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Application of probability distributions to the modeling of biogenic CO_2 fluxes in life cycle assessment

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Abstract

In life cycle assessment (LCA), the same characterization factors are conventionally applied irrespective of when the emissions occur (the same importance is given to emissions in the past, present, and future). When the assessment is constrained by fixed timeframes, the appropriateness of this paradigm is questioned and the temporal distribution of emissions becomes of relevance. One typical example is the accounting for biogenic CO_2 emissions and removals. This article proposes a methodology for assessing the climate impact of time-distributed CO_2 fluxes using probability distributions. Three selected wood applications, such as fuel, nonstructural panels, and housing construction materials are assessed. In all the cases, CO_2 sequestration in growing trees is modeled with an appropriate forest growth function, whereas CO_2 emissions from wood oxidation are modeled with different probability distributions, such as the delta function, the uniform distribution, the exponential distribution, and the chi-square distribution. The combination of these CO_2 fluxes with the global carbon cycle provides the respective changes caused in CO_2 atmospheric concentration and hence in the radiative forcing. The latter is then used as basis for climate impact metrics. Results demonstrate the utility of using emission and removal functions rather than single pulses, which generally overestimate the climate impact of CO_2 emissions, especially in presence of short time horizons. Characterization factors for biogenic CO_2 are provided for selected combinations of biomass species, rotation periods, and probability distributions. The time discrepancy between biogenic CO_2 emissions and capture through regrowth results in a certain climate impact, even for a system that is carbon neutral over time. For the oxidation rate of wooden products, the use of a chi-square distribution appears the most reliable and appropriate option under a methodological perspective. The feasibility of its adoption in LCA and emission accounting from harvested wood products deserves further scientific considerations.

Keywords: bioenergy, biomass, distributed emissions, global warming, LCA

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Introduction

Background

With the increasing acknowledgement of the threats caused by global warming (GW) and the continuous international efforts on reaching a post-Kyoto agreement on greenhouse gas emission reduction (GHG), there is a growing scientific, political, and economic interest to ensure that we have robust and scientifically sound methods to appropriately account for GHG fluxes caused by human activities. Life cycle assessment (LCA) is the dominant framework for the assessment of environmental impacts, including GHGs, from production systems. Even if the accounting procedures in LCA may keep track of temporal distribution of emissions from different processes (e.g., at different phases in a product life cycle), the prevailing paradigm assumes equal importance across time for all stressors. The appropriateness of this assumption for specific cases has resurfaced in last few years. In particular, tipping point issues and commitment periods and targets provide motivation for time-constrained assessment approaches. Time boundaries are also implicit in the utilization of the Global Warming Potential (GWP) index, which has fixed time horizons (THs). Because of them, the climate impact caused by an instantaneous single pulse emission is different from the impact due to the same magnitude released in a different year or at a small rate over a certain number of years. In general, the issues associated with the timing of emissions and removals in LCA have been recognized in earlier studies (Azar & Sterner, 1996; Hellweg *et al.*, 2003; Hofstetter, 1996). In particular, Hellweg *et al.* (2003) explored the possibility to use economic discounting in the con-

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text of LCA, arguing that temporal cutoffs are a special case of discounting with a discount rate of zero for the TH considered and of infinity thereafter (because emissions occurring beyond the temporal cutoff are entirely disregarded).

In recent years, the debate around timing of emissions has been revitalized by the need to consistently include in bioenergy LCA emissions from essentially two sources: direct and indirect effects associated with land-use change (LUC), and delayed emissions from biomass storage in the anthroposphere or biosphere. Concerning LUC emissions, they usually occur in the first years after establishment of bioenergy systems, and a straight-line amortization of these emissions over a certain time period is traditionally applied. Examples of this practice can be found both in primary research studies (Cherubini & Ulgiati, 2010; Gnansonou *et al*., 2008; Searchinger *et al*., 2008) and methodological standards or guidelines (EU, 2009; IPCC, 2003; PAS2050, 2008). Concerning delayed emissions due to carbon storage, the majority of the papers assumes that CO_2 is released as a single pulse after a specific storage period in the biosphere (Fearnside *et al*., 2000; Kirschbaum, 2003, 2006; Moura Costa & Wilson, 2000) or in the anthroposphere (Clift & Brandão, 2008). Moura Costa & Wilson (2000) calculate the time period over which sequestered carbon should be stored to counteract the radiative forcing (RF) effect of a CO_2 emission. Kirschbaum, (2003, 2006) addresses the consequences for the climate of storing carbon in vegetation, concluding that permanent storage can lower atmospheric CO_2 concentration, whereas temporary storage can be beneficial for climate impacts related to cumulative CO_2, but can be counterproductive if other metrics are considered. Fearnside *et al.* (2000) quantify the benefits for the climate of delaying emissions, thanks to the proportional shift of the impact beyond the selected TH. Clift & Brandão (2008) follow this approach to assess the credits from storing carbon in products.

Besides single pulse, some studies also considered emissions as distributed over time. At first, these papers were in the context of emissions from harvested wood products (HWP) in national GHG inventories (Ford-Robertson, 2003; IPCC, 2006; Karjalainen *et al*., 1994; Marland & Marland, 2003; Marland *et al*., 2010; Pingoud & Wagner, 2006; Row & Phelps, 1996). Karjalainen *et al.* (1994) propose the use of a logistic curve to model the CO_2 emission rate, Row & Phelps (1996) use a three segment curve, and Ford-Robertson (2003) compares the linear and exponential decay. Marland & Marland (2003) and Pingoud & Wagner (2006) model the changes in stocks of wood products using differential equations to describe the rates of production and oxidation with first-order exponential decay. The IPCC (2006) Guidelines[1] recommend the adoption of a first order decay for the oxidation of wood products based on their half-life, at the same time acknowledging that this is not the only possible assumption (IPCC, 2006). Marland *et al.* (2010) insightfully propose the use of a distributed approach to account for carbon in wood products. In addition to the debate around HWP, time-distributed emissions have been increasingly investigated within a pure LCA context as well (Cherubini *et al*., 2011; Kendall *et al*., 2009; Levasseur *et al*., 2010; Müller-Wenk & Brandão, 2010; O'Hare *et al*., 2009). Kendall *et al.* (2009) elaborate a time correction factor to be applied to emissions from LUC treated as a single pulse amortized over time. O'Hare *et al.* (2009) develop alternatives to simple discounting and summing of GWPs over the life cycle after straight-line amortization of emissions. Levasseur *et al.* (2010) investigate the challenges in harmonizing the TH used in GWP and the time boundaries of the analysis: the climate impact of an emission at year 50 is considered for 100 years in GWP, that is, from year 50 to 150, even if the analysis has a time boundary of 100 years. They overcome this issue making the TH for the integral in GWP flexible, so to get dynamic characterization factors for each year of the assessment period. Müller-Wenk & Brandão (2010) assume that LUC emissions occur as a pulse, but sequestration for restoring the ecosystem occurs over several years, so that the lifetime of biogenic CO_2 in the air is directly proportional to the ecosystem relaxation time. While developing characterization factors for the climate impact of CO_2 emissions from biomass combustion, Cherubini *et al.* (2011) focus on the interaction between biogenic CO_2 emissions and the global carbon cycle, modeling the carbon sink created by biomass regrowth as a dynamic CO_2 removal flux from the atmosphere.

Aims and objectives

Greenhouse gas balances of bioenergy systems generally follow the standard conventions regarding no-preference for time (zero discount rate) in LCA, and therefore, they usually bypass the temporal issue of time discrepancy between CO_2 emissions (through combustion or oxidation) and removals (through vegetation growth). This results in implicitly adopting the common conven-

[1]The IPCC 1996 guidelines suggested the default assumption that in a given year, there is no net change in the carbon stored in the pool of HWP. The rationale for this was the assumption that the oxidation rate is equal to the production rate, on an annual basis. This is mathematically equivalent to assuming that all the carbon is released to the atmosphere soon after harvesting as a single pulse.

tion of the carbon and climate neutrality of bioenergy. In the recent years, this convention has been criticized by an increasing number of studies (Cherubini *et al.*, 2011; Johnson, 2009; Möllersten & Grönkvist, 2007; Reilly & Asadoorian, 2007; Searchinger, 2010; Searchinger *et al.*, 2009). Neglecting the distribution over time of CO_2 fluxes is appropriate if the analysis has an infinite time frame, but is questioned when specific time boundaries are set. The international debate on climate mitigation policies and agreements make extensive use of time-related targets. Tipping point concerns have strengthened demand for short-term targets. This also has some implications for LCA practices related to GHG and climate impacts. As the questions posed by policy makers change, the tools and metrics to answer them might also need some adaptations.

In this article, we aim at providing more insights into the modeling of time-distributed CO_2 fluxes and their climate impacts, investigating options to assess delayed and distributed emissions from biogenic sources with different metrics. In theory, estimating the rate of CO_2 fluxes to and from the atmosphere can be based on statistical data on production and fate of all organic products, but this implies a considerable accounting effort. This article proposes a simpler approach, showing a methodology where relatively simple mathematical methods are used to model time-distributed CO_2 flows and their climate effects. Different probability distributions are used to model the oxidation rate of three biomass products (wood as fuel, nonstructural panels, and housing construction material), whereas the Schnute function (parameterized with the default values from IPCC for boreal forest) is used to model CO_2 sequestration through biomass regrowth. In the next section, the methodology to account for the change in CO_2 atmospheric concentration caused by time-distributed fluxes is presented. Then, each distribution is described and applied to the selected wood applications. The resulting CO_2 atmospheric profiles are used to calculate the respective changes in RF, and then the corresponding climate impacts are quantified and discussed using different metrics. The focus here is placed on CO_2 fluxes from biomass systems, which are a perfect example of distributed emissions (through combustion or oxidation) and removals (i.e., sequestration from biomass growth), but the same methodology can be successfully applied to other types of emissions or resources.

Methods

Dynamics of atmospheric CO_2 concentration

All types of CO_2 emissions and removals cause a perturbation to the CO_2 atmospheric concentration, thereby causing a climate impact. The change in atmospheric CO_2 concentration can be modeled by means of the impulse response function (IRF), which describes the perturbation of a dynamic system caused by some external change. Among the existing IRFs, the IRF from the Bern CC model is here used to predict the atmospheric decay of anthropogenic CO_2. This function represents the fraction of CO_2 remaining in the atmosphere after a single pulse emission depending on the interactions between the atmosphere, the oceans, and the terrestrial biosphere (Joos *et al.*, 1996, 2001). This IRF $y(t)$ has the following analytic form (Forster *et al.*, 2007):

$$y(t) = A_0 + \sum_{i=1}^{3} A_i e^{-t/\beta_i}, \tag{1}$$

where $A_0 = 0.217$, $A_1 = 0.259$, $A_2 = 0.338$, $A_3 = 0.186$, $\beta_1 = 172.9$, $\beta_2 = 18.51$, $\beta_3 = 1.186$. The profile of this curve is shown as a benchmark in the Results section. The amplitude A_0 represents the asymptotic airborne fraction of CO_2 which remains in the atmosphere because of the equilibrium response of the ocean–atmosphere system. The amplitudes A_i may be interpreted as the relative capacity of the other sinks, which are filled up by the atmospheric input at rates characterized by the relaxation time scales β_i.

The time-distributed emissions and removals of CO_2 follow this decay, and the analytical combination of these fluxes with the IRF for anthropogenic CO_2 provides the corresponding change in CO_2 atmospheric concentration. In mathematical terms, this is implemented with a convolution between the emission and removal functions with the CO_2 decay from the air:

$$f(t) = \int_0^t \left[C_0 e(t') - C_0^* g(t')\right] y(t - t') \mathrm{d}t' \tag{2}$$

where t' is the integration variable from the time since harvest, t is the time dimension, C_0 is the intensity of the emission (here a unit pulse is assumed, so $C_0 = 1$), C_0^* is the intensity of the removal (a carbon neutral system is modeled, so $C_0 = C_0^* = 1$), $e(t')$ is the emission function, $g(t')$ is the CO_2 removal rate from the atmosphere (due to biomass regrowth), and $y(t)$ is the IRF from the carbon cycle climate model. This equation integrates the dynamics of the biomass system within the global carbon cycle to get the resulting CO_2 atmospheric profile. Further physical implications and interactions of the biomass system with the global CO_2 fluxes and sinks can be found in more specific papers (Cherubini *et al.*, 2011; Sitch *et al.*, 2003; Strassmann *et al.*, 2008). Following Eqn (2), we can write:

$$f(t) = \int_0^t e(t') y(t - t') \mathrm{d}t' - \int_0^t g(t') y(t - t') \mathrm{d}t'. \tag{3}$$

The first part of the integral represents the atmospheric CO_2 concentration response to distributed CO_2 emissions, whereas the second integral considers distributed CO_2 removals due to biomass regrowth, here modeled as a negative emission. Solutions are computed via numerical approximations.

Distributed CO_2 removal

In this article, we consider that biomass comes from a plantation kept under continuous rotation. This means that once biomass resources are harvested and converted into products, the same species are replanted and they start sequestering CO_2 from the atmosphere, sometimes before the harvested carbon is oxidized. In this article, the Schnute model (a comprehensive growth model with statistically stable parameters; Schnute, 1981) is used to reproduce the sequestration of atmospheric CO_2 in the growing forest, following common practice in forest modeling (Feng, 1997; Yuancai *et al.*, 1997; Zhao-gang & Feng-ri, 2003). The growth model can be expressed by the following function:

$$G(t) = \left(\alpha + \beta e^{\gamma t}\right)^{\delta}, \tag{4}$$

where

$$\alpha = y_1^b + \frac{\left(y_2^b / y_1^b\right)}{1 - e^{-a(T_2 - T_1)}}, \tag{5}$$

$$\beta = \frac{e^{aT_1}\left(y_2^b - y_1^b\right)}{1 - e^{-a(T_2 - T_1)}} \tag{6}$$

$$\gamma = -a \quad \text{and} \quad \delta = \frac{1}{b}, \tag{7}$$

The variable t is the time dimension, T_1 and T_2 are the initial and final age of the interval, y_1 and y_2 are the corresponding values of the function at T_1 and T_2, a is the constant acceleration in growth rate, and b is the incremental acceleration in growth rate. Equation (4) represents the cumulative growth. The annual growth rate needed for Eqn (3) is given by its derivative:

$$g(t) = \delta\beta\gamma e^{\gamma t}\left(\alpha + \beta e^{\gamma t}\right)^{\delta - 1}. \tag{8}$$

The IPCC default factors for managed and native coniferous boreal forest (with average above ground carbon stock of 40 and 50 t C ha^{-1}, respectively) are used to customize this growth curve. Additional conditions and details about the definition of the other parameters for this function can be found in a recent paper (Cherubini *et al.*, 2011), together with the resulting curve profile.

Distributed CO_2 emissions

In this section, we investigate the use of probability distributions to model the oxidation rate of C over time. We assume specific mean lifetimes (τ) for the three selected wood uses: 2 years for fuel (Marland *et al.*, 2010), 30 years for nonstructural panels (IPCC, 2003),[2] and 150 years for housing construction material (Skog, 2008).[3] The following probability distributions are modeled: a delta dirac function (simply called delta function), used to simulate a single pulse emission; a uniform distribution, where the emission is equally spread over a certain number of years; an exponential distribution, based on a first-order decay; a chi-square distribution, where the emissions are distributed around the expected lifetime. All these distributions are normalized, so that their emission intensity is always equal to one (in mathematical terms: the integral of all the curves from zero to infinity is one). Figure 1 shows the profiles of these distributions for wood use as fuel and Fig. 2 for wood as nonstructural panels (distributions for wood as housing construction material are not shown because the curves are similar to those in Fig. 2, but translated over t to model the mean lifetime at 150 years). The analytical derivations and logical implications of these functions are explained hereinafter.

*Delta function $\delta(t)$*We use the delta function to model CO_2 emissions occurring at a specific point in time as a single pulse. The use of this function is a common practice in the literature, both for emissions occurring at $t = 0$ or after a certain number of years if a storage period in the anthroposphere or biosphere is considered (Kirschbaum, 2003, 2006; Pingoud & Wagner, 2006). The delta function is a generalized function that it is zero for all values of the parameter but a single point, when all the carbon is oxidized to the atmosphere. We assume that this point corresponds to the expected lifetime, τ, except when wood is used as fuel (for which we assume $\tau = 0$, so to better reproduce mainstream practice in LCA). This function, which can be formally defined as a distribution, has the following analytical form:

$$\delta(t;\tau) = \begin{cases} \infty & t = \tau \\ 0 & t \neq \tau \end{cases}, \tag{9}$$

and its integral over time is by definition constrained to satisfy the identity (i.e., equal to one). The delta function is then included in Eqn (3) in place of $e(t')$ to get the biogenic CO_2 decay corresponding to this emission profile:

$$f(t) = \int_0^t \delta(t';\tau) y(t - t')\mathrm{d}t' - \int_0^t g(t') y(t - t')\mathrm{d}t'. \tag{10}$$

Thanks to the sifting property of the delta function (Bracewell, 1999), we have:

$$\int \delta(t';\tau) y(t - t')\mathrm{d}t' = y(t - \tau). \tag{11}$$

So that Eqn (6) can be written as follows:

$$f(t) = \begin{cases} -\int_0^{\tau} g(t') y(t - t')\mathrm{d}t', & \text{for } 0 \leq t < \tau \quad \text{(a)} \\ y(t - \tau) - \int_{\tau}^{t} g(t') y(t - t')\mathrm{d}t', & \text{for } t \geq \tau \quad \text{(b)} \end{cases}, \tag{12}$$

where $y(t - \tau)$ represents the onward decay of the pulse emission from $t = \tau$ ahead. The term (12a) describes the change in

[2]Table 3a.1.3 of the IPCC Good Practice and Guidance reports a default value of 20 years for the half-life ($t_{1/2}$) of nonstructural panels, like particle board. The mean lifetime is calculated using the formula $\tau = t_{1/2}/\ln(2)$, and corresponds to 28.85 (rounded to 30).

[3]Skog estimates a half-life of solid wood for single-family housing of 105 years in 2010, which corresponds to a mean lifetime of 151.5 years (rounded to 150 years).

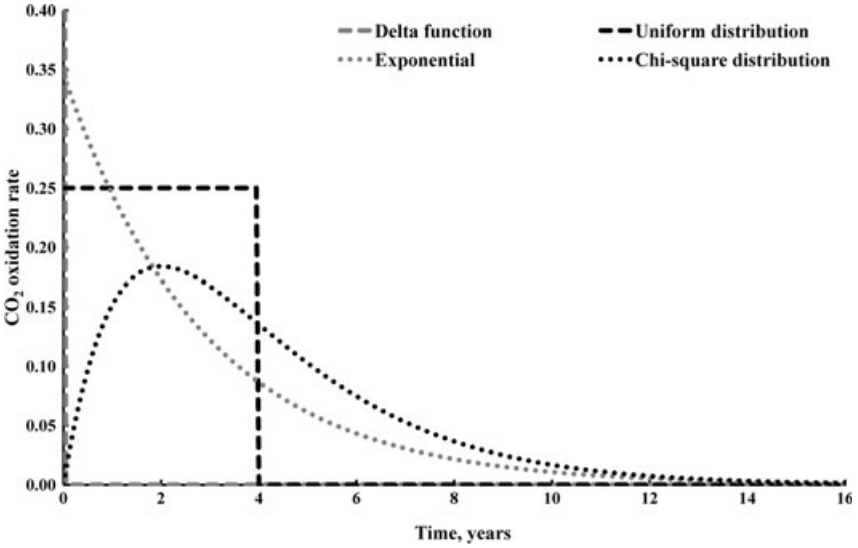

Fig. 1 Comparison of the probability distributions used to model the CO_2 emission rate for wood use as fuel.

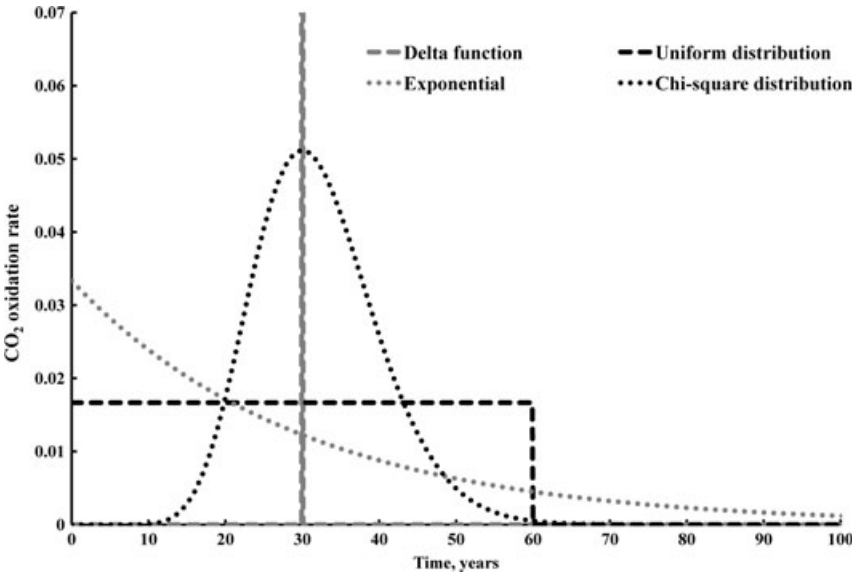

Fig. 2 Comparison of the probability distributions used to model the CO_2 emission rate for wood use as nonstructural panels.

CO_2 atmospheric concentration for the time period before the pulse emission, where the CO_2 sequestration from biomass regrowth is the only flux, whereas (12b) describes the decay after the pulse emission (with the remaining part of the growth).

Uniform distribution $\upsilon(t)$Rather than as a single pulse, emissions can be distributed over time. For instance, LUC emissions are frequently linearly amortized over a certain timeframe, implicitly assuming that each year has an equal share of CO_2 emissions. This practice, which can also be applied to wood products, is here modeled with a uniform distribution, where the amortization occurs over a period equal to two times the mean lifetime of the products:

$$\upsilon(t) = \begin{cases} \frac{1}{2\tau} & 0 < t < 2\tau \\ 0 & \text{otherwise.} \end{cases} \quad (13)$$

This function is then included as $e(t')$ in Eqn (3).

Exponential distribution $\varepsilon(t)$The exponential distribution is currently the dominant approach to model CO_2 emissions from wood products, as recommended by the IPCC guidelines for national GHG inventories. This is a first-order decay model, that is, the oxidation rate is proportional to the size of the pool (here assumed to be one, representing the carbon in a single product), which has the following expression:

$$\varepsilon(t) = e^{(-t/\tau)}. \quad (14)$$

The C oxidation rate, to be included in Eqn (3) as $e(t')$, is the first derivative of this equation. The adoption of this probability distribution means that the largest rate of oxidation occurs in the first years after production, and then gradually decreases over time, up to asymptotically approaching zero. Such an oxidation rate can be appropriate for few products only, because, in general, it is most likely that a particular product is oxidized at various times, but with the highest probability near its expected lifetime. Even wood used as fuel does not usually decay within the first year after harvest, because most of it is seasoned over several months to lower its water content so to increase its energy density and combustion efficiency. In the next paragraph, a more realistic oxidation rate is introduced.

*Chi-square distribution $\chi^2(t)$*A recent paper suggested the use of a gamma distribution to model the oxidation rate of wooden products (Marland *et al*., 2010). The gamma distribution, largely adopted for expected lifetime in probability theory and statistics, has two parameters that are used to customize the distribution to the specific case: a scale parameter β and a shape parameter α. Since no simple closed form expressions exist for the cumulative distribution function (Tadikamalla, 1978), these parameters can be estimated via numerical approximation using at least two data points, such as the expected lifetime and another point of the decay (e.g., the year when 95% of the biomass is oxidized). Due to the absence of extensive data on decay rates of wooden products besides expected lifetimes, this distribution has limitations for being routinely applied in LCA. To overcome this issue, a special case of the gamma distribution is considered in this article. When $\alpha = k/2$ and $\beta = 2$, where k is a positive integer, the chi-square distribution with k degrees of freedom is obtained. This distribution is of course less flexible than the gamma distribution, because it has a single variable parameter, but is sufficiently appropriate to model the oxidation rate of wooden products using their expected lifetime. In this article, we estimate k assuming that the year of maximum oxidation rate (e.g., the peak of the distribution) occurs in correspondence of the mean lifetime τ, knowing that the mode of the distribution is equal to $\max[k - 2, 0]$. For the wood products considered in this analysis, k is equal to $\tau + 2$, that is, 4, 32, and 152 for wood as fuel, nonstructural panels, and housing construction material, respectively.

The chi-square distribution can be analytically expressed in terms of the gamma function, with $t \geq 0$:

$$\chi^2(t;k) = \frac{1}{2^{k/2}\Gamma(k/2)} t^{((k/2)-1)} e^{(-t/2)}, \quad (15)$$

where t is the time dimension and $\Gamma(k/2)$ is the gamma function, defined as:

$$\Gamma(k/2) = \int_0^\infty x^{k/2-1} e^{-x} \mathrm{d}x. \quad (16)$$

Equation (15) can be included in Eqn (3) as $e(t')$ to model the resulting effect in atmospheric CO_2 concentration.

Climate metrics

Two main types of climate metrics can be identified, in relation to the treatment of time (Peters *et al*., 2011): absolute metrics, which compare the climate impact caused by different emissions over time (e.g., change in CO_2 atmospheric concentration, instantaneous and cumulative RF, instantaneous and cumulative temperature change), and normalized metrics, which quantify the climate impact relative to a reference gas (e.g., GWP). In the LCA community, the latter are dominating.

Marginal changes in atmospheric CO_2 concentration are computed using the following equation:

$$\Delta CO_2 = h_{CO_2} f(t), \quad (17)$$

with

$$h_{CO_2} = \frac{10^6 \text{ ppmv}/\text{MW}_{CO_2}}{m_{air}/\text{MW}_{air}} \left[\frac{\text{ppmv}}{\text{kg}}\right], \quad (18)$$

where MW_{CO_2} is the molecular weight of CO_2 (44 kg kmol^{-1}), m_{air} is the mass of the atmosphere (5.14×10^{-14} kg), and MW_{air} is the molecular weight of air (28.97 kg kmol^{-1}). Results are calculated assuming a constant background CO_2 atmospheric concentration (conservative estimate).

The function $f(t)$ is also the basis for the estimation of the resulting impact on GW through the concept of RF. The latter is the perturbation of the earth energy balance at the top of the atmosphere by a climate change mechanism. The time evolution of a change in radiative forcing, ΔRF, from 1 kg of emission at time zero is proportional to the atmospheric decay of the gas. This is the instantaneous RF equal to:

$$\Delta\text{RF} = \alpha_{CO_2} f(t), \quad (19)$$

where α_{CO_2} is the radiative efficiency of CO_2 per kg of emission (1.81×10^{-15} W m^{-2} kg^{-1}), assumed to be constant over time (Forster *et al*., 2007). The absolute global warming potential (AGWP) is given by the integral of ΔRF from zero up to a specific TH (either 20, 100, or 500 years). This value is compared with that of anthropogenic CO_2 in the GWP index. For the particular case of CO_2 emissions from biomass, we use the recently introduced notation GWP_{bio} (Cherubini *et al*., 2011):

$$\text{GWP}_{bio} = \frac{\text{AGWP}_{bioCO_2}}{\text{AGWP}_{CO_2}} = \frac{\int_0^{TH} \alpha_{CO_2} f(t)\mathrm{d}t}{\int_0^{TH} \alpha_{CO_2} y(t)\mathrm{d}t}. \quad (20)$$

Instead of considering only a pulse emission, we elaborate GWP_{bio} indices for emission distributed over time using the selected probability distributions.

One common criticism about GWP relates to the fact that, despite its name, it does not purport to represent the impact of gaseous emissions on surface temperature. In this article, we explore the possibility to use another indicator for GW, the global temperature change potential (GTP), which is gaining increasing interest in the research community (Boucher & Reddy, 2008; Fuglestvedt *et al*., 2010; Shine *et al*., 2005). This metric is a step further down in the cause and effect chain of the potential climate effect of emissions, and hence more relevant

than GWP, and provides the surface temperature change at a particular time in the future. The AGTP is defined as the global change in surface temperature at a TH induced by 1 kg of emission and has a unit of K kg^{-1}. It is computed here as a convolution of an impulse temperature response function $\delta T(t)$ with the time profile of the change in RF. The function $\delta T(t)$ is the climate response in terms of global surface temperature change and is estimated from an IRF to RF:

$$\delta T(t) = \sum_{i}^{2} \frac{c_i}{d_i} e^{-t/d_i}, \tag{21}$$

where $c_1 = 0.631$ and $c_2 = 0.429$ in $K(W\ m^{-2})^{-1}$ and $d_1 = 8.4$ and $d_2 = 409.5$ in years. This function was derived from more than 1000 simulated years of an experiment with the HadCM3 climate model (Boucher & Reddy, 2008). The climate responds with a short time scale d_1 and a longer time scale d_2, and the equilibrium climate sensitivity, as the sum of the c_i coefficients, is 1.06 K $(W\ m^{-2})^{-1}$. This function is used to estimate the global surface temperature change at a TH from a given RF profile:

$$\mathrm{AGTP} = \int_0^{\mathrm{TH}} \Delta \mathrm{RF}(t)\delta T(\mathrm{TH} - t)\mathrm{d}t. \tag{22}$$

The GTP is finally presented as the ratio between the AGTP for a given species to that of CO_2:

$$\mathrm{GTP} = \frac{\mathrm{AGTP}_{\mathrm{bioCO_2}}}{\mathrm{AGTP}_{\mathrm{CO_2}}} = \frac{\int_0^{\mathrm{TH}} \Delta \mathrm{RF}_{\mathrm{bioCO_2}}(t)\delta T(\mathrm{TH} - t)\mathrm{d}t}{\int_0^{\mathrm{TH}} \Delta \mathrm{RF}_{\mathrm{CO_2}}(t)\delta T(\mathrm{TH} - t)\mathrm{d}t}. \tag{23}$$

Results

Absolute metrics

The first tier results from our modeling efforts are the curves portraying the outcomes of the absolute metrics: changes in atmospheric CO_2 concentration (proportional to the instantaneous RF), cumulative (or integrated, AGWP) RF, and instantaneous and integrated change in surface temperature.

Figure 3 shows the perturbation response functions (PRFs) obtained for the different wood uses (constant background atmospheric CO_2 concentration is assumed and the value at year zero is set equal to zero). These curves are obtained by combining the global carbon cycle model with the different probability distributions introduced above (used to model the oxidation rate of the three selected wood applications) and the Schnute function that simulates the CO_2 sequestration from growing trees. The graph compares the profiles of atmospheric CO_2 concentration when the delta function (δ-PRF), the uniform distribution (υ-PRF), the exponential distribution (ε-PRF), and the chi-squared distribution (χ-PRF) are used to model CO_2 oxidation rates. The atmospheric decay of anthropogenic CO_2, emitted as a single pulse at $t = 0$, is also shown for comparison in Fig. 3a. The latter is appropriate for biogenic CO_2 in case of biomass combustion soon after harvest and deforestation (i.e., no biomass regrowth). The profiles of the curves in Fig. 3a show differences for the first decade after harvest, and then follow a similar trend. The δ-PRF is the case in which forest wood is directly used for bioenergy and all the CO_2 is released as a single pulse at $t = 0$. It shows a profile similar to anthropogenic CO_2 in the early years, and then accelerates its decay trend when the sequestration rate from growing trees increases. Even if a C neutral system is modeled here (the same quantity C_0 of CO_2 is emitted and removed), the effect of this biogenic CO_2 emission on atmospheric concentration is evident, and the biomass system is not climate neutral.

When other emission functions are used, the intensity of the pulse is distributed over time and the maximum value of the resulting PRF is lower, because a fraction of the CO_2 emitted at time $t - 1$ has already decayed at time t. The larger the distribution of the emission over time, the smaller the maximum value of the respective PRF is. In the long run, all the curves asymptotically tend to zero. At first sight, the presence of negative values, especially for the δ-PRF, may appear inconsistent, because the amount of CO_2 in the atmosphere is lower than the level before the emission, even if a carbon neutral system is modeled. There is a physical interpretation for this effect (Cherubini *et al.*, 2011). Soon after the emission, when the biomass growth rate is still slow, a significant fraction of the CO_2 originally released is quickly stored in the ocean upper layer. The following transport of this C to the deep ocean layers is slower, and when the uptake by the onsite biomass regrowth increases, the C initially stored in the ocean upper layer will be released back to the atmosphere at a low rate to compensate the initial over-absorption (out-gassing). In the long term, the airborne fraction of CO_2 approaches zero.

Figure 3b shows the profiles of the atmospheric CO_2 concentration when the different distributions are used to model the oxidation rate of wood used as nonstructural panels. Here, the differences among the curves are more pronounced. The δ-PRF starts with a sequestration and then emission at $t = 30$ years as a single pulse, the χ-PRF goes below zero in the first two decades because emissions are distributed around $t = 30$ years and the other PRFs are based on functions where emissions are distributed over time starting from year zero. Because of that, they do not turn to negative values soon after $t = 0$, as the δ-PRF and χ-PRF. The υ-PRF reaches a constant value until a clear inflection point at $t = 60$ years, when the emission function goes to zero, and so does

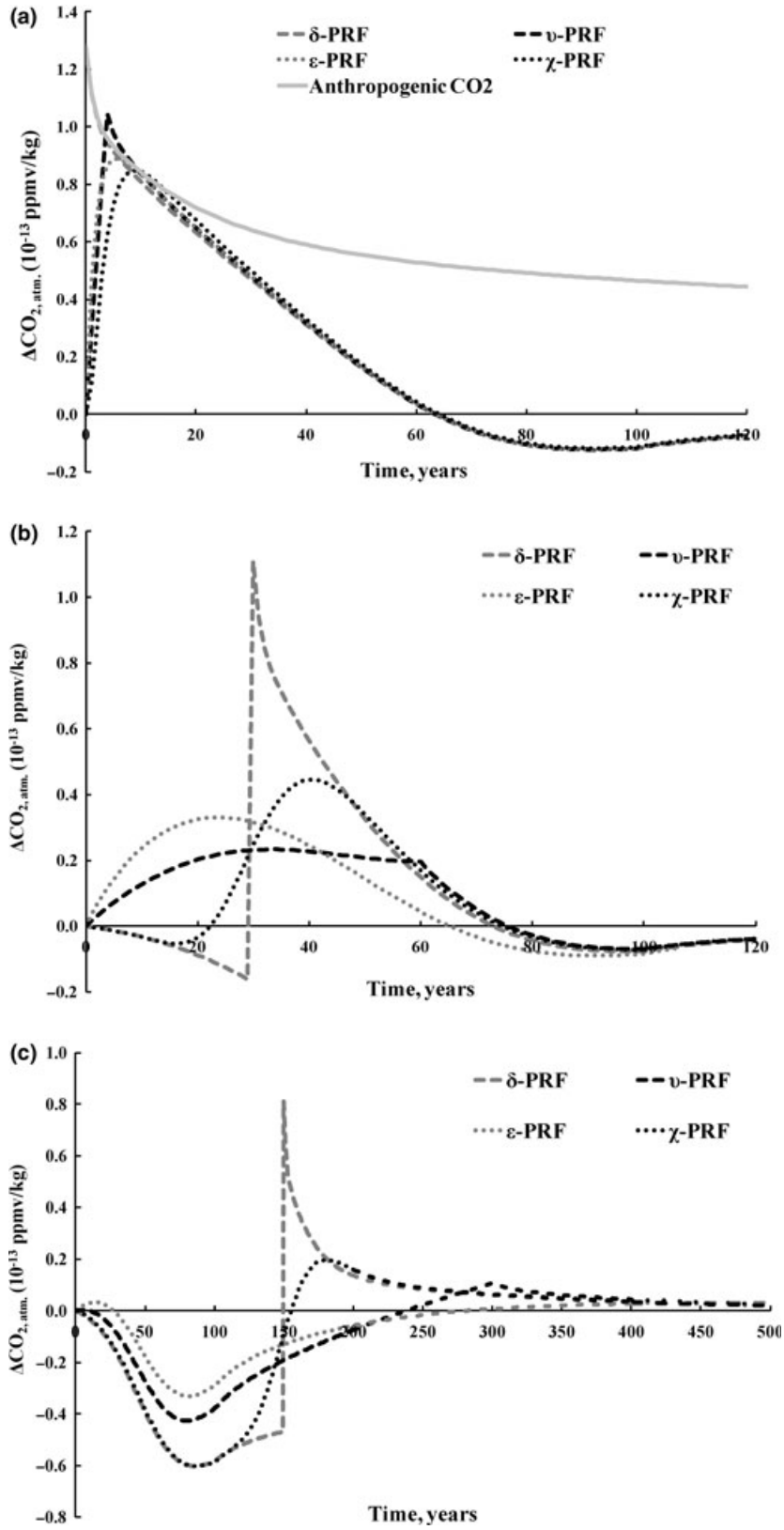

Fig. 3 Marginal changes in CO_2 atmospheric concentrations when wood is used as (a) fuel (τ = 2), (b) nonstructural panel (τ = 30), and (c) housing material (τ = 150) according to different emission functions.

the PRF. After approximately 100 years, the curves show similar profiles.

Figure 3c shows the results obtained by modeling the oxidation rate of wood for housing construction materials with different distributions. In this case, the differences among the curves are largely distributed over time, suggesting that the influence of the emission function on the results increases with the mean lifetime of the products. All the PRFs have negative values for a relatively long timeframe and the δ-PRF reaches the lowest negative values, because it has no emissions until year 150, where all the CO_2 is released as a single pulse. During this time period, the sequestration of CO_2 through biomass regrowth is the only perturbation of the system. The χ-PRF has a profile similar to δ-PRF for the first years, because it assumes emissions distributed around the year of maximum oxidation rate, so that emissions are very limited in the first years. The υ-PRF has a small fraction of emissions over 300 years (two times the mean lifetime), where it has a clear inflection point, after which the CO_2 atmospheric fraction asymptotically tend to be zero as the other curves. The ε-PRF is characterized by the largest rate of emissions in the first years, so that this emission of CO_2 partially offset the CO_2 sequestered by growing trees occurring in the first 100 years. This is the reason for the smaller values of this function while negative.

Figure 4 shows the cumulative or integrated radiative forcing (AGWP), of the three wood uses for the different probability distributions. The AGWP of a pulse of anthropogenic CO_2 released at $t = 0$ is shown for comparison. While the AGWP from a pulse emission of anthropogenic CO_2 gradually increases over time because of the nonzero asymptotic value of the decay (see Eqn 1), all the AGWPs of biogenic CO_2 tend toward a similar constant value within a specific timeframe. As for the previous cases, the influence of the type of probability distribution used is small for the case of wood as fuel (Fig. 4a) and as nonstructural panel (Fig. 4b), while it is more relevant for longer biomass storage periods (Fig. 4c). In the latter case, AGWPs are largely negative, meaning that a total cooling effect occurs.

Changes caused in surface temperature are shown in Fig. 5, only limited to the case in which the oxidation rate of the wooden products is modeled with the chi-square distribution. Again, the effect caused by a pulse emission of anthropogenic CO_2 at year zero is shown as a benchmark. Figure 5a shows the instantaneous surface temperature change, whereas Fig. 5b shows the cumulative effect. Results are in line with the other outcomes, highlighting the large long-term benefit for the climate of CO_2 emissions from biomass rather than fossil and the relatively long storage periods needed to have a total cooling effect when boreal forest biomass is used.

Normalized metrics

Rather than showing climate impacts as a function of time, LCA studies traditionally report the final outcomes using normalized metrics like the GWP. Results for the three most common THs of 20, 100, and 500 years are shown in Table 1. The use of the GWP_{bio} index is identical to the other GWP equivalency factors: it is a characterization factor to be multiplied by the total CO_2 emissions from biomass oxidation (or total CO_2 sequestered in biomass) to get their relative contribution to GW in terms of kg CO_2-eq. The values are always smaller than one. Values close to one mean that the release of a unit of biogenic CO_2 has the same climate impact (in terms of cumulative emissions for the GWP_{bio} and surface temperature change potential for GTP) of a single unit pulse emission of anthropogenic CO_2 at year 0. When the index is smaller than zero, there is a net cooling effect.

Results show the importance of the probability distributions used to model emissions and the TH considered. When wood is used as fuel, the results for the delta function represent the climate impact of CO_2 from direct combustion for bioenergy, which is not zero because of the time discrepancy between emissions and removals. The use of other distributions leads to smaller values, meaning that the more distributed the intensity of emission over time, the lower the climate impact is. In general, the chi-square distribution shows the lowest values. For long THs, the influence of the emission function is reduced. The delta function and the chi-square distribution show similar figures, except for the case of wood used as fuel. The uniform and exponential distribution have the highest values for TH = 20 for long storage periods, because they simulate emissions from the beginning. Of particular interest are the results when wood is used as housing construction material. For TH = 20 and 100, the delta function is the only function that does not have any emissions (which occur at $t = 150$), only sequestration of CO_2 from regrowth during the first 100 years. This points out an important aspect: the value of GWP_{bio} with TH = 100 is -0.57, and not -1.00, as it would be expected, since up to 100 years there is only the sequestration of CO_2 in growing trees and no emissions from carbon oxidation. This means that the climate impact of CO_2 fluxes cannot be estimated by simply summing up the flows to and from the atmosphere to get either a positive or a negative net balance (as traditionally done in LCA), but the time profile of emissions is of capital importance in presence of a TH. A physical interpretation of this aspect is also possible: the removal of CO_2 from the air changes the concentration gradient between the atmosphere and the other carbon sinks, the oceans, and the

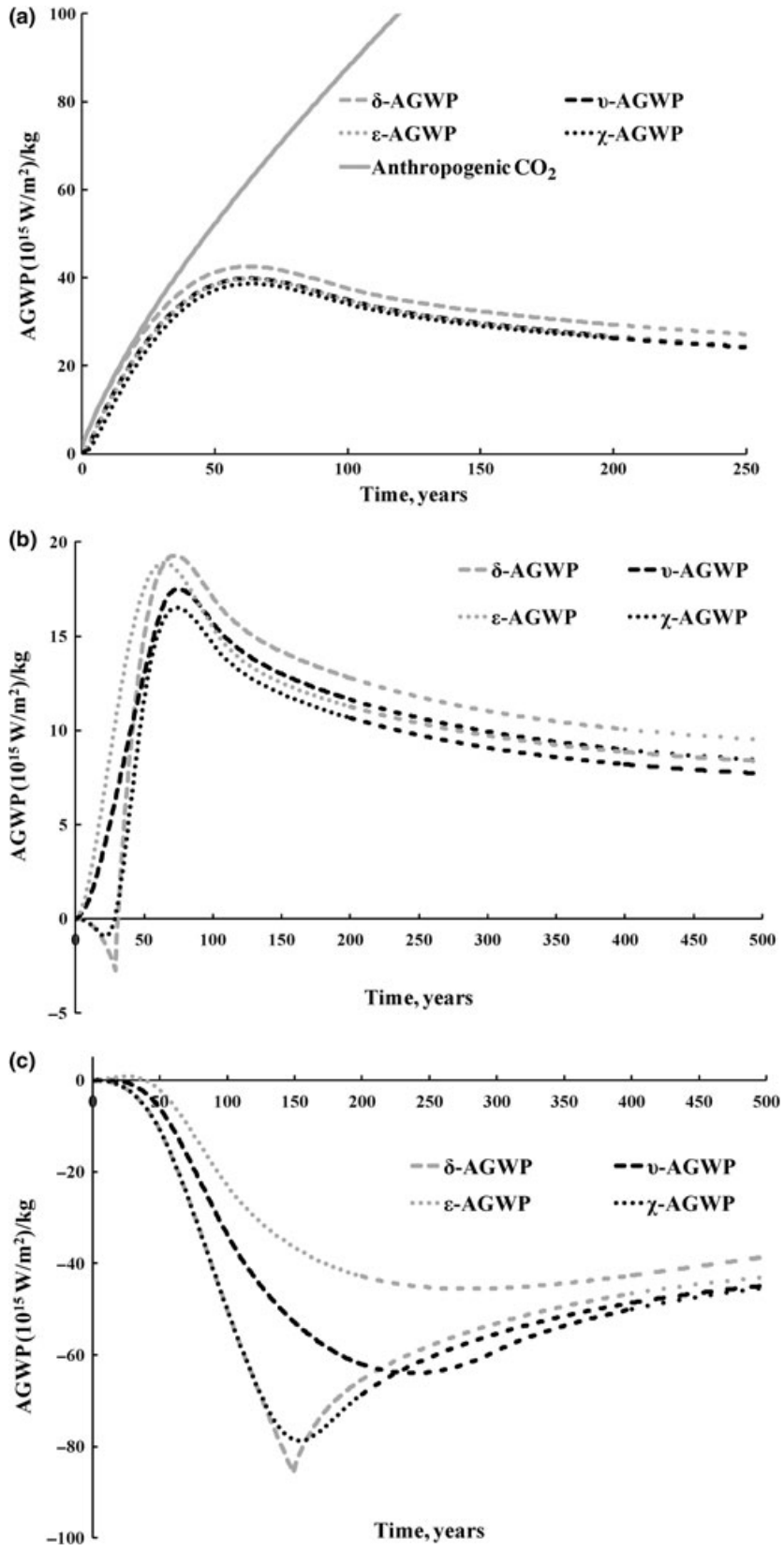

Fig. 4 Cumulative radiative forcing (or absolute global warming potential, AGWP) when wood is used as (a) fuel (τ = 2), (b) non-structural panel (τ = 30), and (c) housing material (τ = 150) according to different emission functions.

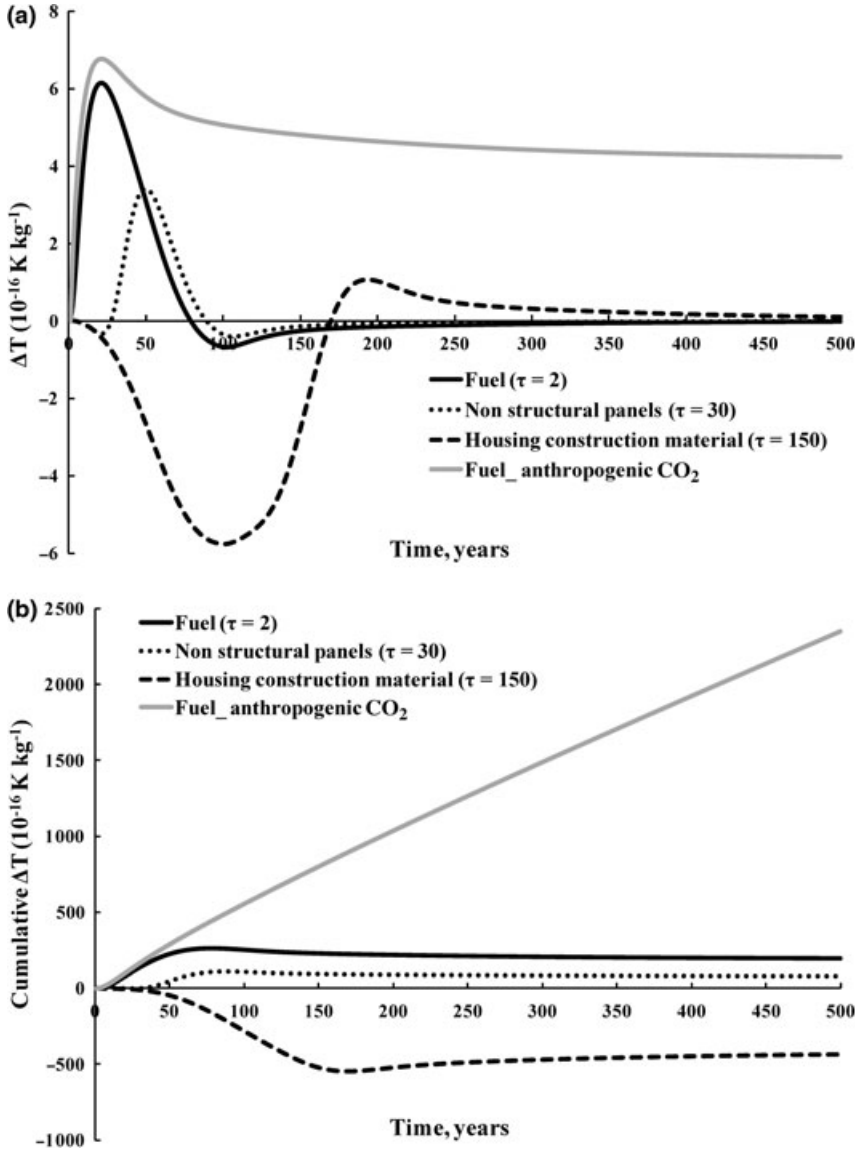

Fig. 5 Instantaneous (a) and cumulative (b) surface temperature change caused by CO_2 emissions from different wood uses (fuel, nonstructural panels, and housing construction material), using the chi-square distribution to model the oxidation rate. Results for emissions of anthropogenic CO_2 from combustion of fossils are shown for comparison.

terrestrial biosphere, and thereby reduces their subsequent inherent rate of CO_2 removal from the atmosphere. Some CO_2 is hence released from the other sinks, especially the oceans, to the atmosphere, so to compensate for the change in the concentration gradient and tend to a new equilibrium. This effect has been already observed in other papers as well (Kirschbaum, 2003, 2006).

The values of GTPs differ slightly from those of GWP_{bio}, since they give more weight to the RF that comes later in the time period. In particular, it appears that the use of the GWP index for short-term mitigation targets significantly overestimate the effective climate impact in terms of surface temperature change of biogenic CO_2 emissions, while it is the opposite for longer TH.

Table 2 shows some characterization factors (GWP_{bio} with TH = 100) for selected combinations of biomass species, represented by the different rotation periods (r = 1 year for annual crops and r = 100 years for boreal forest), and wood uses, represented by the expected lifetimes, when a chi-square distribution is used to model the CO_2 oxidation rate. These values include the CO_2 sequestration from biomass regrowth, simply modeled using a Gaussian distribution centered on the year corresponding to half the rotation period. For short

Table 1 GWP_{bio} and GTP for three wood uses using different probability distributions as emission functions

	GWP_{bio}			GTP		
	TH = 20	TH = 100	TH = 500	TH = 20	TH = 100	TH = 500
Wood as fuel						
Delta function	0.96	0.43	0.07	0.97	0.49	0.09
Continuous distribution	0.87	0.41	0.07	0.84	0.46	0.08
Exponential distribution	0.87	0.40	0.07	0.84	0.46	0.08
Chi-square distribution	0.79	0.39	0.07	0.71	0.45	0.08
Wood as nonstructural panels						
Delta function	−0.04*	0.19	0.03	−0.03*	0.21	0.04
Continuous distribution	0.14*	0.18	0.03	0.11*	0.20	0.04
Exponential distribution	0.25*	0.18	0.03	0.20*	0.21	0.04
Chi-square distribution	−0.04*	0.17	0.03	−0.03*	0.19	0.03
Wood as housing construction material						
Delta function	−0.04*	−0.57a	−0.15	−0.03*	−0.51a	−0.18
Continuous distribution	−0.01*	−0.34a	−0.16	0.00*	−0.29a	−0.18
Exponential distribution	0.03*	−0.26a	−0.14	0.03*	−0.23a	−0.15
Chi-square distribution	−0.04*	−0.58a	−0.16	−0.03*	−0.51a	−0.19

*TH shorter than τ.
GWP, global warming potential; GTP, global temperature change potential; TH, time horizon.

Table 2 Characterization factors (GWP_{bio} with TH = 100) for selected biomass rotation periods and expected lifetimes of biomass products in the anthroposphere or biosphere

	Expected lifetime τ (years)									
Rotation period (years)	2	4	6	10	15	20	30	50	70	100
1	−0.02	−0.04	−0.06	−0.09	−0.13	−0.17	−0.25	−0.43	−0.63	−0.93
4	−0.01	−0.03	−0.05	−0.08	−0.12	−0.16	−0.24	−0.42	−0.61	0.91
8	0.00	−0.01	−0.03	−0.06	−0.10	−0.14	−0.22	−0.40	−0.60	−0.90
12	0.02	0.00	−0.01	−0.05	−0.09	−0.13	−0.21	−0.38	−0.58	−0.88
16	0.03	0.02	0.00	−0.03	−0.07	−0.11	−0.19	−0.37	−0.56	−0.87
20	0.05	0.03	0.02	−0.01	−0.05	−0.09	−0.18	−0.35	−0.55	−0.85
40	0.13	0.12	0.10	0.07	0.03	−0.01	−0.09	−0.27	−0.47	−0.77
60	0.22	0.20	0.19	0.16	0.12	0.08	−0.01	−0.18	−0.38	−0.68
80	0.31	0.29	0.28	0.25	0.21	0.17	0.08	−0.09	−0.29	−0.59
100	0.39	0.38	0.36	0.33	0.29	0.25	0.17	−0.01	−0.20	−0.50

The oxidation rate of biomass products is modeled with a chi-square distribution, the sequestration through vegetation growth with a Gaussian distribution.
GWP, global warming potential; TH, time horizon.

biomass rotation periods, values are negative (revealing a total cooling effect), whereas when the length of the rotation increases, longer expected lifetimes of the products are needed to have characterization factors lower than zero.

Discussion

Implications

The explicit modeling of CO_2 fluxes with probability distributions and their integration within the global carbon cycle represents a flexible and consistent methodology to assess the climate impact of the various biomass and bioenergy systems (including direct combustion, wood storage, afforestation, and others). This type of dynamic analysis, adaptable to different metrics, meets the target of policy makers for studies where impacts from emissions should be assessed within specific time boundaries.

In this article, we have provided examples where wood is used for direct production of energy, as nonstructural panels or as housing construction material. For each of them, probability distributions are used to

model the CO_2 oxidation rate of the products. When biomass is directly used as fuel, the δ function is appropriate for modeling CO_2 emissions as a single pulse, because the other functions lead to similar results (except when TH = 20). When energy production is not the primary use of the biomass, and its average lifetime in the anthroposphere increases, modeling emissions as occurring as a single pulse might not be appropriate anymore, especially for short THs, and probability distributions should be used to better represent the oxidation rate of the product. The choice of the probability distribution should be consistent with empirical observations and logically correct. For instance, if a wood product is going to be burnt after a certain number of years, the use of a delta function is still correct because it is the best representation of emissions from stationary combustion. However, this condition is not common and quite impractical. Once biomass is harvested, it is sold to the market and the producers usually do not have precise information about the end of life of the product. So rather than a delta function, it is often better to model emissions from biomass oxidation with time-distributed functions, so to better take into account the probability of product oxidation for each year. The use of a uniform distribution is a first attempt toward this direction, but it has the risk to be an excessive oversimplification. In fact, it is conceptually based on the amortization of emissions over a specified, sometimes arbitrary, timeframe, rounding the effect of CO_2 on the ΔRF. The use of an exponential distribution, as promoted by the IPCC guidelines, implies that the product has the largest oxidation rate in the first years after its production. In general, the longer the expected lifetime of the product, the less likely the oxidation rate follows an exponential trend. The chi-square distribution represents an appropriate function to be used for this purpose, because it considers that a particular product will most likely be oxidized near its mean lifetime. Given the limited availability of reliable data on the oxidation rates of HWP besides mean lifetimes, the use of a chi-square distribution rather than a gamma distribution is introduced to simplify the modeling in LCA applications. If more specific data on decay rates will be publicly available in the future, the utilization of a gamma distribution becomes preferable, because of its larger flexibility.

Furthermore, the probability distributions can be parameterized in a way to account for the different pathways a biomass product can have in the anthroposphere prior to being oxidized, such as recycling or oxidation under anaerobic conditions in landfills. Concerning the modeling of CO_2 removal from the atmosphere by growing biomass after harvest, a single negative pulse is appropriate for annual crops, but becomes inadequate for biomass with a longer rotation period. In these cases, more specific biomass growth functions should be considered.

Limitations

Although the methodology to model the change in CO_2 atmospheric concentration and RF caused by time-distributed fluxes is solid and robust, uncertainty and, potentially, inaccuracy are brought on by the choice of the metric to measure the impact on the climate. The choice of the metric is a debated issue (Fuglestvedt *et al.*, 2003, 2010; IPCC, 2009; Shine *et al.*, 2005). The interpretation of results in Tables 1 and 2 should follow the considerations that they are based on fixed timeframes, from zero to TH, independently of when emissions occur. When emissions are distributed over time, especially if they are near or beyond the TH, these normalized metrics have serious shortcomings, despite their large use in the LCA community. Regarding the cases analyzed in this work, this particularly applies for temporal wood storage in products, where emissions can overlap with the TH considered. As already noticed by other authors (Melillo *et al.*, 2009; Peters *et al.*, 2011; Schwietzke *et al.*, 2011), in these cases absolute metrics are preferable, because they portray the instantaneous (Fig. 3) or integrated (Fig. 4) climate impact as a function of time. In the case of carbon storage, when looking at instantaneous impacts, analysts and policy makers are challenged by the proper evaluation of the short-term cooling effect against a possible warming effect in the later years, whereas integrated impacts provide clearer indications on the dynamics of the total climate effects (Fig. 4c clearly shows that the total contribution is a cooling effect). The presence of a TH simultaneously requires an accurate modeling of the CO_2 fluxes occurring before and a consideration of the potential impacts occurring afterwards. Because the impacts after the TH are entirely disregarded and not measured, caution should be paid to those activities that simply move the warming impact beyond the TH.

As an example of this issue, Fig. 5 shows the change caused in the surface temperature of CO_2 emissions from the oxidation of the three investigated wood products when the chi-square distribution is used to model the oxidation rate. This figure clearly shows that the effect on surface temperature lasts for more than 150 years for wood use as fuel and nonstructural panels, and ca. 500 years for wood as housing construction material. The selection of a shorter TH would lead to partial results: for example, if a TH of 100 years is chosen, for τ = 2 years only the initial warming effect is measured while the long-lasting cooling effect is missed, whereas for τ = 150 years only a part of the cooling

effect is covered and the following long-lasting warming contribution is completely ignored (it is the opposite for integrated impact, Fig. 5b, where a substantial cooling occurs after 100 years).

Net CO_2 fluxes from biomass systems have varying dynamics and several metrics can be used to assess the impacts on climate, bearing different and sometimes contrasting information. These issues should gather increasing attention from LCA practitioners. As insightfully noticed by Peters *et al.* (2011), 'a debate should be open in the LCA community on the impact category GW', aiming at revisiting the emission metrics considered and the treatment of time in complex biomass and bioenergy systems.

Finally, the results presented in Tables 1 and 2 should not be over-interpreted. The objective here is to compare different options at a methodological level, and before deriving general conclusions about the suitability of one wood option over the other, there are life cycle-based considerations and specific local parameters to be considered. Aspects that can potentially overturn the results are efficiency in biomass conversion processes, number of rotations, selection of proper time and spatial boundaries, LUCs, and other life cycle implications (such as material and energy inputs for cultivation, harvesting, processing, and transport).

Final remarks

In presence of time boundaries, the climate impact of biomass or bioenergy systems cannot be estimated through a net balance of the CO_2 fluxes to and from the atmosphere, but it is to be computed using their temporal profiles and integrating the biomass system within the global carbon cycle. This article elaborated a flexible methodology, based on specific probability distributions, which is not restricted to CO_2 emissions from biomass but can be adapted to other stressors and energy sources. Among the investigated functions, the chi-square distribution emerges as a promising option that can be adapted to describe the oxidation rates of all the selected product classes, requiring only one parameter (e.g., the mean lifetime) for its definition. The choice of the metric with its TH is crucial for the climate assessment of the system, and caution should be made when interpreting results in cases where large perturbations occur close to the end of the time window. For biomass systems characterized by time-distributed emissions, absolute metrics showing the variation of the climate impact over time are preferable over more traditional normalized metrics, such as GWP. Results vary depending on the TH, the probability distribution used to simulate emissions, and the type of biomass. In general, the analysis showed that relatively long storage periods are needed to get a total cooling effect when boreal forest biomass is used. If wooden products are produced from biomass having a shorter rotation period, this storage period decreases. Thanks to its flexibility and consistency, this methodology is highly suitable to be routinely applied in LCA case studies. As an extended application, this approach warrants further research investigation for a possible consideration in the accounting of emissions from HWP and in processing data by emission inventory experts within the Kyoto protocol and its successor.

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