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Published in:
Building and Environment

Link to article, DOI:
10.1016/j.buildenv.2020.107399

Publication date:
2021

Document Version
Publisher's PDF, also known as Version of record

Building and Environment 187 (2021) 107399

Contents lists available at ScienceDirect

Building and Environment

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

Estimating dynamic climate change effects of material use in buildings—Timing, uncertainty, and emission sources

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ARTICLE INFO

MSC:
00-01
99-00

Keywords:
Buildings
Life cycle assessment
Embodied emissions
Dynamic
Biogenic
Carbonation

ABSTRACT

Material use in buildings affects the climate over centuries, however, temporal aspects are often ignored in Life Cycle Assessment (LCA). Results too often promise uncontested precision of impacts occurring far into the future. Additionally, the validity of building LCAs is being questioned over inadequate scope and inventory.

A dynamic LCA method for material use in buildings that addresses those concerns is presented, along with a case study of 20 buildings. In particular, a novel solution to account for delayed emissions is presented, along with future technological improvements. Climate change effects of material use in construction, operation, and end-of-life phases are estimated, from production, transport, construction-waste incineration, biogenic carbon-sequestration, and cement carbonation. Building subpart metrics reveal drivers of impacts and are used for generating statistical emission profiles.

Application on a bottom-up harmonized dataset produces statistical results for building types (typology, timber/concrete) and building subparts (building elements, material categories). Global warming policy targets requires that the building industry focuses on interventions with short-term effects, such as low-impact materials in the construction phase and reduced construction waste.

Uncertainty is estimated, and parameter influence assessed with global sensitivity analysis. Time horizon (TH), building lifetime, and construction waste parameters are found most sensitive. The method reduces uncertainty of postulated future impacts; an important step in the direction of policy-relevant modeling. We recommend that building LCA modeling practice adopts the presented methodological concepts to gain trust and policy-relevance.

1. Introduction

Buildings are a large global source of anthropogenic greenhouse gas (GHG) emissions, which can be estimated by Life Cycle Assessment (LCA) methods. Results can be used to identify promising mitigation interventions and design improvement strategies, benchmark individual building performance, and guide effective policy measures. With growing focus on material embodied emissions in buildings, GHG emissions are usually quantified in $kgCO_2e$ per unit of material consumed or per m^2 of floor area, according to the 100-year Global Warming Potential (GWP_{100}) indicator and with data from Environmental Product Declarations (EPDs) from given manufacturers. The information from EPDs, together with material quantities and other data specific to the building form the basis for modeling its emission profile throughout its postulated lifetime. However, the validity of building LCAs has been questioned due to varying system boundaries and assumptions, lack of completeness, transparency in methodological choices, and reproducibility [1–3], and for ignoring time-dependent effects [4–7]. There are also large uncertainties that are often not quantified and communicated [8].

1.1. Complexity and uncertainty of LCA modeling

Modeling the environmental impact of buildings is inherently uncertain due to their long service life and large variation in design and composition. Nevertheless, LCA too often promises uncontested precision [8]. Saltelli et al. (2020) [8] offer five principles that society should demand to ensure quality from modeling: Minding the assumptions, hubris, framing, consequences, and unknowns. LCAs of buildings too often ignore those principles, thereby damaging their trust. In general, results of unclear LCAs lack significance and inhibit conclusions that could aid environmental paradigm shifts [3]. We suggest that the principles can be implemented in LCA modeling as follows.

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https://doi.org/10.1016/j.buildenv.2020.107399
Received 17 August 2020; Received in revised form 2 October 2020; Accepted 22 October 2020
Available online 27 October 2020

Assumptions: By exploring the entire parameter space, a global sensitivity analysis (GSA) can determine to which parameters a model is particularly sensitive, and will thereby reveal parameters that demand high confidence. GSA stands in contrast to local sensitivity methods, limited in their ability to quantify how individual parameters contribute to the overall uncertainty [9]. Sensitivity analysis methods best fit for building LCAs were investigated in [10], who found that the most used methods were regression-based or local sensitivity analyses and that the choice of method was rarely justified. The study concluded that the variance-based Sobol analysis was best fit to precisely determine the factors' influence when ignoring its much higher computational cost. Sobol analysis is also able to identify interactions and non-linearities. Using this method, the study found the three most influential parameters to be the building lifetime, the time horizon, and the choice of an hourly versus yearly electricity mix [10].

Hubris: Complexity should only be added to a model if it reduces the overall uncertainty. By determining factors responsible for model variance, less influential factors can be assigned default values while priority is given to the most influential, hence simplifying the model description. Future events are highly uncertain. This should be reflected in the modeling by avoiding superfluous complexity, and the greatest uncertainties should be reduced first.

Framing: The outcome of an LCA highly depends on modeling choices and scenario assumptions [3]. One normative question that can be asked is how to reduce the building's impact on climate change over a defined time horizon (TH). Within a short TH, future emissions will have less time to warm the atmosphere. LCA studies usually consider the impact over the same TH for emissions happening at whatever point in time (for example, construction and dismantling emissions are both assumed to happen at year 0 and their impact assessed with GWP_{100}, i.e. a time horizon of 100 years). According to the IPCC, however, emissions must be cut rapidly if we are to stay within the 1.5 °C and 2 °C targets, making timing highly relevant [11]. Furthermore, if the goal is to reduce the overall impact of a building's materials, the scope must include all relevant materials and emission sources.

Consequences and unknowns: Results of building LCAs are profoundly uncertain; some parts more than others. The degree of confidence should be conveyed when presenting LCA results, to stimulate effective climate mitigation in the construction industry. Likewise, unknowns must be communicated.

1.2. Time-dependent effects

Non-dynamic LCA aggregates GHG emissions over the lifetime and ignores time-dependent effects. For products with long lifetimes, such as buildings, the timing of events will influence both the likely magnitude of future emissions and their aggregated effects over a defined TH. A dynamic LCA (DLCA) can be used to include those effects, but this requires lifecycle inventory (LCI) emission data for each year in the TH, as well as the temporal development of the dynamic effects.

A dynamic LCA framework proposed in [4] was applied in multiple studies, e.g. [4,5,12–14]. Various frameworks for dynamic LCA for buildings were proposed in [6,7,15–19].

The most common application of time-dependent emission effects for buildings is related to carbon sequestration and temporary storage of biogenic carbon in building products. Ref. [20] presents a critical review of the main approaches to include time considerations in LCA of biogenic carbon. Of the different methods available, the dynamic LCA approach [4] is based on a temporal explicit life-cycle emission inventory, which can be produced by using probability density functions (PDFs) to model the timing of future events and distribute future emissions [20]. The use of PDFs to model the decay of carbon-containing products is better suited than the more common first-order decay approaches [21]. In [22], different PDFs were compared and it was concluded that a chi-square distribution, also used in e.g. [23], appears most reliable and appropriate. In a study of the sensitivity of parameters in dynamic LCA, it was concluded that dynamic climate change is not sensitive to LCI time steps lower than 1 year [24]; the difference in results is rather dominated by the choice of TH.

Moreover, future emissions will be affected by technological development. Technological development of material production was implemented in [14], and by a dynamic emission factor for electricity in [15]. The effects of technological progress on material production and transport were investigated by Resch et al. [25], where the future magnitude of emissions were adjusted by the modeled technological improvement in the year of their occurrence.

1.3. The climate change impact of buildings

Several previous studies have presented statistical LCA results, however, they are often based on varying system boundaries and offer no assessment of uncertainty. A global study from International Energy Agency Annex 72 analyzed the carbon footprint of 238 buildings [2]. For advanced building energy-performance classes, the first and third quartiles of embodied emissions range between 0.1 and 0.5 tons CO_2e/m^2 for residential buildings and between 0.3 and 0.5 tons CO_2e/m^2 for office buildings.[1] The resolution of the data analyzed was only aggregated results extracted from literature. The study separated embodied from operational emissions, but there is no distinction between methodological choices and no separation between emission sources, building elements, and lifecycle phases. Thus, they were not able to do a thorough normalized comparison. Without such information, there is no way of knowing which building elements and which parts of the lifecycle these numbers represent, and hence if the results are reliable.

Large variation between building LCA studies is shown in another comparison of 116 cases from 47 scientific articles and reports [1]. Methodological issues and subjective choices of the LCA practitioner are found to cause huge variance in the results. The construction phase emissions vary between 0.03 and 2.00 tons CO_2e per m^2 gross floor area. The study concludes that "published building LCAs do not offer solid background information for policy-making without deep understanding of the premises of a certain study and good methodological knowledge".

Another meta-analysis of over 250 case studies from 70 papers mapped methodological aspects and found a need for clarity in methodological choices and a lack of uncertainty and sensitivity analyses. This study also called for more advanced LCA modeling such as including biogenic CO_2 dynamics, carbonation in concrete, and dynamic modeling to increase robustness and avoid false incentives [3].

1.4. Aims and objective of this study

To address the limitations discussed above, we present a novel method for estimating the lifecycle impacts on climate change imposed by material use in buildings over clearly specified THs.

The methodology builds upon previous research, including studies by the authors: structuring and storing inventory data [26], weighted average emission metrics for building subparts and including the effect of future technology improvements [25], using these to estimate average emission and material use profiles for building types [27], and a dynamic LCA of a cluster of buildings [28]. In this study, the methodologies are combined and developed further, additional methodological concepts are introduced, and the scope of emission sources is expanded along with the dataset.

We apply this method on primary inventory data acquired from 20 previously reported building LCA studies. Missing data in one building is imputed based on data from the remaining buildings, in this way

[1] Converted to a functional unit of heated floor area over a 50 year lifetime, which was the lifetime used in most studies.

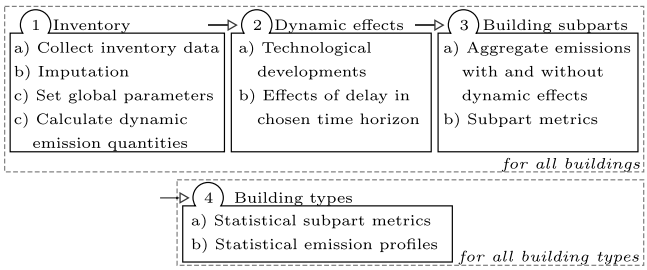

Fig. 1. Methodological steps.

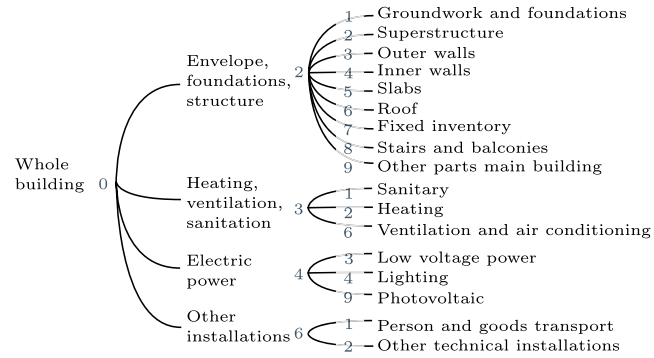

Fig. 2. Hierarchy classification of included building elements. Numbers, names, and hierarchy according to NS3445 [29].

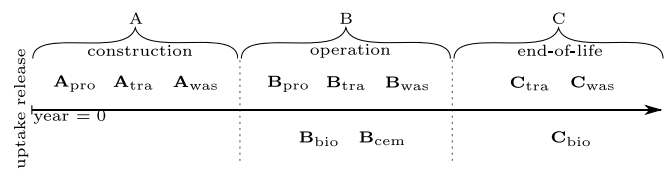

Fig. 3. Timeline of included emission sources and lifecycle phases.

ensuring more equal system boundaries of each study, thereby reducing underestimation of results due to incomplete system boundaries. This, together with the advantage of recalculating each study with equal model parameters, means that the given studies are harmonized bottom-up, for a more consistent statistical analysis. We perform this climate change impact analysis of the dataset based on building types, building elements, material categories, and emission sources.

The model's sensitivity to changes in methodological choices and parameters is thoroughly investigated, thereby determining which model choices and parameters are essential for obtaining high-quality LCA results that can be used to guide design choices and material-use policy.

2. Methods

This section first describes the goal and scope of the LCA 2.1 and methods for obtaining probability distributed dynamic inventory 2.2, future technology improvements and emission delay 2.3, biogenic carbon 2.4, and carbonation 2.6.

Then, descriptions of the methodological steps shown in Fig. 1 follow. Yearly emissions are first calculated for inventory items and *then* adjusted to the dynamic effects 2.7, which are then used to calculate emissions for building subparts, together with aggregated quantities and average emission-, technology-, and delay factors 2.8. These metrics are used to calculate statistical emission profiles of building types 2.9.

2.1. System definition

The goal of the analysis is to quantify the GWP_{TH} of an average square meter of heated floor area (HFA) in a building, over a given time horizon (TH), while also testing assumptions and methodological choices. The focus is on process-based, attributional LCA. The functional unit is m^2 of HFA over given building lifetimes and THs. In our dynamic interpretation of the GWP_{TH} impact, the accumulated radiative forcing impact of emissions occurring late in that period have less warming potential than emissions occurring early in the period, and the impacts of emissions occurring beyond the given TH are zero. Emissions are thus weighted by their time of occurrence to account for the accumulated effect on radiative forcing *during* that TH. Non-weighted emissions are also calculated for comparison; the effect of emission delay on the importance of future emissions is quantified in the *delay factors*, τ.

2.1.1. Scope of building elements

Fig. 2 shows the included building elements, structured according to the hierarchy classification in Norwegian standard NS 3451 'Table of building elements' [29]. The standard is widely used in the Norwegian construction sector to categorize building inventories, and consequently, also in building LCAs. Building elements available in at least one of the collected LCAs are included.

2.1.2. Scope of emission sources

The study estimates material embodied emissions during the entire TH, i.e. the defined time of interest in the analysis (may differ from the building lifetime). The building lifecycle is separated into lifecycle modules as shown in Fig. 3: initial impacts from building construction in module A, impacts during operation throughout the building lifetime in module B, and end-of-life impacts in module C. In each temporal module, the model includes the emission sources material production (pro), material transport (tra), material waste (was), biogenic carbon uptake (bio), and carbonation of cement products (cem).

The widely used European standard EN 15978 separates modules into numbered submodules, e.g. A_{1-3} is cradle-to-gate material production. That module is here instead termed A_{pro}. This terminology is applied to all emission sources to ensure consistency and avoid ambiguity.

$\mathbf{A}_{pro}$ is the production of building materials, including construction waste. $\mathbf{B}_{pro}$ is the production of replacement building materials throughout the building lifetime, calculated as the statistically distributed $\mathbf{A}_{pro}$ emission for all replacement years.

Equivalently, $\mathbf{A}_{tra}$ is the transport of building materials and construction waste, and $\mathbf{B}_{tra}$ is the transport of replaced materials throughout the building lifetime, calculated as the statistically distributed $\mathbf{A}_{tra}$ emission for all replacement years. $\mathbf{C}_{tra}$ is the transport of all building materials to waste processing at the end of building life.

$\mathbf{A}_{was}$ is the oxidation of construction waste incinerated during initial construction. $\mathbf{B}_{was}$ is the oxidation of the replaced materials and construction waste of the new materials. $\mathbf{C}_{was}$ is the oxidation of the materials in the building at the end of building life. It is assumed that half of the carbon in the materials is oxidized by waste incineration and released into the atmosphere. The remaining half of waste materials could be either reused, recycled, or landfilled, however, related emissions are beyond the scope of the study.

$\mathbf{B}_{bio}$ and $\mathbf{C}_{bio}$ are the carbon sequestration from regrowth of trees due to use of biogenic materials in the building, both initial and replacement materials. The separation between the B- and C-phases depends on if the sequestration happens during the building service life (B) or after (C).

$\mathbf{B}_{cem}$ is the carbonation of concrete during the building's lifetime. Carbonation effects at end-of-life is not attributed to the building.

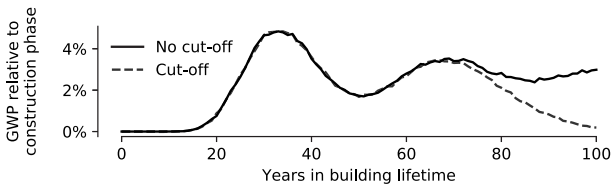

Fig. 4. Replacement emissions are chi-square distributed. Shows an example product with 35 years service life and 100 year building lifetime.

Table 1
Adjustments to future emissions. y=year in time horizon.

	Decay function	Half-life	Applies to
Technological progress			
Production	$e^{-.01y}$	69 years	B_{pro}
Waste	$e^{-.01y}$	69 years	B_{was}, C_{was}
Transport	$e^{-.02y}$	35 years	B_{tra}, C_{tra}
Production PV	$e^{-.037y}$	19 years	B_{pro}
Effects of delay			
T-year TH	$2-e^{\frac{\ln(2)}{T}y}$	–	all
20-year TH	$2-e^{.0347y}$	–	all
100-year TH	$2-e^{.00693y}$	–	all
500-year TH	$2-e^{.00139y}$	–	all

Climate change effects outside the study scope include the choice of building site, direct and indirect land-use change, albedo change, by-products of wood products (treetops, branches, roots, and chips), commute of construction workers and building users, energy use in operation, construction site (energy use and production of machinery, heating, temporary barracks, etc.), end-of-life substitution effects of reuse and recycling, and consequential LCA effects of choosing one product over another.

2.2. Probability distributed future emissions

The timing of future emissions relates to replacement times. The exact timing of a replacement is uncertain and uncertainty increases with time. To account for this, the years of future emissions can be represented by a random variable with increasing variance. This study uses the chi-square distribution, as shown in Fig. 4. The 'cut-off' assumes no replacements take place beyond the building lifetime. However, a sharp cut-off at the end of the building lifetime will not reflect that building lifetime is highly uncertain. The 'no cut-off' version, used in this study, acknowledges that building lifetime is an unknowable parameter by including parts of the emissions from replacements after the building lifetime. The effect of choosing other distributions is investigated in D.1 and found the 'no cut-off' chi-square distribution to transition smoothly as lifetimes change, and not underestimate, i.e. it includes the probability of early and late replacements.

2.3. Applying dynamic effects

Future climate change effects are adjusted by (1) expected technological progress, and by (2) their accumulated impact on climate change over a TH. Technological adjustments reduce emissions over future years, while emission delays reduce their *importance*. The calculation and effect on the results are equal for both adjustments: a lower climate change effect over the TH. Their effects on results are quantified as percentage reductions in total emissions by the tech factors ω and delay factors τ (see Section 2.8). The exponential e is often used to model natural decay when a quantity decays continuously by a fixed percent. Here, it is used to model both technological progress and the effect of delay by the functions shown in Table 1.

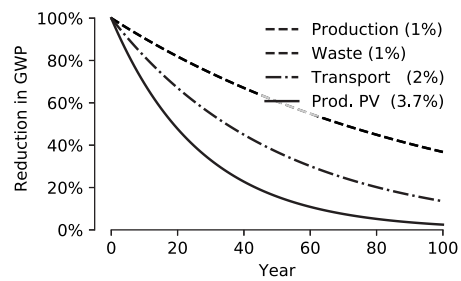

Fig. 5. Emission reductions due to technology improvements. Decay factors shown in parentheses.

2.3.1. Technological progress

Technological progress is implemented by weighing the probability distributed future emissions by exponential decay functions starting in the year of construction, see Table 1 and Fig. 5. With a ~1% yearly improvement for production of building materials, it takes 69 years for emissions to be cut in half. This improvement rate will in reality depend on material category, but distinguishing between types of materials will only have a noticeable effect on the results if the category makes up a significant share of the total. Faster development is applied to PV panels since they represent a large share, and historically, development has been steeper than average [30]. A ~ 1% development is also used for waste processing as reuse and recycling increases, and a lower share of combustible building waste is expected to be incinerated without carbon capture and storage (CCS) technology. For transport, the 2% decay factor cuts emissions in half in 35 years, due to efficiency gains and electrification. This implementation is a further development of a method by the authors [25].

The decay functions should not be interpreted as predictions, rather, they quantify the effect of *possible* development paths. The sensitivity of the decay factors was tested in the global sensitivity analysis, where each decay factor was varied between 0.5 and 4%. Results were sensitive to the decay factor of waste incineration, but not much to those of production and transport. Further description of these modeling choices can be found in B.1.

2.3.2. Delayed emissions

A GHG emission will heat the atmosphere as long as it is present, and its decay rate depends on the type of GHG. Hence, emissions that occur later in the TH have less time to trap heat in the atmosphere during that TH, and therefore have lower cumulative radiative forcing.

One way to calculate the cumulative radiative forcing over the TH (providing high accuracy and flexibility), is to integrate the Impulse Response Functions (IRF) of each GHG [4]. Without compromising accuracy, we here offer an approximated methodology. There are specific reasons for this simplification: Building LCAs often rely on EPD data, making it impossible to separate the different GHGs and therefore not possible to use IRFs; Simplification facilitates widespread application in research and the practice of building professionals; It is easy and computationally efficient to estimate results for a wide range of THs.

All LCA approaches rely on the choice of a TH, even if it is infinite or not explicitly stated [4]. For coherence, the delay of emissions must be considered for all emission sources [4,31]. Time-discounting with a TH of T years provides *the building's impact on climate change over the next T years*, thus being consistent with the physics of climate science.

An example TH of 100 years is plotted in Fig. 6. Weighting factors were first calculated with IRFs for every tenth year based on the method in [4], and the analytical function was fitted thereafter. It was found that an exponential decay function of $2-e^{\frac{\ln 2}{100}y}$ fits the curve for a 100-year TH. Similar functions are used for other THs, where the decay factor for a TH of T years is $\ln 2/T$, making it easy to change TH. A detailed description including other THs can be found in B.2.

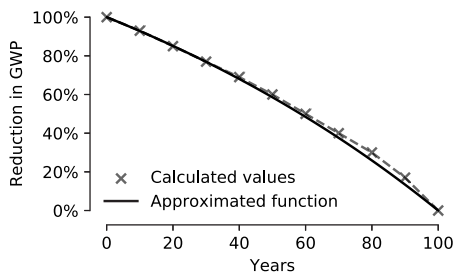

Fig. 6. Reduction in climate change impact due to delay in 100-year TH.

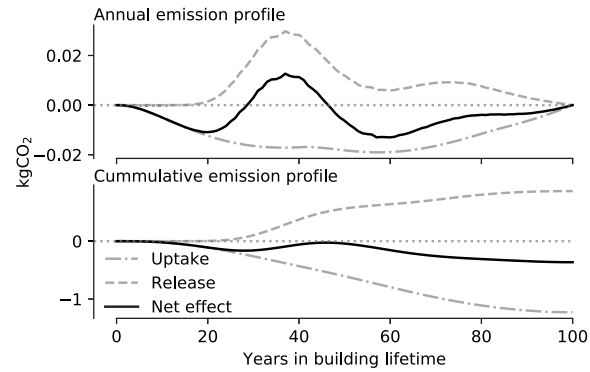

Fig. 7. Biogenic carbon uptake and release from 1 kg wood product and its replacements every 40 years. Effect of delay in a 100 year TH is considered. Construction waste omitted.

To test the accuracy of this simplified method, a calculation was performed for emissions of 1 kg CO_2e every year in a 100-year TH, with this method and with the original method [4] on which the simplification is based. The method proposed here achieves results that are only 0.2% off from an equivalent IRF calculation, making this accuracy fully acceptable compared to remaining model uncertainty.

2.4. Oxidation of stored carbon

Storing carbon in building products prevents release of that carbon to the atmosphere as long as it is in use. At the end-of-life stage, the stored carbon may be released in waste incineration, or stored further in other reuse and recycle products or landfills, and it may be subject to CCS technologies.

The carbon can be of biogenic or fossil origin. Although the biogenic carbon cycle is much shorter than that of fossil-based materials, the effect of carbon release from a building product to the atmosphere will be independent of its origin. All carbon stored in building products is therefore treated equally. The oxidation occurs far into the future, making both the timing and the fraction released into the atmosphere unknown. Therefore, timing is statistically distributed and we assumed that 50% of the stored carbon is released to the atmosphere at the end of the product life. Technological progress reduces the fraction released to the atmosphere by $\sim 1\%$ annually. The LCA results were found to be highly sensitive to these two parameters in the global sensitivity analysis (GSA).

2.5. Biogenic carbon uptake

Biogenic carbon stored in harvested wood products contributes to climate mitigation by postponing its release to the atmosphere, while simultaneously leading to accelerated regrowth of new trees. Over time, this is a nearly carbon-neutral system, while fossil carbon permanently adds CO_2 to the atmosphere. The net effect of biogenic carbon (emissions minus uptake) can become negative when the effects of delaying and avoiding oxidation are considered. This is a benefit that fossil-based products do not have.

The wooden building materials are assumed to originate from sustainably managed forests kept under continuous rotation. Within the rotation period, i.e. the time of a full regrowth and trees ready for reharvest, the same amount of carbon will have been sequestered as was cut down. Carbon sequestration is attributed to the regrowth of the forest after harvest and not to the actual carbon stored in the building materials. Harvesting will not increase the carbon stored in the harvested trees, but it *will* increase the sequestration rate of the forest; it is this consequence we assess here. Alternatively, uptake can be considered to happen before harvest in the actual trees cut down, which would significantly affect results since no effect of emission delay would apply and no TH cut-off. The time distribution of the uptake of CO_2 over the years y in the rotation period is modeled by the first derivative of the Chapman–Richards (CR) growth function

$$f_{\mathrm{CR}}(y) = kpe^{-ky}(1-e^{-ky})^{p-1}, \tag{1}$$

where $k = 0.23$, $p = 3$ are model parameters describing the growth rate and catabolism of the trees. Eq. (1) is multiplied by the CO_2 content of the material and then normalized to account for an assumed rotation period of 100 years

$$f_{\mathrm{bio},\ i}(y) = m_{\mathrm{CO_2},i} \cdot f_{\mathrm{CR}}(y) / \textstyle\sum_{y=0}^{100} f_{\mathrm{CR}}(y), \tag{2}$$

where $m_{\mathrm{CO_2},i}$ is the mass of stored CO_2 in inventory product i. Fig. 7 shows emission profiles of biogenic uptake and release including replacements and the effect of delay. The regrowth profile will depend largely on the type of trees and climate, leading to different parametrizations of this function. The normalization reduces the importance of parameters k and p, leaving a 100-year rotation period the most sensitive parameter. The GSA found results to be highly sensitive to rotation period when equal to the THs but insensitive in shorter and longer THs. Further description and figures are presented in B.3.1.

2.6. Carbonation of cement

Cement products will, over the building lifetime, bind carbon dioxide from the ambient air in a process called carbonation. Such a carbon sequestration mechanism gives negative emissions that may partly compensate for emissions from production of the materials. It is uncommon for building LCAs to consider carbonation in cement but some studies were briefly reviewed in [3]. The carbonation rate varies widely between cement-based products and between studies. The sequestration is lower for low-carbon concrete mixed with fly ash or slag. In general, the review found that the carbonation did not deeply affect the net emissions over the product's service life. When crushed and used as recycled aggregate in its next lifecycle, an uptake of ca. 20% of initial emissions can be sequestered. However, that uptake is not part of the product lifecycle and C_{cem} is therefore zero.

Without detailed data on each cement product in the inventory and their exposure to ambient air, it is not possible to accurately assess the carbonation of these products. Nevertheless, a general assumption of 0.1 $kgCO_2$ uptake per kg cement over 100 years was made. About half of the 100-year uptake happens the first 25 years, using an exponential decay function $1-e^{-.03y}$ normalized for the years y in the building lifetime. This sequestration model was constructed based on information from [32]. Calculation details are given in B.3.2.

Carbonation is modeled for products in the material categories 'cement' and 'concrete'. The cement content in concrete varies, but a minimum of 400 kg/m^3 concrete is recommended [33]. For a concrete density of 2400 kg/m^3, this corresponds to a cement content of 17%,

which is the assumed fraction in this study. The cement content was varied in the global sensitivity analysis from 10 to 23% (upper and lower values used in [33]) and was found to be one of the least sensitive parameters.

2.7. Calculation of building material emissions

Building material data is organized in a material inventory where each item is assigned to a building element and material category. For calculation, each inventory item must have a specified quantity q (per m^2 HFA), density ρ (if the unit of q is not kg), emission intensity per unit f, estimated lifetime of the material l, transport distance from factory d, and transport emission per weight and distance t. When any of these are not known for a given inventory item in one building they are estimated by approximation, using the existing data for similar inventory items in all case buildings. The methodology developed for imputation of missing data is described in A.4.

The imputed inventory data, together with the global study parameters (summarized in Fig. 13 and C.1), are used to calculate emissions as described above. Further calculation details are given in B.3. Each emission source is first calculated for every inventory item, for each year in the TH. To incorporate the dynamic effects, the yearly emissions for each inventory item are then adjusted by the technology and delay vectors.

2.8. Aggregation metrics for building subparts

The materials in a building are organized into building *subparts*. Subparts are building elements, material categories, or a combination of the two. The building elements are here organized in the hierarchical system in NS 3451 [29], shown in Fig. 2. The material categorization is based on the material groups described in C.2.

Both original and tech- and delay-adjusted inventory results are aggregated up to building subparts. From these aggregated subpart results, one can calculate average metrics that, for each subpart, describe the impact of each emission source and the magnitude of the dynamic effects.

For each subpart, the total mass is given by *quantity* Q, and the mass-weighted mean transport *distance* by D. The *emission factors* α, β, γ are the mass-weighted mean emission intensities, for the construction, operation, and end-of-life phases, respectively. The *tech factors* ω and *delay factors* τ are the emission-weighted average of the functions in Table 1 and Figs. 5 and 6, and describe how much future emissions (phases B and C) are reduced due to technological improvements and a subsequent effect of delay; these are calculated by division of the adjusted and unadjusted subpart results. Analytical equations for these metrics are given in B.5.

Emissions can be directly recalculated from these aggregation metrics; relationships between the metrics and emissions are shown in Table 2.

2.9. From buildings to building types

General characteristics of the case studies, such as location (climate, construction practice, etc.), typology (building form, special requirements, etc.), and type of superstructure (timber, concrete, etc.) influence material use and emissions. Statistical material use and emission profiles are therefore only representative for buildings of similar characteristics.

The case studies are here classified by such building types, for which statistics are calculated. The most general building type includes all buildings, which is used to analyze subpart emissions by building elements and by material categories. Another building type groups by typology. A third type groups buildings by their timber content; a total weight ratio of 1/4 or more biogenic materials is considered a timber building and a lower ratio a concrete building. The case studies are all from similar climate zones in Norway. Most are designed to reduce emissions from material use.

The average quantity and emission-, tech-, and delay-factors of the case buildings are used to calculate building type emissions with the equations in Table 2. The resulting emission and material intensity profiles can be used as reference values or benchmarks for buildings with similar characteristics.

2.10. Dataset of case buildings

The full inventories from 20 previously reported building LCA case studies were collected from sources in academia and industry, presented in Table A.1. None of the studies had a defined TH for the climate change impacts, neither did they consider technological progress (only for energy use in operation; some assumed improvements in production of PV panels). All studies used a 60 year building lifetime, which is much lower than the national empirical average, but often used in LCA studies. These methodological aspects and the ones explained in the sections above are harmonized in this study. Missing data are imputed based on the remaining dataset. A full description of the dataset and the preparation of it for use in this study is given in A.1–A.4.

2.11. Sensitivity analyses

A variance-based GSAs (Sobol analysis) is performed to determine the influence of changes in the global study parameters (see C.1) on the final emission results. The SALib Python library [34] is used for this calculation. Model results are first sampled and then analyzed. The output, for which the sensitivity is quantified, is the sum of all emission sources and years in the TH, for the entire inventory from all buildings in the dataset. It should be noted that the uncertainties of the inventory (LCI) data for the 20 case studies are not considered. The sampled results are also plotted and a confidence interval is calculated, providing an estimate for the uncertainty due to variation in the global study parameters.

The analysis is performed four times both for a varying TH and for fixed THs (20, 100, 500 years). This allows for a distinction between the uncertainty for each TH.

Table 2
Calculation of building subpart emissions [$kgCO_2e/m^2$] from aggregation metrics. The emission factors (α, β, γ) are without dynamic effects, which are adjusted for by the tech (ω) and time (τ) factors. Lifecycle phases and emission sources shown in parentheses, e.g A_{pro}.

	Const. (A)	Operation (B)	End-of-life (C)	Adjusted future (B+C)
Production (pro)	$Q\alpha_{pro}$	$Q\beta_{pro}$	–	$Q\beta_{pro}\omega_{pro}\tau_{pro}$
Transport (tra)	$Q\alpha_{tra}$	$Q\beta_{tra}$	$Q\gamma_{tra}$	$Q(\beta_{tra}+\gamma_{tra})\omega_{tra}\tau_{tra}$
Waste (was)	$Q\alpha_{was}$	$Q\beta_{was}$	$Q\gamma_{was}$	$Q(\beta_{was}+\gamma_{was})\omega_{was}\tau_{was}$
Biogenic uptake (bio)	–	$Q\beta_{bio}$	$Q\gamma_{bio}$	$Q(\beta_{bio}+\gamma_{bio})\tau_{bio}$
Cement uptake (cem)	–	$Q\beta_{cem}$	–	$Q\beta_{cem}\tau_{cem}$

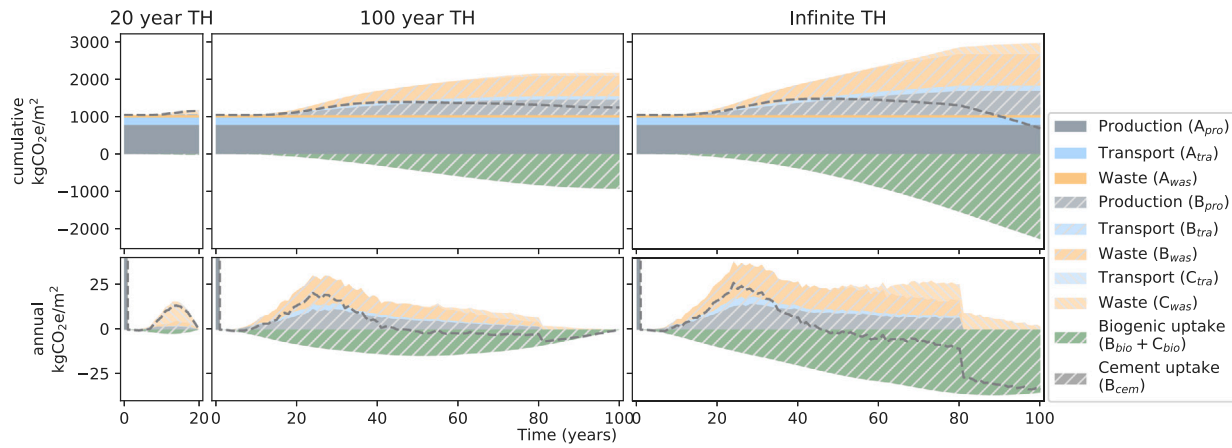

Fig. 8. Cumulative (top) and annual (bottom) climate change effect for different time horizons (TH). The stippled lines show the net climate change effect.

3. Results

3.1. Dynamic emission profiles

Fig. 8 shows the dynamic emission profiles of various THs, for a building with 80 years' lifetime. This building makes a good explanatory case due to significant future emissions. Results for the other buildings in the dataset can be found in E.4.2, many of which have much lower future impacts.

During a 20 year TH, the construction emissions are the only emissions that matter and the benefits of biogenic uptake are absent. If the goal is to minimize the climate change effect of the building within the next 20 years, one should focus solely on reducing construction phase emissions.

If the goal is to reduce the warming effect during the next 100 years, operation phase emissions become important for this particular building and benefits of biogenic uptake are highly present. The end-of-life phase will barely contribute to warming during those 100 years and should not be a priority.

With an infinite TH (equivalent to not including the effect of emission delay) all three phases are relevant. It is worth noting that for the infinite TH, the future emissions become highly uncertain, to the degree that these should preferably not be used to guide policy. It is highly uncertain and not meaningful to predict how the model parameters will develop over the next centuries. This uncertainty is greatly reduced in the 20 and 100-year THs, making them better suited for informing mitigation efforts.

3.2. Statistical emissions of building types and subparts

Figs. 9–12 show emissions for various building types and subparts with 80 year lifetimes and 100-year THs. Equivalent figures for other THs can be found in E. With a limited number of buildings, the material use, design characteristics, and study specifics of individual buildings will highly influence the emission profile. The building type and subpart emissions must, therefore, be interpreted together with the error bars showing the standard deviation (if sample size > 1).

Buildings with larger quantities of wood tend to have lower emissions, both due to biogenic carbon sequestration and lower emissions from material production, where wood products substitute the use of higher emission intensity products. The high waste emission factors (α_{was}, β_{was}, γ_{was}) for buildings and subparts with large quantities of wood products is compensated by high uptake factors (β_{bio}, γ_{bio}), especially in long THs. The carbonation factor (β_{cem}) is low compared to other emission factors; its mean value for all buildings lies within −13 and −8.5 gCO_2 per kg of all building materials in the buildings (95% confidence). Carbonation accounts for an average of $4 \pm 1\%$ (95% confidence) of total construction phase emissions for all buildings, given a 100-year lifetime and an infinite TH. Shorter lifetimes and finite THs reduce the importance.

The tech factors cause roughly a halving of future emissions (B- and C-phases), and the delay factors roughly another halving on top of that. Two effects explain the variation of tech factors among emission sources: technological development (Table 1) and timing of replacements. The variation in delay factors is explained solely by the timing of future emissions.

Fig. 9 shows metrics for each typology and emissions calculated from the metrics. The comparison is restricted to the buildings' envelope, foundation, and structure (building element 2) since this is the system boundary in most case studies. There is no clear correlation between higher emissions and their quantities and emission factors. The construction phase (A) dominates, while the future lifecycle phases operation (B) and end-of-life (C) are much less significant. The average net emissions in the construction phase are 402 ± 89 $kgCO_2e$, in the operation phase they are -54 ± 59 $kgCO_2e$, while the end-of-life phase is barely present at 9 ± 6 $kgCO_2e$ (95% confidence). The relative contributions of A, B, and C will, however, largely depend on the chosen TH and building lifetime. The construction phase is the same in all THs, but the equivalents for B and C are -4 ± 4 $kgCO_2e$ and 36 ± 17 $kgCO_2e$ in a 20-year TH, and -130 ± 100 $kgCO_2e$ and 284 ± 208 $kgCO_2e$ in a 500-year TH. The confidence intervals are expected to be smaller for a dataset with more case buildings of similar characteristics.

Fig. 10 shows metrics for timber and concrete building types and emissions calculated from the metrics. The comparison is restricted to building element 2. Although the timber buildings perform better on average, there is large variation within both building types. The timber content cannot alone explain this variation.

Figs. 11 and 12 explore building elements and material categories of all buildings. Fig. 11 shows metrics for each building element and emissions calculated from the metrics. The figure is split into three hierarchies, where the top hierarchy 0: 'Whole building' shows the results for all materials included in the system boundaries. The next hierarchy shows these same emissions split into building elements (one-digit), that are again split into more specific building elements (two-digit). The majority of emissions can be attributed to the main building structure (building element 2; corresponds to 'All buildings' in Fig. 9). 'Electric power' is also responsible for a significant proportion due to photovoltaic panels on some buildings.

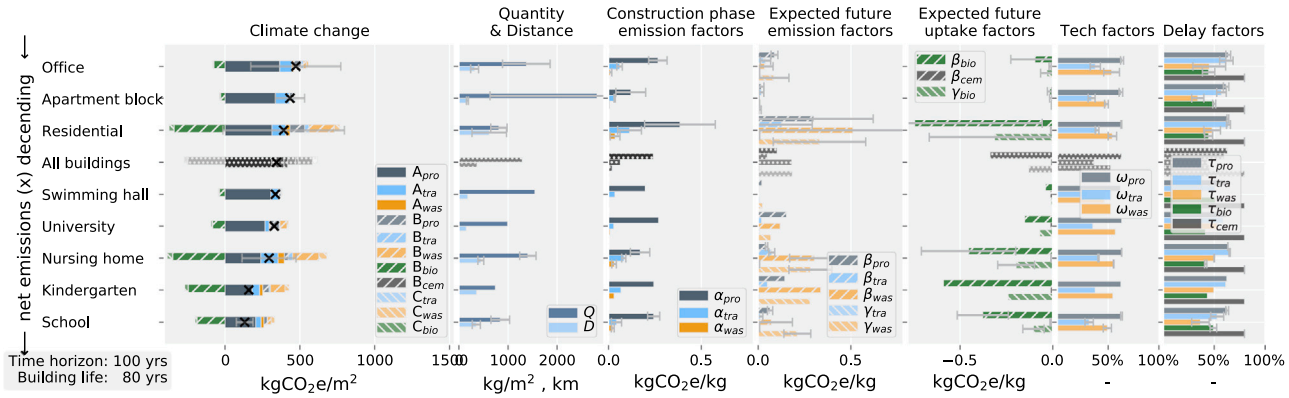

Fig. 9. Emissions and average metrics for building types; building element 2. Average building type metrics used to calculate emissions. Standard deviation shown in error bars.

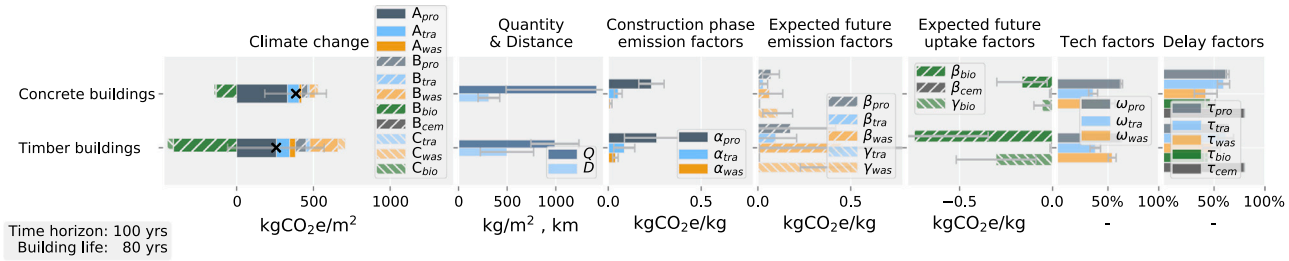

Fig. 10. Emissions and average metrics for timber (>1/4 biomaterials by weight) and concrete building types (≤ 1/4 biomaterials); building element 2. Average building type metrics used to calculate emissions. Standard deviation shown in error bars.

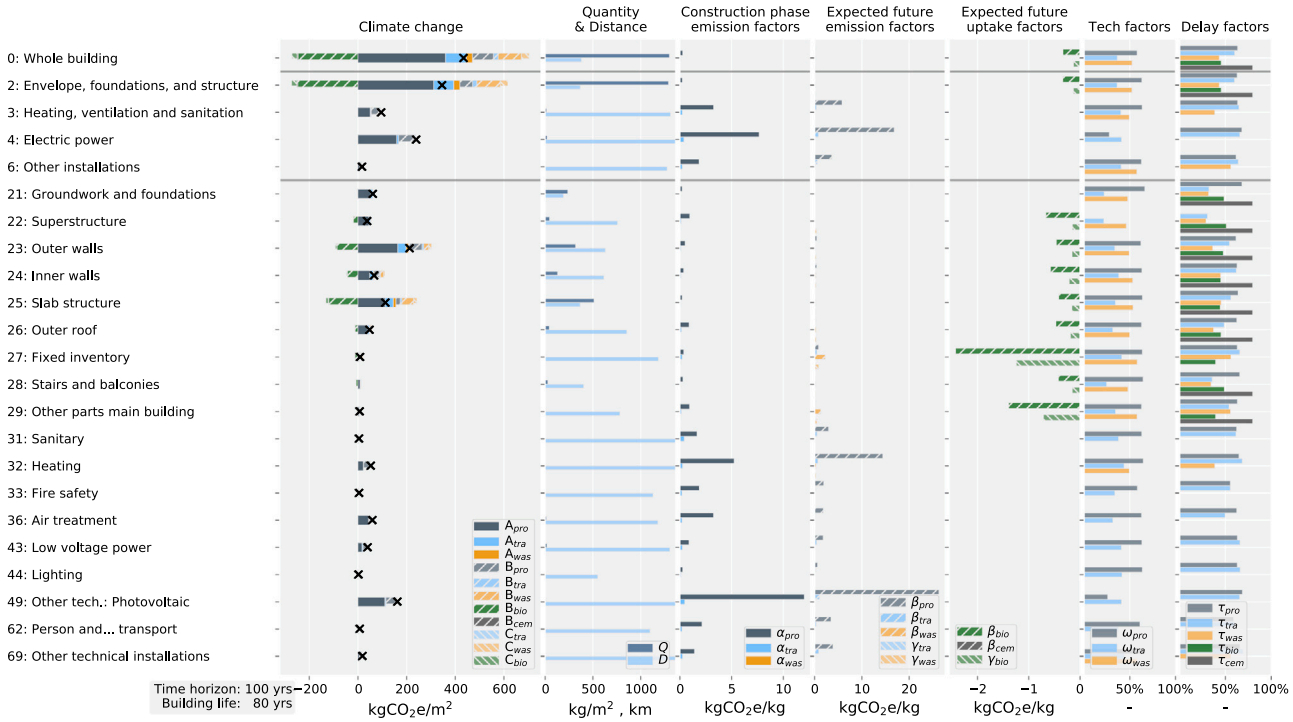

Fig. 11. Emissions and average metrics for building elements; all buildings; all building elements where data exists. Horizontal lines divide the three hierarchies. Average building type metrics used to calculate emissions. Standard deviation shown in error bars.

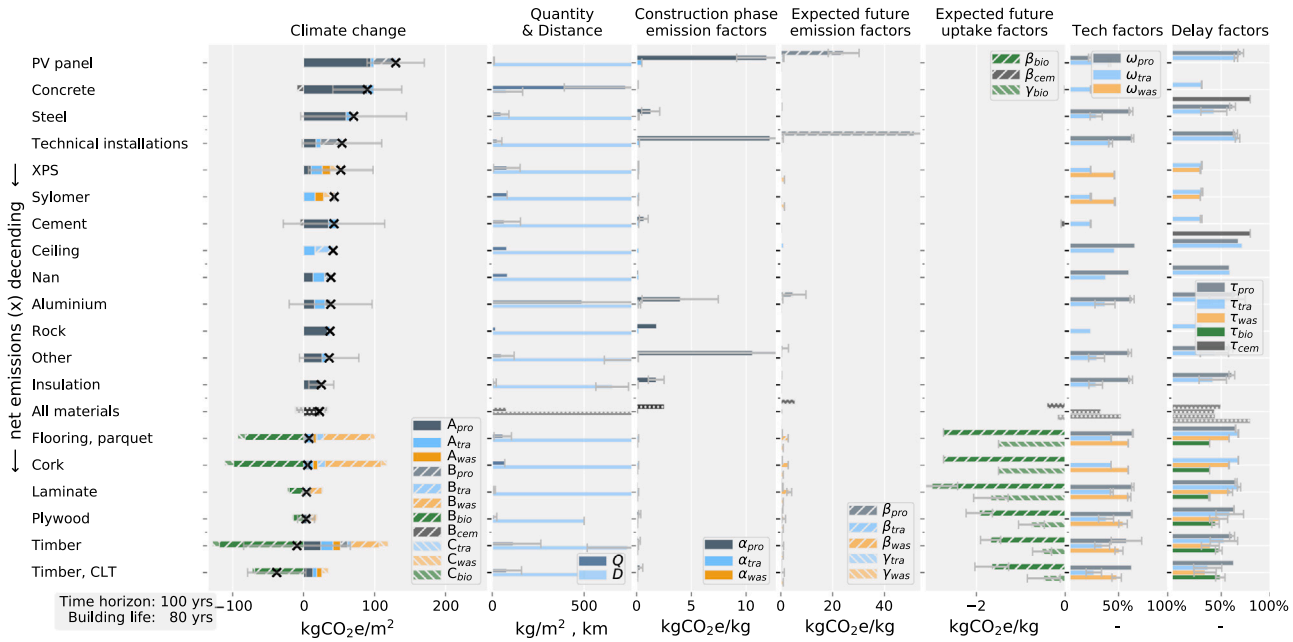

Fig. 12. Average emissions of material categories in all buildings (not calculated from metrics). Material categories with low contribution (positive and negative) omitted. Standard deviation shown in error bars.

Fig. 12 shows the average emissions of each material category (not calculated from metrics). Material categories contributing little to total building emissions are excluded from the figure.[2] Of the remaining material categories, the ones with biogenic carbon have the lowest average contribution to building emissions. Emissions vary widely within most material categories, seen as standard deviation in the error bars. Based on the material use in the case buildings, both promising material categories for reduced climate change and culprits can be identified. However, the material categories must be evaluated together with their structural, functional, thermal, and aesthetic properties.

3.3. Sensitivity of methodological choices

Fig. 13 shows the distributions of sampled results and the resulting total sensitivity indices of the global parameters. The assumption is uniform distributions within the parameter ranges shown in the figure. Only sensitivities of the global study parameters are investigated, not those of the underlying material inventory data.

Parameter sensitivities highly depend on the TH, which is a normative choice. GSAs are therefore performed for varying (20–500 years) as well as fixed (20, 100, 500 years) THs. When TH is allowed to vary together with the parameters, it is by far the most sensitive model parameter and is responsible for $61 \pm 10\%$ (95% confidence) of the model variance, followed by building lifetime at $16 \pm 3\%$ (95% confidence). The remaining sensitivities relate mainly to the end-of-life incineration of construction waste and biogenic carbon sequestration. The sampled results vary widely, between −0.3 and +0.5 tons CO_2e/m^2 (95% confidence). Thus, climate change impact cannot be determined with any meaningful accuracy without specifying TH; results are not very useful for policy if the sensitive parameters are not precisely known.

For shorter THs, however, results become much more precise. With the assumption of an accurate material inventory, 95% of results are between 0.39 and 0.53 tons CO_2e/m^2 in a 20-year TH, and between 0.20 and 0.50 tons CO_2e/m^2 in a 100-year TH. In the 500-year TH, the variation is on scale with the GSA where TH varies. Thus, shorter THs yield more precise results, while long THs (i.e. predicting impacts far into the future) are highly uncertain. Parameter sensitivities change in short THs: building lifetime is not relevant for THs around 100 years or shorter. The rotation period is highly sensitive for the 100-year, but not for other THs.

Independent of TH, carbon content of bioproducts, fraction incinerated, and waste fraction are always highly sensitive. This calls for refining both the modeling of these effects and the data inputs used, to reduce these uncertainties. For policy, it suggests that limiting construction waste and increasing reuse, recycling, and CCS should be high priorities.

Values of sensitive parameters should be chosen with care. Uncertainties of insensitive parameters do not affect the model output much, hence, it is less important that these are precise. The TH should be a deliberate normative model choice defining the temporal scope of the research question. For the remaining sensitive parameters, more precise estimates can be obtained empirically, which will reduce their sensitivities.

Choice of statistical distribution for future events is explored in D.1: The chi-square distribution and normal distribution with time-dependent variance are found most fit. Integer numbers of replacements should be avoided since they will lead to abrupt changes in results when material and building lifetimes change, and fractional numbers will underestimate replacement emissions. The importance of choosing an appropriate distribution is especially important if dynamic effects are not considered or under long THs.

Choice of TH is further explored in D.2: The A-phase is independent of TH. Longer THs lead to higher emissions from the B-phase. The importance of the C-phase increases for THs longer than building lifetime.

Choice of building lifetime is further explored in D.3: In general, shorter lifetimes lead to lower impact from the B-phase and higher impacts from the C-phase. The A-phase is independent of building lifetime, while the B- and C-phases greatly depend on it in long THs.

[2] The excluded categories contribute less than 10% of the maximum absolute sum of positive and negative emissions, and are 'Acoustic insulation' 'Asphalt' 'Bitumen roofing' 'Brick' 'Carpet' 'Coating' 'Copper' 'Doors' 'EPS' 'Elevator' 'Flooring' 'Flooring, ceramic tiles' 'Flooring, tiles' 'Glass' 'Glass wool' 'Granite' 'Gravel' 'Gypsum' 'Gypsum, plaster' 'Heat pump' 'Hot water tank' 'Insulation, mineral' 'Linoleum' 'Membrane' 'Paint' 'Plastics' 'Rubber' 'ST collector' 'Sink' 'Timber, Gluelam' 'Vinyl' 'Windows' 'Wood wool'.

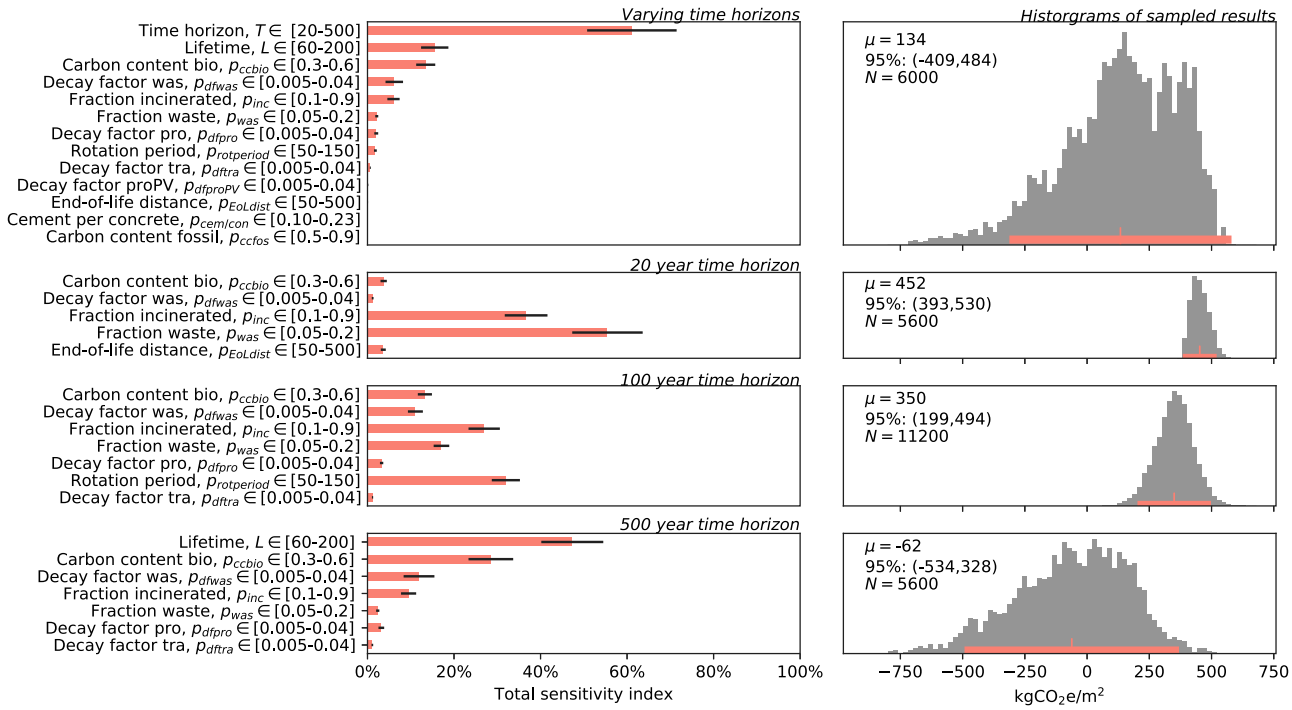

Fig. 13. Relative sensitivity of the global study parameters for various THs (left) calculated from sampled model results (right). The black lines (left) are 95% confidence intervals of the sensitivity indices. The orange bar (right) shows the mean μ and 95% confidence interval of the N sampled results. For the 20, 100, and 500-year THs, parameters that contribute less than 1% are not shown.

Building lifetime is an unknowable parameter, and under long THs it contributes to large uncertainty in the results of the future lifecycle phases, while its contribution to uncertainty is greatly reduced with shorter THs.

4. Discussion

4.1. Acknowledging uncertainty

In the complex system of processes related to a building and the quantification of impacts many decades into the future, there are great uncertainties that one should be aware of. First, the inventory data must be accurate for its intended purpose, which again must match the purpose of the assessment. This is not always the case for emission intensity data, inventory quantity data, etc. Secondly, both the timing and the nature of several future events cannot be known with any certainty. This should be reflected in the implementation of the dynamic effects, which is here modeled without adding superfluous complexity. This makes the method transparent, understandable, and open to scrutiny while reducing the chance of errors.

A major advantage of the method offered in this study is that the temporal assessment of dynamic effects reduces model uncertainty. Future technological progress is uncertain, indeed, but the assumption of *some* development is better than *none*; including the phenomena of technological progress improves on previous methods. The inconsistency of products with different THs is resolved by accounting for delayed emissions. An additional benefit of factoring in the timing of emissions is that the discounting is inversely proportional to the uncertainty due to time. The further into the future, the larger are the uncertainties, however, these increasing uncertainties will be offset by weighting emissions by their distance into the future. Technological development has the same uncertainty-reducing property. Additionally, results are less sensitive to uncertain parameters such as building lifetime. By significantly reducing the uncertainty of postulated future impacts, this is an important step in the direction of more policy-relevant modeling. The shorter the TH, the more the results can be trusted.

Imputation of missing data involves uncertainties. Nevertheless, a sufficiently good imputation strategy enables use of more data in the analysis, contrary to excluding that data and accepting underestimation and weaker analyses. The imputation strategy is based on the expected value of similar materials, implying that the larger the dataset the better the strategy will work.

A GSA should be performed for all complex models, especially for models used to guide policy [8]. The GSA ranks the model's sensitivity to changes in parameters. Parameters with high sensitivity indices are contributing highly to model uncertainty, and are therefore important to assume accurately. It is less important to have precise values for the parameters with low sensitivity indices because a change in these will not change the results much. Additionally, sensitivity was explored by testing the effect of model assumptions.

4.2. Harmonization of data and assumptions

This study has a unique advantage over previous statistical studies in literature, since the complete inventory of each building makes it possible to redefine the system parameters and test assumptions. This allows for a deep harmonization of assumptions and parameters among all case buildings. Furthermore, data uncertainties can be mitigated by statistical power and the representativeness of results improves as the dataset grows. Results are representative only of the range of typologies addressed and Norwegian conditions. The method, however, can be applied to any typologies and geographic conditions.

4.3. Delayed emissions

When using GWP (CO_2 equivalents) for emissions that occur far into the future, it is methodologically and policy-wise inconsistent not to assess impacts by use of a dynamic framework. A TH is included by default in the GWP indicator (usually 100 years) and to later ignore this TH in the LCIA is inconsistent. If there are significant quantities of GHGs other than CO_2 this could invalidate those results. The importance of this inconsistency will, however, be small in cases where CO_2 is the dominant GHG.

Building LCAs often collect climate change data for building materials from EPDs, where single-valued results make time-profile distinction between the GHGs impossible. The dynamic time horizon method presented in this paper can be used even for such aggregated CO_2e emission intensities. A problem remains: the climate change impacts of inventory data in this study are GWP_{100}, thus, the application and results will only be completely consistent for the 100-year TH. Other THs will always be consistent for CO_2 emissions, but not for the share of CO_2e linked to other GHGs. This is a limitation that may be acceptable considering the applicability of the proposition, especially in cases where CO_2 is the dominant GHG. The limitation can be resolved by matching the TH of the GWP of the inventory with the TH used to account for delayed emissions.

The use of a consistent TH not only ensures methodological quality and reduces uncertainty, it also answers a research question much more relevant for policy than does an infinite TH; namely '*What will be the cumulative impact over the TH, of choices made today?*' in contrast to the impossible question of what will happen in the unforeseeable future.

4.4. Subpart metrics

The quantity, distance, emission-, tech-, and delay factors are weighted average values of the inventory items in the subpart, describing the subpart's environmental performance. In this paper, the metrics are used for generating statistical emission profiles of building types. Additionally, these metrics are relevant for the interpretation of results, as design drivers, and for benchmarking and verifying LCA calculations. Another use is as proxy values in early-phase planning and for emission sources and building elements outside the study scope. Furthermore, non-dynamic building LCA results can be adjusted for technology and delay effects by multiplication with the tech and delay factors.

4.5. Limitations

There are some limitations that the reader should be aware of. Climate change effects outside the study scope are listed in the Methods section; this study focuses on material use in buildings. Emission sources such as energy use at the construction site and during operation are also highly important to consider.

This study uses process-based attributional LCA. Input–Output, Hybrid, and Consequential LCA are more relevant for answering certain research questions and are compatible with the presented methodology.

A specific indicator is used; dynamic GWP within a TH. Other aspects of the climate system such as feedback mechanisms, temporal impacts to radiative forcing and temperature changes are not targeted, and results can change when using other indicators.

The GSA results in this study depend upon the inventory; an inventory with different material composition would result in other sampled distributions and parameter sensitivities. In further work, the GSA should incorporate the variability of the material inventory, additional variables, mathematical relationships, and boundary conditions for a complete assessment of sensitivity. The GSA results also depend heavily on the uncertainty ranges of the parameters given in its input; further work should revise the ranges empirically.

The carbon content of timber products is a highly sensitive parameter and should in future studies be determined individually for each inventory item where possible, instead of assuming a fixed percent for all wood products.

Results are only representative for buildings of similar characteristics and are biased by the case-specific conditions and designs of these buildings. The case studies are designed and constructed according to Norwegian practice for Norwegian climate and designed for low lifecycle emissions. This limitation does not hinder the applicability of the proposed method, just the extrapolation of numerical results.

The proposed solution to account for delayed emissions provides an estimate of the total radiative forcing during any chosen TH, in units of CO_2 equivalents. Thus, GHGs other that CO_2 must first be converted to that unit. As discussed in 4.3, the method is accurate for any TH *as long as the GWP of the inventory uses the same TH*. When the TH of the inventory is different from the TH of the study, calculations will be correct for CO_2 emissions, however, inaccuracies will arise for the share of CO_2e representing GHGs other than CO_2. One should therefore consider if the share of non-CO_2 GHGs is significant, and in that case adjust the inventory to the respective TH or else be aware of this limitation.

For systems of radical uncertainty, i.e. unknowable uncertainty, as defined by [35], qualitative judgments are needed. Not all types of uncertainties and not all problems can be quantified. Building LCAs over large periods involve radical uncertainties that should be investigated further.

4.6. Implications for building LCA practice

Dynamic effects are obviously important in building LCAs. Technological progress is very likely to happen during the coming decades and should no longer be ignored in modeling. Time horizons of warming effects should also be clearly defined, where the chosen TH should reflect the goal of the LCA. Future events should be represented by random variables with time-dependent variance. Model choices and parameters should be conveyed and their global sensitivities should be assessed.

Biogenic carbon sequestration and end-of-life incineration of stored carbon in building products have important effects on climate change that should always be included, especially for long THs. Carbonation of cement products seems to play a minor role during the use phase and may be ignored.

This paper presents a simplification of the DLCA method [4] for including effects of delayed emissions, which can facilitate its implementation into building LCA practice. It works for any TH and enables application with emission intensities from EDPs. This simplification preserves the underlying assumptions and adheres to the physics of climate change. Previous research has argued that dynamic approaches need to be simple to allow wider use both by academics and practitioners, and that methodological developments should aim at striking a balance between improving accuracy and limiting additional complexity [20]. This paper presented a simple method that does not compromise accuracy. LCA software should adopt the best available scientific methodology and not vice versa.

4.7. Implications for policy

The proposed method increases policy-relevance. As a consequence of future technology improvements, reduced climate change effect of delayed emissions, and less uncertainty, reduction of near-future emissions should be prioritized over distant future emissions. Encouraging the active choice of a TH forces policymakers to make an important choice regarding the rate of mitigation efforts.

Even with equal assumptions and methodology, the differences in material inventories of the 20 case buildings lead to large differences in results, but despite the variation, there are some trends. Mitigation of carbon embodied in material use should focus on the emissions happening in the construction phase, while emissions in the operation and end-of-life phases are much less important and much more uncertain. Buildings dominated by wood products have lower impacts, especially over long THs. Among the building elements included in the examined case studies, emissions from outer walls, slabs, and PV are dominating. Among the material categories, priority for low-emission products or alternative materials should be on PV panel, concrete, and steel, to mention some. Biomaterials can have climate mitigation effects and are promising alternatives.

5. Conclusions

A building can operate for centuries and this long lifetime introduces time-dependent effects that dynamic LCA can account for: technological progress will lead to lower future emission intensities; postponed emissions have lower warming potentials over a given TH; carbon stored temporarily in building products and the timing of its future oxidation can have mitigation benefits; carbon sequestration happens both in regrowth of trees and in building products containing cement. These effects are usually ignored in LCA studies of buildings. This paper proposed a robust methodology for, first, creating a dynamic inventory, and then, including these effects for any chosen TH.

The IPCC urges nations to rapidly reduce emissions to stay below the global temperature increase targets. The timing of emissions has implications for the climate change effect over the TH, and to limit the warming effect of human activities within the next 20 to 100 years, these effects can no longer be ignored. Overall, the temporal dimension is key to climate mitigation in the building sector. We show that a dynamic TH of T years can be modeled by multiplying dynamic emissions with the simplified function $2 - e^{\frac{\ln 2}{T} y}$ for each year y in the TH. This simplification can potentially make emission delay a default component of building LCA practice.

Future events that are highly uncertain should not be depicted as equally accurate as near-future events. The introduction of technology improvements and delayed emissions greatly reduces uncertainty related to future events. Decisive parameters such as the building lifetime also have less influence on the results, and thus on the conclusions and implications for policy. We regard this as an important step in the direction of more policy-relevant modeling.

The method was applied on the material inventory dataset of 20 case buildings, harmonized to get a more consistent comparison and statistical treatment. The main focus of embodied carbon mitigation efforts should be on the near-future construction phase impacts since these dominate the lifecycle emission profile and can be more immediately influenced in building design as well as by policy. Reducing emissions from waste incineration also has significant mitigation potential. Limiting construction waste and increasing reuse, recycling, and CCS should be high priorities. The use of wood products in buildings can have mitigation effects, mostly over long THs. Carbon uptake in cement products is only a fraction of construction phase emissions; hence, choosing alternative materials or low-carbon concrete is outweighing the effect of carbonation. Future technology improvements may lead to a rough halving of future emissions, and emission delay leads to another halving of their climate change effect the next 100 years, making these dynamic effects responsible for about a 3/4 reduction of future emissions.

Emission results vary widely depending on parameter choices, with time horizon, building lifetime (long TH only), and waste related parameters responsible for most of the model uncertainty. The differences in material inventories of the 20 case buildings also lead to large differences in results. Statistical inference can be improved by applying the demonstrated modeling approaches to a larger dataset of building case studies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.buildenv.2020.107399.

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