLCA model with varying energy supply background conditions is used.

4 Conclusions

This paper explicitly uses DLCA and illustrates the potential importance of the method using a simplified case study of an institutional building. The results show that the environmental impacts of the building over its lifetime vary significantly from what would be predicted if temporal changes were not taken into account. Particularly, the results indicate the importance of changes in building usage, energy sources, and environmental regulations in calculating the overall environmental impacts of the building. Given that temporal changes are rarely accounted for in LCA practice, it seems clear that LCA could be improved by incorporating a more dynamic focus. Previous whole-building LCAs have demonstrated the relative importance of the operations phase in most impact categories, compared to the materials, construction, and end-of-life phases. The DLCA results suggest an additional conclusion; that in some cases, changes in building usage, or changes in external conditions such as energy mixes or environmental regulations during a building's lifetime, can influence the LCA results to a greater degree than the material and construction phases. Correspondingly, adapting LCA to a more dynamic approach as demonstrated herein seems likely to increase the usefulness of the method in assessing the performance of buildings and other complex systems in the built environment. Future research needs to include characterization of uncertainty related to building systems modeling (e.g., future occupant needs and maintenance/renovation schedules), additional exploration of the interactions with dynamic, temporally evolving (and themselves uncertain) LCI and LCIA background variables, and development of additional dynamic CFs and dynamic parameters for LCI databases.

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