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Abstract

Bioenergy systems are promoted in an effort to mitigate climate change, and policies are defined accordingly to be implemented in the coming decades. Life Cycle Assessment (LCA) is used to assess the environmental performance of bioenergy systems, yet subject to the limitations of static approaches. In classical LCA, no temporal differentiation is undertaken: all inventoried instant to long-term greenhouse gases emissions (GHG) are aggregated and characterised in the same way, over a fixed time horizon, by means of fixed characterisation factors. Positive and negative impact contributions of dynamic biogenic carbon (C_{bio}) sum up to zero, yielding the same result as carbon neutral estimates. Climate mitigation results are biased without the temporal consideration of these flows. The purpose of the study is to highlight the time-sensitive potential climatic consequences of policy-driven transport strategies for metropolitan France, in the specific context of the dynamic LCA framework and climate change mitigation. We therefore propose a dynamic approach coupling a partial-equilibrium model (PEM) with dynamic C_{bio} models. The PEM analyses in detail the techno-economic performance of the metropolitan French energy-transport sector. It explores prospective optimisation options (supply-demand equilibrium) of emerging commodity and energy process pathways in response to a policy in question. The C_{bio} model generates dynamic inventories of the C_{bio} embedded in the primary renewable biomass outputs of the PEM. It captures the dynamic C_{bio} exchange flows between the atmosphere and the technosphere over time: negative emissions from fixation (sequestration) and positive emissions from release (e.g. combustion or decay). A dynamic impact method is applied to evaluate the mitigation effects of C_{bio} from forest wood residues by comparing the climate change impacts from complete carbon (fossil + biogenic) with carbon neutral inventories across scenarios. Two sets of results are computed concerning the overall transport (all emissions) and bioethanol (wood-to-fuel emissions) systems. The mitigation effect from long-term historic sequestration allocated to bioethanol (462%) is significantly larger than for transport (3%), expressed as the difference with carbon neutral estimates. The fossil-sourced emissions from bioethanol production represents only 5.4%. In contrast, a comparison with an alternative reference scenario involving wood decay demonstrated higher impacts (i.e. an increase of 316%) than carbon neutral estimates. The representation of the actual climatic consequences depends on the chosen fixed end-year of the dynamic impact assessment. Moreover, the mitigation effect is proven sensitive to the rotation length of forestry wood: the shorter the length the lower the mitigation from using renewable forest resources. Other energy-policy scenarios, C_{bio} modelling approaches and consequences of indirect effects should be further studied and contrasted.

Keywords: biogenic carbon from renewable resources, climate change mitigation, time-dynamic life cycle assessment, transport sector, partial-equilibrium model.

Acronyms

1G	First generation
2G	Second generation
BAU	Business-as-usual
C	Carbon
C_{bio}	Biogenic carbon
CF	Characterisation factor
CH_4	Methane gas
CLCA	Consequential life cycle assessment
CO_2-eq	Carbon dioxide equivalent
EC-JRC	European Commission Joint Research Centre
FoWooR	Forest wood residues
GHG	Greenhouse gases
GWP	Global warming potential
IPCC	International Panel on Climate Change
LCA	Life cycle assessment
LCG	Lignocellulosic
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
MARKAL	Market Allocation
N_2O	Nitrous oxide
PEM	Partial-equilibrium model
TH	Time horizon
TIMES	The Integrated Markal-Efom System

1 Introduction

The energy sector is the main contributor to global anthropogenic greenhouse gas (GHG) emissions [1]. In France, energy for transport is the principal emitter, accounting for almost one-third of the national emissions[2]. Policy planning faces the challenge of responding to climate change threats and secure future energy supply. Ambitious political targets enforce transitioning into renewable resources and increased energy efficiency, to limit temperature rise to 1.5 to 2 degrees Celsius [1]. The French Energy Transition for Green Growth Act), adopted in 2015, directs the energy sector towards low-carbon strategies and multi-annual energy programs [2]. France anticipates major renewable shares in the transport sector –aimed at mitigation of GHG emissions– gradually increasing up to the year 2050.

Energy modelling has become a key instrument to inform robust decision-making in energy system planning [3]. A wide variety of prospective models have emerged in the last half-century to support multilateral cooperation in macroeconomic energy system analysis. Top-down general-equilibrium models analyse the energy systems of a whole economy to identify cross-sectoral substitution alternatives [4]. In contrast, bottom-up partial-equilibrium models (PEM) analyse in detail the techno-economic performance of single energy sub-sectors [5,6]. Among the most used model generators featuring detailed technology databases are the MARKAL (MARKet ALlocation) and TIMES (The Integrated Markal-Efom System) of the International Energy Agency's Energy Technology System Analysis Program [7–9]. More recently, hybrid models combine economy-wide perspectives with neoclassical growth models, sectoral and technological details [10,11]. Coupling with macroeconomic models at global scales, in the view of decarbonisation mechanisms to internationalise environmental externalities, is commonly discussed in climate change abatement efforts [8].

Biofuels are promoted as low carbon energy carriers to meet climate change and energy policy targets. However, these substitution alternatives have been questioned in the past. Environmental and social concerns have arisen from expanding food crop based biomass (e.g. corn, wheat, rapeseed), particularly concerning land use and food security [12–16]. Dedicated or residual lignocellulosic biomass (e.g. forest wood, agricultural straw, miscanthus) are non-food alternatives to energy crops feeding a wide range of emerging energy pathways for heat, electricity or transport fuels. Techno-economic and environmental research has been conducted linked to bioenergy from innovative biomass supply chains, for instance, from forest wood residues [17–19], crop-residues [20–22], and miscanthus [23,24]. Advanced transport biofuels, from dedicated or residual lignocellulosic biomass, are under development to partially substitute petroleum fuels [25]. From 2020 onwards, it is expected that second generation (2G) biofuel pathways will generate cellulosic ethanol and Fischer-Tropsch biodiesel, at commercial scales, competitive with conventional fuels [26–28].

Life Cycle Assessment (LCA) is widely used to assess the climate change impacts and other potential environmental effects of bioenergy systems. Several bioenergy LCA studies have been carried out concerned with lignocellulosic biomass for electricity and heat generation, as reviewed by Muench and Guenther [29]. LCA has been increasingly combined with PEM in consequential LCA (CLCA) studies [30–37]. CLCA quantifies the environmental burden, and its variation, associated with changes in demand, often driven by policy decisions, beyond the boundaries of a particular production system [38]. It studies how flows change in response to a prior (retrospective) or future (prospective) decision [39]. The environmental consequences of a change in bioenergy systems are linked with expansion, displacement [40,41] or intensification [40,42].Combined LCA and PEM has been applied to assess the prospective consequences of emerging markets (advanced commodity and bioenergy pathways), to estimate how future decisions would change material and energy flows. Menten and colleagues applied the French TIMES-MIRET model to improve consistency in prospective CLCA studies of biofuels and biomass-to-liquid processes [31]. Levasseur and colleagues used the Canadian TIMES NATEM model and complemented its outputs with LCA of alternative butanol from forest biomass pathways [30].

However, combined LCA and PEM approaches are usually static. The assessment of GHG emissions, for instance, focus on fossil fuels, while disregarding the time-sensitive climate change effects of biogenic carbon (C_{bio}) embedded in biofuels. C_{bio} refers to the carbon fixed in the biomass/plant resource through photosynthesis. The C_{bio} is temporally sequestered and stored in biomass and released back to the atmosphere at the end-of-life (e.g. through combustion or decay). The climate change impact category is based on the IPCC Global Warming Potential (GWP) metric [43]. The GWP method represents the weighted sum of all GHG emissions, such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), over a 20 or 100-year time horizon (TH), relative to the CO_2 reference gas, computed by means of characterisation factors (CFs). The GHG emissions are then expressed per functional unit of a product or service (e.g. per km driven by an average passenger car). This static method disregards the time dimension affecting climate change results [44–51]. In other words, GHG emissions are not differentiated through time.

The exclusion of dynamic C_{bio} elementary flows in the GHG inventories is justified by the carbon neutral hypothesis. This simplification, based on the classical static approach, balances out the sequestration and release flows through the weighted sum of all emissions at time zero [52–54]. The bio-sourced GHG emissions, thus, yield zero climate change impact. However, this static methodological choice has been challenged for biomass resources with long rotation lengths, particularly from forestry [53,55,56]. Long CO_2 (re-)sequestration periods (e.g. forest trees) have time-sensitive effects, whereby rotation lengths lower than one-year (e.g. annual crops) may have small to zero impacts (equivalent to carbon neutral estimates) [57,58]. Long-term carbon stocks (e.g. forest trees) have a negative atmospheric impact, however they are reversible (i.e. reemitted) at some point in time, making it highly debatable whether or not assigning a value to it is justifiable [59,60]. Non consideration of long-term C_{bio} sequestration and the timing of this emissions release thus produce biased results [61].

In the last decade, new dynamic LCA approaches have emerged focused on time-sensitive climate change effects from bioenergy [46,47,50,56,62–64], and more specifically, linked to biogenic carbon accounting and forest resources [63,65–70]. Cherubini and colleagues proposed the biogenic global warming potential (GWP_{bio}) metric for bioenergy systems, using the impulse response function [71], to predict the biogenic CO_2 decay, as a function of biomass rotation dynamics [56]. The factors assign lower impacts to fast-growing vegetation and vice-versa. Yan developed CFs for different rotation lengths and harvest intensities based on forest-specific carbon cycle models [72]. The dynamic LCA method by Levasseur and colleagues enables assessing temporal emission profiles of fossil or biogenic flows, as a function of time [47]. The dynamic method computes time-dependent CFs for any year following an emission. It's application requires dynamic inventories, differentiating each emission flow from and to the atmosphere through time. Time-explicit C_{bio} inventories of forestry resources have been proposed by De Rosa and colleagues, through a simplified parametric model for aboveground and belowground forest carbon stocks [67]. To this day, no consensus exists on how to model dynamic C_{bio} inventories from renewable resources.

The purpose of this study is thus to assess, ex-ante, the time-sensitive potential climatic consequences of policy-driven transport strategies for France, by means of a full carbon accounting approach. We propose the coupling of a techno-economic and biogenic carbon models in the specific context of the dynamic LCA framework and climate change mitigation. The novel model coupling bridges the gap between research, development of emerging bioenergy systems and their actual mitigation effects.

2 Material and method

The proposed model-coupling of the PEM and the dynamic C_{bio} model is shown in Fig. 1. The overall coupling strategy is as follows: The renewable commodity forest wood residues (hereafter referred as FoWooR), described by the PEM, is selected for the first coupling attempt. The dynamic biogenic carbon is assessed through a C_{bio} modelling tool developed for this coupling strategy. It models the dynamic C_{bio} exchange between the atmosphere and the technosphere over time: negative emissions from fixation (sequestration) and positive emissions from release (e.g. combustion or decay). The model generates dynamic inventories of the C_{bio} embedded in the renewable FoWooR biomass (hereafter referred to as C_{bio} balance. For the climate change impact assessment, a dynamic method is applied to compare the climatic consequences of carbon neutral (without C_{bio}: hereafter referred to as "C neutral") and complete carbon balances (with C_{bio}: hereafter referred to as "complete C") in response to policy scenarios. The complete C balance is built upon both fossil and biogenic material and energy flows from production and consumption of petroleum fuels and biofuels, while the C neutral approach accounts for the fossil ones only. The coupled model thus produces a dynamic climate change impact assessment of prospective renewable biomass and energy pathways driven by and representing policy decisions. All necessary steps for the model coupling are detailed in this section, following the classical LCA steps: goal and scope, life cycle inventories (LCI), and life cycle impact assessment (LCIA).

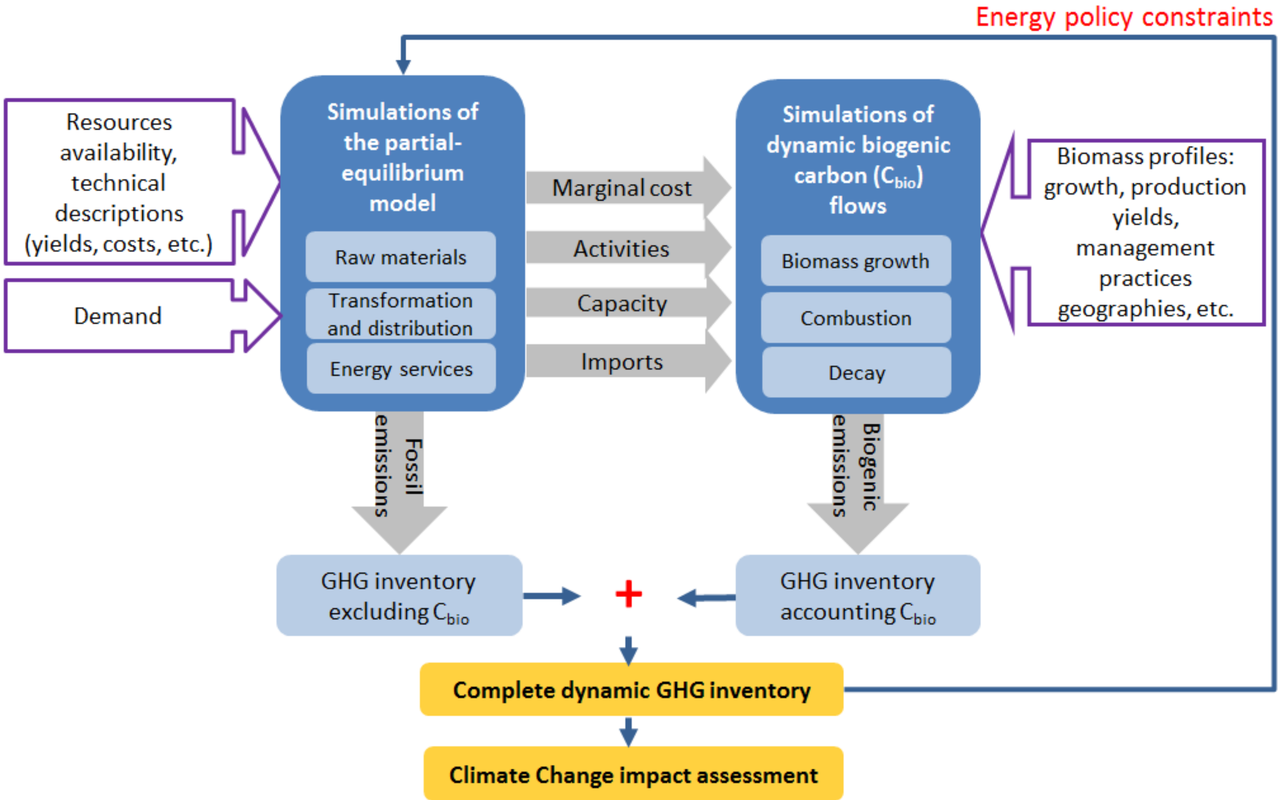

Fig. 1. Conceptual diagram of the model coupling strategy of the TIMES-MIRET partial-equilibrium model with dynamic biogenic carbon modelling

2.1 Goal and scope: temporal boundaries

The goal of the present study is to highlight the time-sensitive potential climatic consequences of policy-driven transport strategies for France. The system boundary is the transport sub-sector, with special focus on 2G biofuels. Energy services from electricity and heat for other end-users (e.g. industrial, domestic) are excluded from the study. The C_{bio} balance represents the supply of FoWooR, as a primary renewable resource for biofuel production. The LCIA is based on time-dependent CFs [47] and is expressed here in mega-tonnes of carbon dioxide equivalent. Other LCA environmental impact categories are outside the scope of the study, as the main focus is the time sensitive clime change impact assessment of dynamic C_{bio} flows and its comparison with C neutral approaches.

The dynamic LCA approach, aims at developing a dynamic complete C balance (fossil + biogenic emissions). Therefore, the temporal differentiation of all emission flows, particularly of biogenic origin, is a fundamental precondition. The temporal system boundary requires all necessary time specifications of the entire study under assessment, namely the time step as well as both the LCI time horizon (LCI TH) and the LCIA time horizon (LCIA TH), specified below.

The time step defines the temporal frequencies over which the emissions are inventoried and assessed (e.g. per minute, hour, day or year). It is set by the inherent time scales of the impact categories [73,74]. Inherent features of impact categories (e.g. climate change, acidification, eutrophication, etc.) relate to several biogeochemical processes, defining the temporal resolution at which dynamic inventories can be modelled. LCA methods encompass different impact categories, however the present study is only concerned with climate change category. For this impact category, the time scale of the flows is recommended at annual frequencies [47,75]. Therefore, the dynamic computation of the technical flows and elementary flows are modelled on an annual basis.

The LCI TH defines the timeline over which the GHG emission are considered in the study, describing each emission flow through time. We perform a full-time inventory of all GHG emission with no temporal cut-offs. Since the model-coupling in this study aims at assessing the PEM outputs, the negative and positive flows are aligned with the TH of the PEM simulation. TIMES-MIRET runs over multiple-periods (3 to 5 years) until the year 2050. For this study the PEM outputs from 2019 to 2050 are taken into consideration. A linear-interpolation is performed to track the multi-period outputs on an annual basis and develop annual values for the dynamic inventories. The LCI TH of all negative emission flows is defined by the chosen modelling approach taking into account historic or future C_{bio} fixation time perspectives (described in section 2.3.1).

We inventoried the C_{bio} sequestration flows *before* the final harvest of FoWooR (historic perspective). A full rotation length accounts for 200 years in this study. The long-sequestration period follows [76], as detailed in section 2.3.1. It represents all main tree species of the French wood industry, with Sessile Oak (*Quercus petraea*) having the longest sequestration length. For the historic C_{bio} computation, the TH of the PEM simulation represents the last year of the C_{bio} fixation, at which final harvest of FoWooR occurs. For instance, for the period 2019-2050, the first fixation flow starts 200 years in the past (year 1819) for the year 2019, 1820 for the year 2020 and so forth until 1850 for the last simulation year (2050).

The LCIA TH, likewise, defines the period over which the climate change impact is considered by means of setting a fixed reference year or an end-year of the impact assessment. The commonly use TH for the climate change characterisation in LCA is one century, as per the default GWP metric [43,77,78]. We therefore fix a future reference year to 2119, 100-years after the first PEM simulation year (2019). Yet, any end-year or TH can be chosen when dynamic LCIA is performed with time-dependent CFs.

Finally, the temporal system boundary for the entire study under assessment can be described. The annual time step consideration of a full-time accounting approach with historic fixation flows and a fixed future reference year, sets the overall temporal system boundary over the period 1819 to 2119: 300 years in total. This temporal specification provides transparency and allows a systematic comparison among all assessed PEM policy scenarios. Moreover, the selected period represents consistency between the LCI and the LCIA

TH, with no temporal cut-offs. Accordingly, we ensure that all inventory flows are projected over the same TH into the future.

2.2 Life cycle inventories: partial-equilibrium model outputs

2.2.1 Description of the key elements

The economic partial-equilibrium model used in this study is the TIMES-MIRET, adapted to the modelling framework from the MARKAL/TIMES family of models [7–9]. TIMES-MIRET analyses the energy-transport system of metropolitan France over a multiple-period horizon based on prospective demographic and economic projections [79]. The model conducts a detailed bottom-up techno-economic analysis, describing the primary resource supply (petroleum fuels and biomass), its transformation to secondary fuels via different process pathways (refinery), and the final energy consumption (electricity, heat and transport fuels) [8,79]. Petroleum- and biomass-based commodities represent the supply of energy sources to meet the future energy demand. Each source has an attribute, detailing the availability/import, capacity and marginal cost. The demand curve is represented by the energy services in transportation (automobiles, trucks, rail, aviation), domestic and commercial (space heating, lightning, cooling), industry (chemicals, steel) and agriculture segments [9]. In TIMES-MIRET the assessed useful energy includes electricity and heat (hereafter referred to as "energy mix"), and transport fuels (hereafter referred to as "transport sub-sector"). The output from the supply-demand equilibrium assumes a perfectly competitive market, in which producers and consumers maximise their net total surplus or minimise their net total costs, while meeting several (policy) constraints [5,9].

The TIMES-MIRET PEM scenario simulations disregard cross-sectoral interactions within a whole economy (in contrast to general-equilibrium models). However, each scenario explores the linear programming optimisation of supply-demand in detail based on a technology-explicit database linked with different commodities. For instance, for the transport sub-sector the functional unit of the sectoral output is the kilometres travelled by a specific transportation means (e.g. average passenger car, heavy trucks, etc.). In bottom-up PEM models, the existing and future technologies to produce that given unit are explicitly specified [9].

2.2.2 Definition of policy scenarios

TIMES-MIRET outputs are scenario-dependent. The assessed policy scenarios are compared with a reference policy scenario (business-as-usual, BAU). The BAU scenario represents a baseline against which alternative policy scenarios are compared. BAU is formulated from historical and established norms considered valid until the end of the PEM simulation TH. The reference policy draws back to the 2009 EU Directive and National Renewable Energy Action Plan, pursuing renewable energy targets in the gross final energy consumption by the year 2020. Therefore, the initial period of the TIMES-MIRET is calibrated to the year 2009, fixing the historic values and main variables, yet considering changes in future demand.

The alternative policy scenario assessed in the present study is named 15Bio. It corresponds to the national long-term, multiannual energy transition plan, partly formulated from the French Energy Transition for Green Growth Act. For the 15Bio scenario, we adopted the 15% RE share in the transport sub-sector by 2030, in reference to the year 2012. This specific target for the transport sector was subjected to the EU Renewable Energy Directive, legally binding Member States to increase the RE share in addition to limiting food crop-based biofuels (first generation, 1G) to 7% by 2020. For the French national energy plan, this target remains effective up to the year 2030. Hence, the 15Bio scenario involves all constraints of the BAU reference, including the new set of policies (i.e. limiting 1G biofuel share to 7% and increasing the renewable energy share by 15% by 2030). A comparison with the BAU scenario, allow identifying the policy-induced consequences of energy-transport pathways in response to fossil fuel and energy-crop substitution targets to mitigate climate change.

2.2.3 Selection of the model outputs

In the LCA context, the PEM commodities represent the technical flows, while all life cycle carbon and GHG emissions the elementary flows. For the model coupling, the technical and elementary flows of the PEM are exported per BAU and 15Bio policy scenarios. All flows associated with the transport sub-sector are separated from the pathways for other end-users. For instance, cogeneration processes (heat and electricity generation) and biochemical or thermo-chemical processes (bioethanol production) are both linked to FoWooR commodity in the 15Bio scenario. For the present study, we exclusively focus on the pathways associated with transport fuels only.

Concerning the technical flows for modelling C_{bio} inventories, the selection of the biomass commodity followed two main criteria: lifespan of the vegetation with a full rotation length longer than one year and contribution to 2G transport biofuels. FoWooR is an energy carrier with mid- to long-term sequestration periods, and under the new set of policies, it is expected to contribute to 2G bioethanol with mayor shares. Annual crops are excluded from the C_{bio} modelling, as their C_{bio} fixation-release dynamics occur within one year (equivalent to carbon neutral approaches), thus no climate change impact is estimated. Other long-lived renewable biomass resources, such as short-rotation coppices or perennial crops, could have been modelled to included their C_{bio} balances in the dynamic GHG inventories. However, their contribution to 2G biofuels is comparatively small or absent in the 15Bio scenario, and thus negligible for the C_{bio} analysis under the assessed 15Bio policy scenario.

The PEM input data for FoWooR in the 15Bio policy scenario is based on national forest inventories for the French wood supply chain and a roadmap 2035 study made about the future availability of this renewable resource in France [80]. The prospective assumptions consider, among others, harvest losses amounting 8% for merchantable wood, 15% for merchantable and residues, and 50% when FoWooR are harvest separately [80].

Regarding elementary flows for modelling carbon neutral GHG inventories, fossil-based CO_2 and N_2O elementary flows are provided by the PEM associated with all production and consumption pathways: biomass cultivation, transportation, (bio-)refinery, industry, tailpipe, and trade. However, all elementary flows of the transport-pathways are re-calculated, using the updated emission factors of the European Commission Joint Research Centre (EC-JRC) based on the JEC Well-To-Wheels (WTW) method [81]. The emission factors are expressed in equivalent CO_2 emissions per MJ petroleum- or biomass-sourced fuels. To recalculate the CO_2-equivalent values into the respective GHG elementary flows, the values are divided by the IPCC GWP equivalent factors [43]. The proportions of the CO_2, N_2O and CH_4 GHG emission per specific fuel are also taken from the EC-JRC [81]. The fossil-sourced elementary flows from the transport sub-sector are combined with the biogenic-sourced flows to develop a complete C balance and compare its climate change impact with C neutral approaches.

2.3 Life cycle inventories: biogenic carbon model outputs

The technical flow (i.e. the FoWooR commodity) is coupled with the C_{bio} models to compute time-explicit C_{bio} inventories. The mass of FoWooR is expressed in C_{bio} by means of a wood-specific carbon content factors (0.4952) denoting the weighted mean of all assessed forest tree species of the French wood supply chain assessed in Albers et al.(in press). The C_{bio} elementary flows represent the C_{bio} embedded in the primary FoWooR supply flows per tonne of FoWooR [t of C_{bio}]. The coupling with dynamic C_{bio} models further generates annual fixation and release flows. The dynamic C_{bio} balance is converted into biogenic CO_2 and CH_4 for the impact characterisation by multiplying the molecular weight of CO_2 or CH_4 to the atomic substance of C (44/12) or (16/12) respectively. CH_4 is considered for decay estimates only [82–84].

or the Cbio balance, the belowground tree compartment (roots and stump) is also considered, to include both aboveground and belowground Cbio dynamic. This implies allocating a proportion of belowground biomass to the FoWooR. The aboveground compartment represents about 80% of the tree (63% stem and 37% FoWooR). 20% of the tree consists of belowground biomass, as computed with our Cbio modelling tool. The values are congruent with other studies (e.g.[85]). The allocation factor for the belowground biomass corresponding to FoWooR was estimated at 0.25 of FoWooR, which represents 7.4% of the total tree biomass.

2.3.1 Computation of carbon fixation from forestry resources

Fixation represents the withdrawal of CO_2 from the atmosphere due to photosynthesis. The dynamic C_{bio} modelling of the FoWooR applied dynamic growth models from forestry science, elaborated for the French forest wood industry. The modelled data supports and informs dynamic modelling approaches to predict mean growth and C_{bio} fixation dynamics of a tree or forest stand over a given rotation length. All data and modelling steps for the C_{bio} fixation flows were obtained from yield tables per unit area of forest stands, non-linear growth models and allometric relations (see Table 2 in Albers et al. in press). The tabulated yield table data based on empirical evidence originated from long-standing experimental forest plot surveys of managed forests throughout France [86] or other regions when not available for France [87,88]. The non-linear growth curve is represented by the often used Chapman-Richards (CR) model, a sigmoid and asymptotic curve [89–91]. The CR equation (Eq. 1) expresses the potential growth ω of a tree species i in height and diameter-breast-height or circumference (response growth variables) at age t (independent variable), with species- and site-dependent parameters A, β, k, p [92]:

$$\omega\ (t_i) = A\left(1 - \beta exp^{-kt}\right)^p + \varepsilon \qquad \textbf{Eq. 1}$$

with $p = 1/(1-m)$

For the C_{bio} fixation dynamics, we used annual stocking values from all assessed tree species (Table 2 in in Albers et al. in press) and the weighted mean based on the standing wood production volumes and distribution from national statistics and surveys [93] (see Table 3, 5 and 6 in Albers et al. in press). The annual stocking factors are expressed in tonnes of C_{bio}. Note that, the dynamic C_{bio} fixation model represent monospecific (individual-species) uneven-aged forest stands with homogenous growth. Other site-dependent dynamic elements related with, for instance, mixed forest stands (two or more species per forest stand), and losses from mortalities, including those unexpected due to natural events (e.g. wildfires, diseases, winds) and soil organic carbon, were not modelled. For modelling site or case-specific fixation dynamic, these site-specific parameters would further complement and improve dynamic approaches.

For the computation of C_{bio} fixation, two time-dependent accounting approaches can be followed for the first C_{bio} fixation flow: a) a full rotation length starting *after* the wood-use, in the same year of final wood harvest, when trees are removed from the forest stand and new seedlings are re-planted; or b) a full rotation length starting *before* the wood use. The former refers to C_{bio} fixation flows with future timelines and the latter to historic ones. In previous LCA studies, future [56,67,94], historic [95–97], and both [66,98,99] C_{bio} fixation time perspectives were tested. In the present study, we computed C_{bio} fixation flows with historic timelines. The reasoning behind this modelling approach is based on the assumption that the provision of FoWooR as biofuel feedstock is retained from sustainably managed forests in the French/EU context. According to Lindeijer and colleagues, the origin of the biotic resource defines whether the modelled systems is man-made controlled or a natural ecosystem [100].

The biogenic carbon fixation dynamic [t C_{bio}. y^{-1}] is defined by:

$$\frac{dc}{d\tau} = f(p, \tau) \quad \textbf{Eq. 2}$$

$$\int_{\tau_0}^{\theta} f(p, \tau). d\tau = c_b(\theta) = 1 \quad \textbf{Eq. 3}$$

where c_b the relative biogenic carbon fixation expressed in tonnes, $f(p, \tau)$ is the carbon fixation model with a set of parameters of the Chapman-Richards model (*p*), τ (y) is the time variation between the start time (τ_0) of the biogenic carbon fixation and the cutting time (θ) defined by each thinning and a final cut time (i.e. harvest at the end of the rotation length).

The coupling with the partial-equilibrium model is carried out following Eq. 4 and Eq. 5, where C is the total biogenic carbon, E_{t^*} is the biogenic carbon output from the partial-equilibrium model, expressed in tonnes, at a given time t^*. The fixation dynamic at t^* is computed following the computation in Eq. 6:

$$\frac{dC}{dt} = \frac{dc}{dt} E_{t^*} \quad \textbf{Eq. 4}$$

with *t* the a time of the MIRET scenario and

$$C(t^*) = c(\theta) E_{t^*} \quad \textbf{Eq. 5}$$

Thus,

$$\begin{aligned} \tau &= \theta - (t^* - t) \\ d\tau &= dt \\ \frac{dc}{dt} &= f(p, \theta - t^* + t) \\ \frac{dC}{dt} &= f(p, \theta - t^* + t)\, E_{t^*} \end{aligned} \quad \textbf{Eq. 6}$$

2.3.2 Computation of carbon release from forestry products

The C_{bio} release to the atmosphere is positive, because it contributes to the atmospheric GHG concentration and thus to the radiative forcing effect. The flow occurs when the C_{bio} is emitted back at the EOL of the biomass product. For bioenergy systems, the EOL is the combustion process. EOL combustion of bioenergy is linked with internal combustion engines (transport tailpipe) or cogeneration processes (energy mix). In the present study, it is assumed that the biomass is harvested, processed and used within the same year. This means that the total embedded C_{bio} in the FoWooR, including co-products and wastes, is emitted back to the atmosphere within the same year of harvest.

However, when the residual part from logging operation are not used for the bioenergy market (e.g. 2G bioethanol), they are left in the forest. The alternative EOL pathway corresponds to a reference scenario in which FoWooR are left behind and excluded from economic activities. For comparison purposes, the selection of an adequate reference systems was already highlighted by other authors [106,107]. For the alternative EOL pathway, the left behind FoWooR are subjected to onsite natural decay processes by microbes in the soil in forest ecosystems. After harvest aboveground residues and belowground biomass are assumed to decay completely over time [101]. Emissions due to decay occur over long periods of time, gradually decreasing towards zero. The decay curve of residual dead wood biomass can be estimated via a first-order exponential decay equation (Eq. 1), where M_t is the remaining mass at time t, M_0 the initial dry mass, and τ is the half-life estimates.

$$M_{(t)} = M_0 \times e^{-t/\tau} \quad \textbf{Eq. 1}$$

The negative exponential decay model is commonly used and recommended to estimate forest wood degradation [19,21,102,103]. Half-life values for decay vary depending on the tree compartment. For τ we used eight years for coarse woody debris and thirty years for dead stumps and roots [104]. A part of the embedded C_{bio} in FoWooR is emitted as CH_4 (due to anaerobic degradation), ranging between 0% and 3% (we used 1.5%) for coarse woody debris (branches, twigs and foliage) and 10% for belowground dead stumps and roots [105]. The CH_4 releases are very uncertain and site-dependent. CH_4 ratios for belowground degradation are not easily available, thus we used 10% as a proxy from mulched wood and following a root-shoot rational [101].

2.4 Life cycle impact assessment: dynamic climate change

For the dynamic LCIA of the climate change characterisation, time-dependent CFs proposed by Levasseur and colleagues were applied [47]. The time-dependent CFs assess the annual GHG emission profiles from fossil or biogenic sources as a function of time. The method is based on the radiative forcing (RF) concept, similar to the IPCC default GWP metric [43]. However, the assessment is based on instantaneous RF values with no fixed TH. The CFs have variable THs, as they assess the impact of GHG emissions for any year following the emission at the year of its release to the atmosphere. This dynamic method, thus, allows assessing different THs generated by different emission years [47].

The cumulative annual values of the RF are expressed in watts year per square meter [$W \cdot yr \cdot m^{-2}$]. The values can further be expressed in equivalent CO_2 climate change impact per unit mass assessed. The dynamic characterisation, yet implies a “fixed future reference time” [78], meaning that even though the TH is variable, a reference TH is required. Thus, the dynamic climate change impact expresses the effects between the GHG year (i.e. the time when emissions is released to the atmosphere) and the chosen fixed reference year [99]. In a classic LCA approach, no temporal differentiation is undertaken at both the LCI and LCIA phases: all inventoried GHG emissions are aggregated and characterised in the same way. Positive and negative impact contributions of biogenic emissions sum up to zero, yielding the same result as C neutral estimates. For static climate change impact via the default IPCC GWP thus yield zero for biogenic flows. Many LCA studies use this static approach analogously to climate neutral [108], to express a zero climatic effect from bioenergy systems. However, in recent years, this approach has been questioned and criticised [58,109], as a pulse emission of a given substance into the atmosphere has an effect on the atmospheric concentration and thus on the radiative forcing, regardless whether it originates from biogenic or fossil fuel sources.

2.5 Summary of all steps for the model coupling and computation

A summary of the described model-coupling steps is shown in Fig. 2. Each technical and elementary flow of the PEM (detailed in section 2.2.3) is treated separately. The annual biomass technical flows per PEM scenario are transformed into C_{bio} elementary flows according to biomass-specific carbon content values (see section 2.3.1). The annual C_{bio} elementary flows are computed with the dynamic C_{bio} modelsto capture the dynamic of C_{bio} fixation flows from the atmosphere [$tC_{bio}\cdot yr^{-1}$] (detailed in section 2.3.1), and the C_{bio} release flows to the atmosphere (detailed in section 2.3.2). The annual C_{bio} release factors are specific to the EOL option chosen (e.g. combustion for bioenergy, decay for left-behind biomass). The time-explicit computation of the fixation and release flows forms a dynamic C_{bio} balance [$t\cdot yr^{-1}$]. The C_{bio} balance is subsequently transformed into the corresponding biogenic GHG emissions (here CO_2 and CH_4). The fossil source GHG emissions(here fossil CO_2, CH_4 and N_2O), corresponding to the C neutral approach, are included in the assessment. For a full-time accounting with no temporal cut-offs, all GHG emissions are inventoried over the respective LCI TH. For the LCIA characterisation, all dynamic inventories are computed with time-dependent CFs (detailed in section 0).The variable future fixed reference year, and therefore the LCIA TH, are set by the user. Subsequently, the impact results from a complete C balance (fossil + biogenic) are compared with the C neutral (fossil) flows per policy scenario.

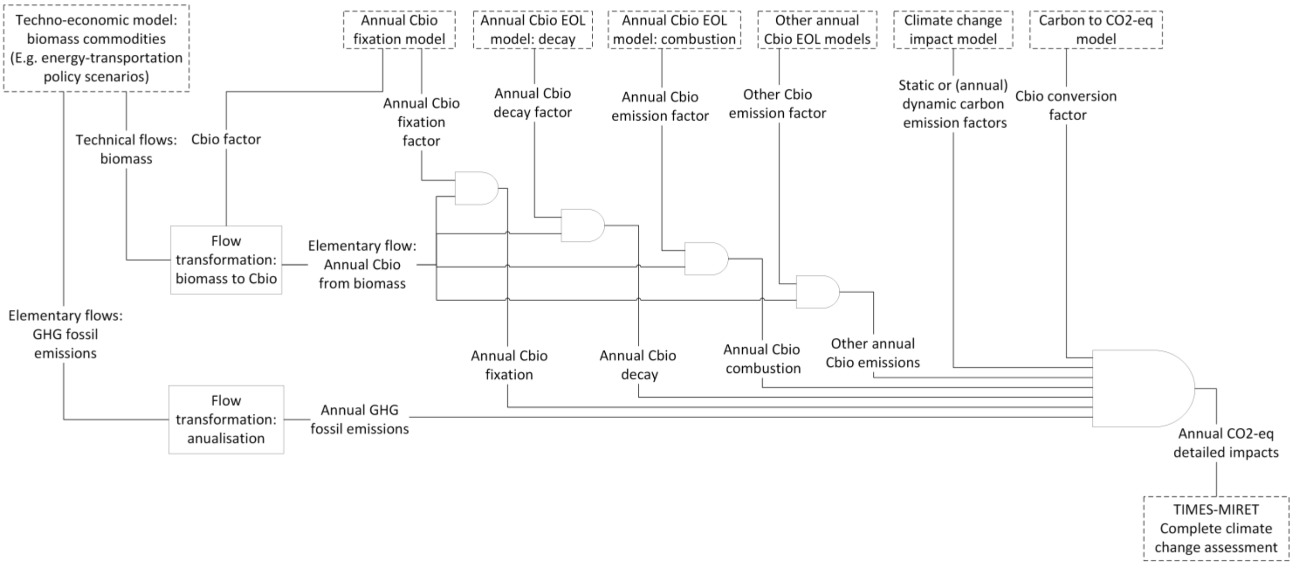

Fig. 2. Diagram for coupling TIMES-MIRET partial-equilibrium model with dynamic biogenic carbon models

3 Results and discussion

The results of applying the coupled model are presented in this section, for both the dynamic LCI and LCIA of the BAU and 15Bio scenarios. The dynamic inventories, based on the TIMES-MIRET PEM outputs, were constructed around the primary biomass supply for all end-users, as well as the mobilisation of renewable commodities and the final energy consumption (petroleum fuels and biofuels) to the transport sub-sector. The dynamic inventories for the C_{bio} balance demonstrate all sequestration and release flows from the FoWooR transport pathway. Additionally, all dynamic inventories of transport were plotted in a Sankey-style diagram specific to the year 2030. For the dynamic impact assessment two systems were computed: i) the transport sub-sector in terms of GHG emissions from all transport pathways, and ii) bioethanol, encompassing GHG emissions from the FoWooR-to-bioethanol pathway only. The results per system and scenario were compared under two distinctive accounting approaches, corresponding to the relative climate change impact based on the C neutral (fossil-only) and complete C (fossil + biogenic) inventories. This comparison strategy is used to identify whether the inclusion of the C_{bio} dynamic, represented with the complete C inventories, leads to climate mitigation effects compared to C neutral estimates. Additionally, the impact of a hypothetical reference system (BAU* scenario) featuring an alternative EOL decay pathway for FoWooR was computed and compared with the EOL combustion pathway. Finally, a sensitivity analysis was carried out to assess the robustness of the applied C_{bio} model as well as the sensitivity of the mitigation results with respect to the chosen rotation/sequestration length.

3.1 Dynamic inventory results

3.1.1 Partial-equilibrium model biomass outputs and energy pathways

Fig. 3 shows the primary biomass supply outputs [in Mt], from the PEM, of the BAU and 15Bio scenarios from 2019 to 2050, whereby Fig. 3a relates to energy mix + transport and Fig. 3b to the transport sub-sector. The biomass commodities described in the PEM were dedicated energy crops (corn, triticale, wheat, sugar beet, rapeseed, sunflower, palm oil, soybean), dedicated lignocellulosic material (LGC: miscanthus and other perennial crops), and residual biomass (FoWooR, from forestry and agriculture). The commodity category "energy crops" includes renewable resources associated with first generation (1G) biofuels, while dedicated LGC material and residual biomass associate with 2G biofuels. All described commodity were first exported from the PEM, as shown in Fig. 3a, to identify the pathways linked to transport end-users. The commodity with the largest primary biomass share of the biomass supply was FoWooR, with proportions of up to 68% and 71% for BAU and 15Bio respectively. Annual mean values for FoWooR were estimated at 32 Mt for BAU and 34 Mt for 15Bio. The new set of policy constraints did not significantly change the FoWooR outputs over the PEM simulation TH, as compared with BAU. However, LGC material was introduced as a new commodity in the 15Bio scenario.

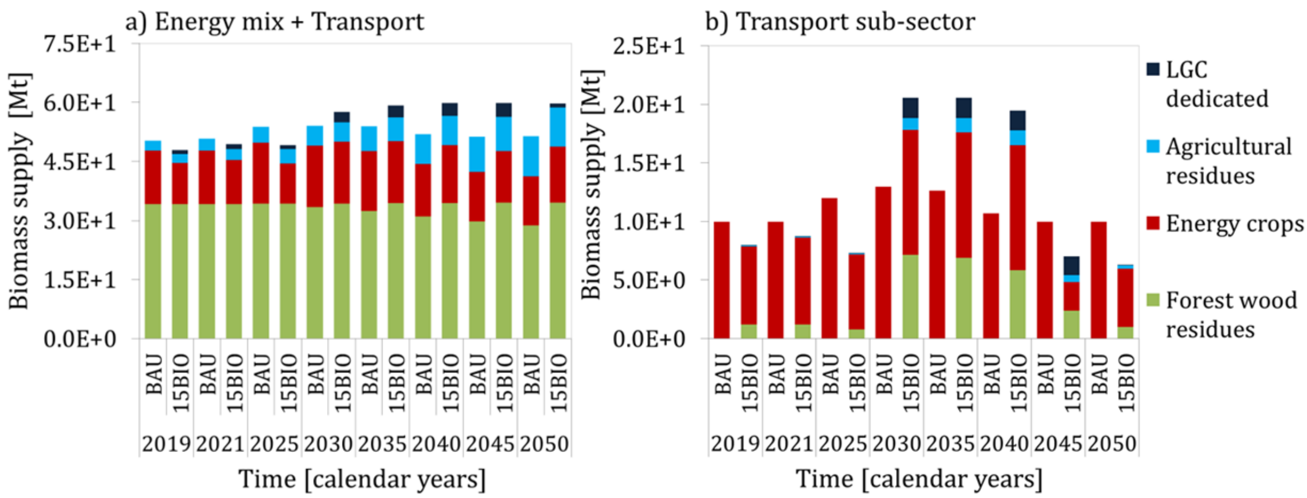

Fig. 3. TIMES-MIRET primary biomass supply from 2019 to 2050 per BAU and 15Bio scenarios of a) Energy mix (heat and electricity) and transport, and b) Transport sub-sector only

An in-depth assessment of the transport sub-sector pathways, demonstrated a shift of the biomass commodities from the energy mix + transport to the transport sub-sector between BAU and 15Bio. FoWooR and agricultural residues, as well as LCG material, were mobilised for transport fuel processes, as shown in Fig. 3b. The LGC material commodity was introduced to feed the transport sub-sector, as compared with all commodities in the energy mix + transport PEM outputs (Fig. 3b). A comparison among the scenarios, demonstrated that under BAU conditions, transport biofuels would exclusively be produced from energy-crops. 1G biofuels would remain the only substitute to petroleum fuel. The other biomass commodity pathways in BAU would feed the energy mix (i.e. electricity heat cogeneration processes for other end-users) only. In the 15Bio scenario, the mobilisation of FoWooR supply to transport was linked to the production of cellulosic bioethanol. It represented the only feedstock for 2G bioethanol. Peak 2G bioethanol production values were estimated in the year 2030, amounting up to 21 Mt (35% of the total biomass share for transport).

Fig. 4 shows the final energy consumption share [in MJ] of the transport sub-sector, per scenario, from 2019 to 2050. The depicted energy carriers represent the end-user energy demand by a wide range of transport means. The prospective supply is based on the number of kilometres travelled per transport means. It is expected that the final energy share will slightly decrease under the given assumptions, as more passengers would travel per trip of all transport means. The bioethanol energy carrier includes both 1G and 2G biofuels, whereas FoWooR represented the main feedstock for 2G cellulosic bioethanol production (in the 15Bio-transport scenario). Other potential biofuel pathways and process outputs, such as Fisher-Tropsch biodiesel, were not simulated under the new set of policies. In contrast, under BAU constraints, only 1G bioethanol from energy crops would be produced.

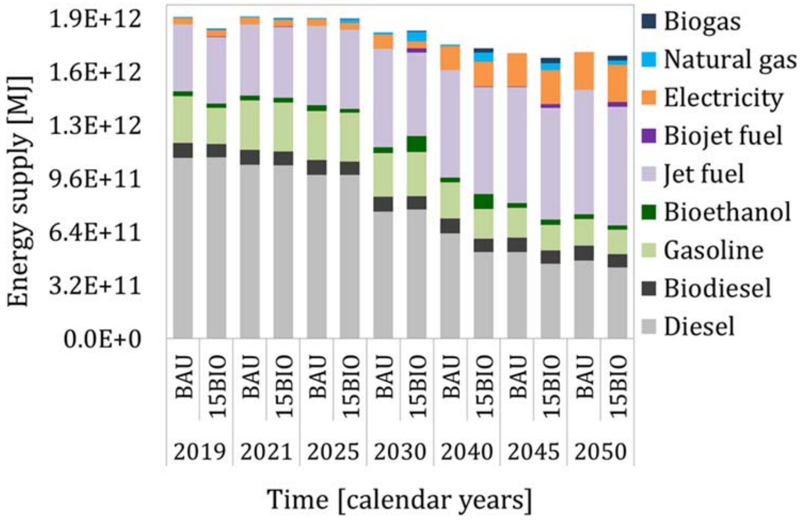

Fig. 4. Final energy consumption in the transport sub-sector per energy carrier and per scenario

The new commodity and energy pathways in the transport sub-sector were created in response to the new policy constraints (15Bio scenario). Compared with the BAU reference, the energy-market dynamics changed in response to the policy constraint by optimising the outputs to secure energy supply by cost-effective means. These outputs are supposed to partially substitute 1G biofuels and petroleum fuels. Yet, the overall share of FoWooR, and thus that of 2G bioethanol to the transport sub-sector, remained less significant than the share of energy crops for 1G biofuels, up to the year 2050.

3.1.2 Biogenic carbon balance from forest wood residues

Fig. 5 shows the C_{bio} balance results of FoWooR for the transport sub-sector, under both BAU and 15Bio scenarios, expressed in Mt C_{bio}. The C_{bio} flows for the BAU reference were zero, as no FoWooR were accounted for the transport pathway (Fig. 5a). The flows from the historic C_{bio} fixation were inventoried as negative (sequestration) and the C_{bio} combustion as positive (release back to the atmosphere). A full-time accounting with no temporal cut-offs, allowed differentiating all C_{bio} flows of fixation and release through time. The LCI TH was defined as the 1819 to 2050 period. The PEM simulation TH (2019 to 2050) represented the years of final harvest (final fixation flow) and the years of production and consumption of FoWooR-based 2G bioethanol (release flows). The first C_{bio} fixation flow started in the year 1819, due to the application of a historic full-rotation length of 200 years (see section 2.3.1). From the year 1819 onwards, the C_{bio} fixation values were accumulated until the final harvest in the year 2019. This has been repeated for each following simulation year until 2050, which is the end year of the C_{bio} balance for both negative and positive emission flows.

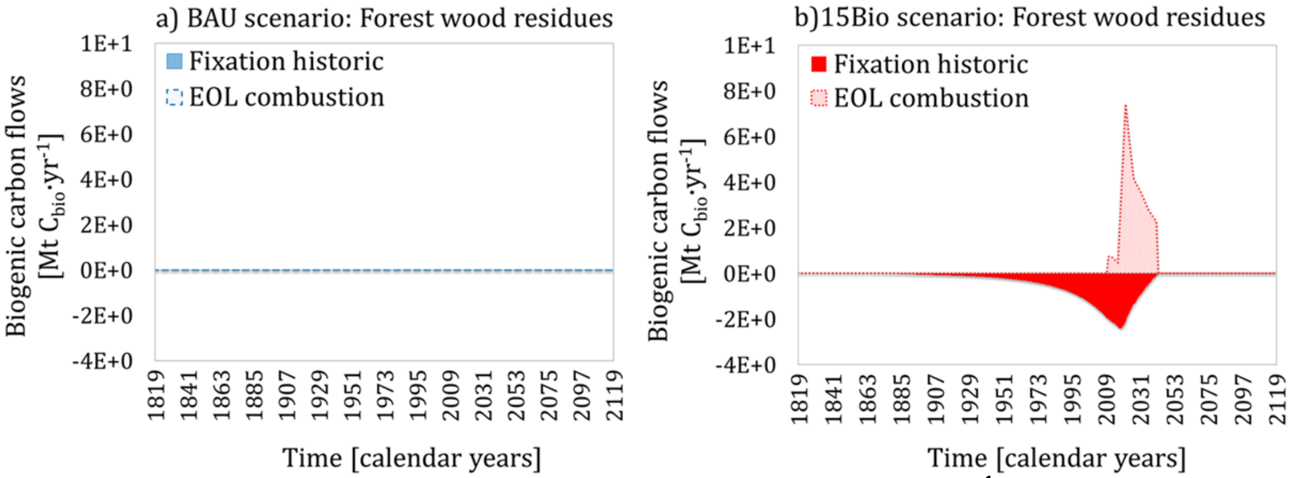

Fig. 5. Dynamic biogenic carbon (C_{bio}) balance of residual forest wood biomass [Mt C_{bio}·yr^{-1}] in the transport sub-sector with historic fixation (positive) and EOL combustion (negative) flows of a) BAU scenario, and b) 15Bio scenario

Under the assumption of combustion as EOL, the total C_{bio} fixation (-1.01E8 Mt C_{bio}) and release (+1.01E8 Mt C_{bio}) flows sum up to zero, with no temporal cut-offs. The area below the curve is equal for both flows, meaning that the total C_{bio} embedded in the FoWooR is emitted back to the atmosphere during 2019 and 2050. This confirms that 100% of fixed C_{bio} is released back, as presumed under the carbon neutral hypothesis. Yet, the annual biogenic values are not carbon neutral and, therefore, not zero. The time-explicit differentiation of the C_{bio} flows, describes the temporal C_{bio} emission profiles on an annual basis. The sum of negative and positive C_{bio} values per year form the C_{bio} balance, representing the dynamic biogenic inventories that can subsequently be assessed by means of the dynamic LCIA method.

3.1.3 Complete carbon flows of a specific year

The dynamic inventories, both from fossil and biogenic sources, can be presented for a specific year of the modelled period. The calendar year representation is informative, as it details the flows and stocks of materials and energy on a key year of the policy-based scenario. We selected the year 2030, a future key target-year of the EU and national climate-energy policy [110], generating top FoWooR supply estimates in the 15Bio scenario of the transport sub-sector. All fossil and biogenic input and output flows were expressed in Mt C. Conversion factors from the EC-JRC [81] were used to express all inventoried petroleum and biomass feedstocks as C. For the FoWooR commodity, we used the weighted mean of C content in wood (0.4952) from the C_{bio} model (Albers et al. in press). The elementary C flows from the feedstock supply, transformation, use and EOL, were plotted in a Sankey-style diagram, using the STAN v6.2 software [111]. The incoming C embedded in petroleum fuels and biofuels equals the outgoing C embedded in atmospheric emissions. Losses from biochemical or thermochemical processes in biofuel production pathways are presented here as wastes. The biofuel from residual lignocellulosic material yield of biochemical processes generates between 110 and 300 litres [26] of bioethanol per dry tonne of wood, with low heating values between 21.1 [26] and 26.8 MJ per litre [112]. The overall conversion efficiency of biochemical process pathway (likewise thermo-chemical processes) is about 35%.

The C flows (fossil + biogenic) of the transport sub-sector under the BAU and 15Bio scenarios are shown in Fig. 6a and Fig. 6b, respectively. The biogenic flow (5.3 Mt C) shown in Fig. 6b corresponded to the C_{bio} balance of fixation + release dynamics at the year 2030. The total emitted Mt of C, including the biogenic flows, is higher for the 15Bio scenario by 4.5 Mt C. Without the biogenic flows, C outputs would be lower for 15Bio. For the specific calendar year 2030, the C_{bio} balance results revealed the highest value from fixation and release, which then decreased to zero in the year 2050. The comparison among the scenarios showed that biogenic flows were only linked with the 15Bio for the transport sub-sector. This questions whether the comparison with the BAU reference is valid. This issues is further addressed in section 3.3 with the introduction of a hypothetical BAU* scenario associated with a C_{bio} balance featuring an alternative EOL pathway.

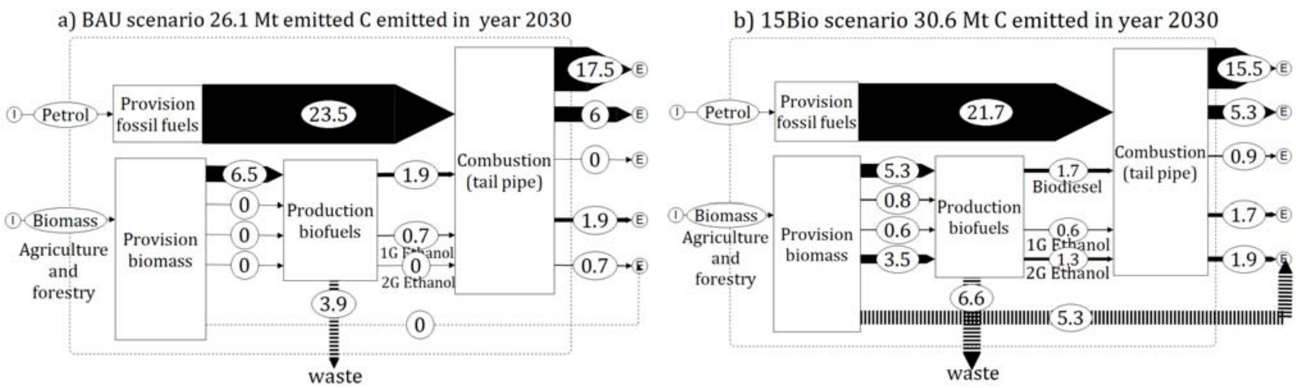

Fig. 6. Carbon flows [Mt C] at year 2030, as Sankey-type diagrams, from biogenic and fossil sources of the transport sub-sector under a) BAU and b) 15Bio scenarios. Advanced second generation biofuels are not accounted for in the BAU scenario

3.2 Dynamic climate change impact results from the transport and bioethanol systems

The dynamic impact assessment of the inventoried GHG emissions was performed with time-dependent CFs [47], expressed as relative climate change impact in Mt CO_2-eq. The LCIA TH is variable in the dynamic method, and therefore an end year for the characterisation must be chosen by the practitioner to compare the results. We set the end year to 2119, 100-years into the future from the first PEM simulation year (2019). The climate impact is computed per scenario as shown in Fig. 7, for both the transport sub-sector (Fig. 7a) and the FoWooR-based 2G bioethanol (Fig. 7b). The impacts per system and scenario were compared as per two sets of results, namely one based on C neutral estimates (without C_{bio}) and on complete C estimates (with C_{bio}). Note that the BAU scenario revealed no climate change impact from C_{bio}, since no C_{bio} balance (i.e. from 2G bioethanol) has been accounted in the reference simulations.

The climate change impact shown in Fig. 7a was based on all GHG emissions of the overall transport flows (i.e. production and consumption of petroleum fuels and biofuels). The climate change impact in 2119 would result in 1.19E3 and 1.11E3 Mt CO_2-eq, for BAU and 15Bio respectively. The new set of policies mitigate the climate change effects by 7% more, compared to BAU in the year 2119. The impacts remained under the BAU curve, even with projections beyond the selected chosen end year (not shown in Fig. 7a). Yet, fossil-based results of both scenarios demonstrated a continuous increase of the atmospheric impacts. This is due to the annually accumulated impacts and the long-term persistency of the dominant gas in the atmosphere (CO_2). Even though CH_4 and N_2O have a higher perturbation capacity in the atmosphere, the atmospheric residence lifetime (i.e. removal time in the atmosphere) of the reference CO_2 gas is in the order of thousands of years [43].

A comparison between the C neutral and the complete C results for transport, across scenarios (Fig. 7a), revealed that the climate change impact, and thus the mitigation effect from C_{bio} estimates from the BAU reference scenario, are zero (as no FoWooR have been accounted for). Therefore, the comparison between C neutral and complete C was only valid for the 15Bio scenario. The 15Bio complete C impacts amount to 1.08E3 Mt CO_2-eq in the year 2019. Compared with the 15Bio C neutral impact (1.11E3 Mt CO_2-eq), it results in a mitigation effect of about 3%. This means that the inclusion of the dynamic C_{bio} would lead to a higher mitigation effect than for 15Bio C neutral estimates. The reduction draws back to the inventoried historic long-term sequestration period. This effect is sustained far into the future, until a steady-state is achieved after about one thousand years (not shown in Fig. 7a). That is to say, in the distant future the complete C impacts become equivalent to the C neutral impacts.

Such a small estimated mitigation effect from the 15Bio complete C of the transport sub-sector, is due to the dynamic C_{bio} balance corresponding exclusively to the FoWooR-based 2G bioethanol pathway, which is minimal compared with all fossil sourced emissions from the entire transport sector. The total 15Bio contributions of FoWooR to the transport sub-sector, in the peak year 2030, amounted to 17% of the primary biomass share and 3% of the final energy consumption. The allocation of C_{bio} emissions to the overall transport system were thus not significantly contributing in the 15Bio simulations. Therefore, an allocation of the C_{bio} emissions restricted to the FoWooR-bioethanol pathway was undertaken to provide insights into the climate change impact and mitigation effect of the bioethanol system.

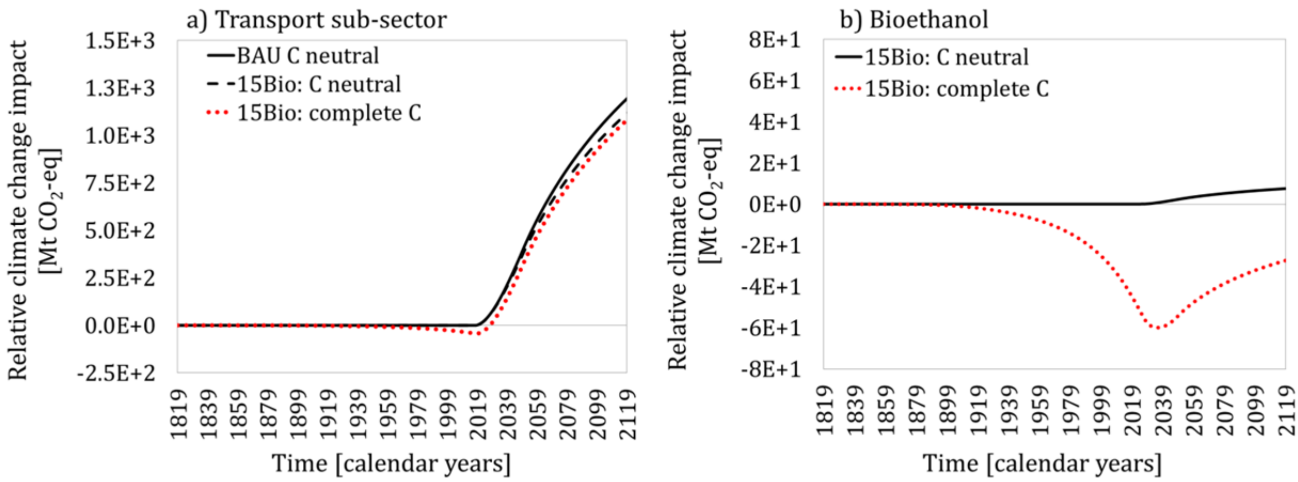

Fig. 7. Relative climate change impact [Mt CO_2-eq], assessed by means of time-dependent characterisation factors based on the radiative forcing method for a) the transport sub-sector, and b) the bioethanol systems

Results from the bioethanol system are shown in Fig. 7b. For the impact assessment of bioethanol, the following conversion factors were applied to the 15Bio FoWooR outputs: low heating value of 18.5 $MJ \cdot kg^{-1}$, bioethanol yield of 0.3428 $MJ_{Etanol} \cdot MJ_{wood}^{-1}$, and fossil-based GHG emission factor of 19.5 g CO_2-eq$\cdot MJ_{Ethanol}^{-1}$. The CO_2-equivalent values were recalculated proportional to the respective CO_2, CH_4 and N_2O elementary flows given by the EC-JRC [81] and divided by the default IPCC GWP_{100} equivalent factors [43]. The complete C balance included the dynamic biogenic emissions from C_{bio} fixation and C_{bio} combustion EOL of FoWooR. The C neutral estimates from bioethanol production were calculated using the EC-JRC WTW method for EU farmed or waste wood-to-bioethanol pathways [81]. The cumulative bioethanol production from the FoWooR output associated with the 15Bio scenario over the entire PEM simulation TH amounted to 1.04E12 $MJ_{Ethanol}$, which corresponds to a carbon footprint of 2.03E7 Mt CO_2-eq (when using the static GWP_{100}). A comparison between the absolute value of the total dynamic biogenic emissions from either C_{bio} fixation or combustion (3.72E2 Mt CO_2-eq) and the total fossil emissions from bioethanol production (2.03E7 Mt CO_2-eq), demonstrated that the fossil sourced emissions represented only about 5.4% of all emissions from the bioethanol system. Although the comparison is static —all technical and elementary flows are summed up in the year 2019, equivalent to the year zero in static inventories—, the outcomes have shown the difference in orders of magnitude between the fossil and biogenic emissions in the bioethanol system.

The relative climate change results from bioethanol (Fig. 7b) in the year 2119 resulted in 7.55E0 Mt CO_2-eq for C neutral and -2.74E1 Mt CO_2-eq for complete C. Note that for the BAU scenario has zero impact, as no

C_{bio} balance from FoWooR was accounted for and thus no production of bioethanol was modelled. A comparison between the two results for 15Bio Bioethanol showed that the climatic impacts for complete C are negative, implying that the sequestration is larger than the positive impact from the release. These complete C results would reduce those of C neutral results by 462%. Such high mitigation effect is explained by the low contribution (5.4%) of fossil sourced emissions to the total bioethanol emissions, and the duration of inventoried (historic) long-term sequestration. Projections beyond the year 2119, revealed that the complete C results would continuously converge towards the C neutral curve. The climate mitigation effect is thus sensitive to a specific year or selected future reference year (i.e. end year of the LCIA impact assessment), as the LCIA TH is variable.

Additionally, we calculated a dynamic emission factor for bioethanol from FoWooR. First, the relative climate impact for the C_{bio} balance (i.e. biogenic only) was computed the year 2119, resulting in -3.49E7 Mt CO_2-eq. This negative value was subsequently divided by the total FoWooR-bioethanol production (1.04E12 $MJ_{Ethanol}$). The resulting dynamic emission factor (-33.6 g CO_2-eq·$MJ_{Ethanol}^{-1}$) was contrasted with the EC-JRC static emission for wood residues from farmed forestry (19.5 g CO_2-eq·$MJ_{Ethanol}^{-1}$). A comparison between these factors demonstrates that the dynamic factor is negative, which would imply that the climate impact from bioethanol production could be reduced by 272%, an almost three-fold reduction for this specific policy scenario. This negative factor derives from the historic long-term C_{bio} sequestration period assessed in this study. However, the more distant into the future the reference year is set to, the lower the mitigation effect becomes, as the impact from biogenic sources approach C neutral results. That is to say, the negative atmospheric impact from sequestration is reduced thorough the positive impact from combustion.

3.3 Comparison of bioethanol impacts with an alternative reference scenario

For the bioethanol system a comparison was undertaken between the 15Bio scenario and a hypothetical BAU* reference scenario featuring a C_{bio} balance with an alternative EOL pathway. This comparison was performed because the previous BAU reference results were zero due to the absence of a C_{bio} balance estimate. We therefore assumed a reference system, in which FoWooR from logging operations are left behind instead of being used for the transport sub-sector. The hypothetical C_{bio} balance for the BAU* scenario was composed from C_{bio} fixation and C_{bio} decay flows. It accounted for the same mass of FoWooR described in the 15Bio scenario with the same historic full-rotation length of 200 years (see section 2.3.1).

Erreur ! Source du renvoi introuvable.a shows the C_{bio} balance from BAU* and 15Bio. The BAU* C_{bio} fixation values were equal to those inventoried in the C_{bio} balance of the 15Bio scenario. The flows from the EOL options however differed for combustion and decay. A comparison between the two inventoried EOL flows, indicated that the BAU* gradual decay of FoWooR shifted the release of emissions further into the future, as compared with the instant emissions from combustion. The last release flow from combustion occurred in the year 2050. For the decay, the last flow was estimated in the year 2119, although <0.01% of the carbon remained in the technosphere. We neglected those remaining emissions and assumed that until the year 2119 the total embedded carbon in the FoWooR returned to the atmosphere.

Erreur ! Source du renvoi introuvable.b shows the relative climate change impact from the bioethanol system for BAU* and 15Bio. For bioethanol C neutral results (i.e. fossil based) are equal for both BAU* and 15Bio, amounting to 7.55E0 Mt CO_2-eq in the year 2119. The impact results of the complete C estimates would attain in Mt CO_2-eq 3.14E1 and -2.74E01 for BAU* and 15Bio respectively. The results for the BAU* with EOL decay are positive compared to those of 15Bio with combustion. This implies that the C neutral results from BAU*or 15Bio would be increased by 316%. This large difference compared to 15Bio derived from the presence of short-lived CH_4, with high perturbation capacity, that was only considered in the EOL of BAU*. The CH_4 decay emissions amounted to 10% of the total emissions associated with belowground biomass ratio, corresponding to the aboveground FoWooR, with a half-life of 30 years.

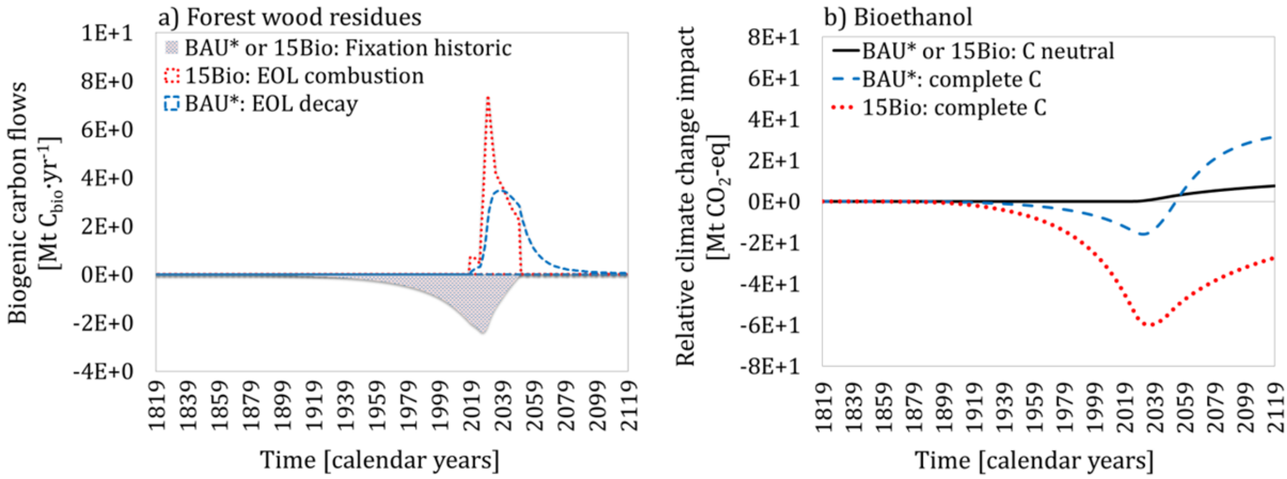

Fig. 8. a) Dynamic biogenic carbon [Cbio] balance of forest wood residues [Mt Cbio·yr-1] with fixation and two EOL options concerning combustion (15Bio scenario) and decay (BAU* alternative scenario), and b) relative climate change impact [Mt CO2-eq] of the bioethanol system of both scenarios BAU* and 15Bio

3.4 Sensitivity analysis

To test the sensitivity of the C_{bio} model to the values of its key parameters, such as the growth rate, we recalculated tree growth for all species with extreme initial values for all the parameters (from the acceptable range of values indicated in the literature). The acceptable range of values for the growth rate parameter *k* (growth rate) lied between 0.2 and 2.5. The CR model is rather robust and converges towards the originally computed results. The model is thus very flexible and accurate, yet it confirms its validity to the "slight expense of biological realism" [113].

Additionally, a sensitivity analysis was performed concerning the rotation length for the C_{bio} fixation of the 15Bio scenario. The previously applied 200-year full rotation length was contrasted against 131 years, which is the weighted mean of rotation lengths of all tree species assessed in the C_{bio} fixation model. For differentiation purposes, the scenario with the alternative full rotation length was named 15Bio*. Fig. 9 shows the sensitivity between the two rotation lengths for both systems under assessment, namely, the transport sub-sector and the bioethanol. The dynamic climate change impact, as per the complete C balance, were compared for 15Bio and 15Bio*. The alternative rotation length generated a new LCI TH, as the first fixation year shifted from 1819 to 1888. The end year 2119 would generate the following climate change impact in Mt CO_2-eq: for the transport sub-sector 1.08E3 (15Bio) and 1.36E3 (15Bio*), and for bioethanol -2.74E1 (15Bio) and 7.28E1 (15Bio*). The outcomes revealed high sensitivity for the rotation length of the C_{bio} fixation: the shorter the length the lower the mitigation effect (expressed as the difference with C neutral estimates).

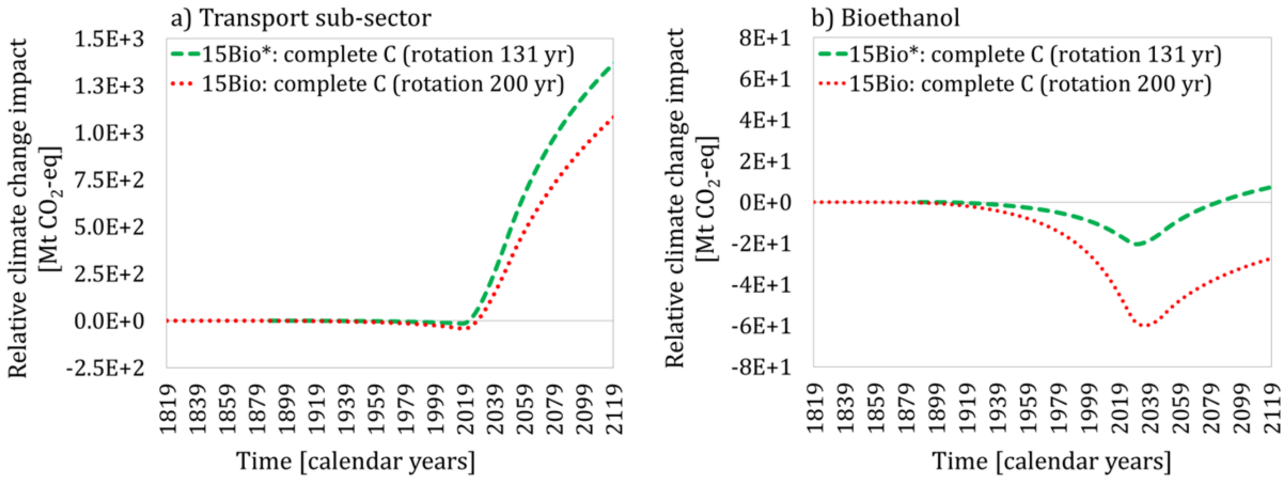

Fig. 9. Sensitivity analysis of the 15Bio scenario concerning the full rotation lengths applied for modelling C_{bio} fixation. Compared are the climate change impact [Mt CO_2-eq] from the complete carbon [C] balance, involving a full rotation lengths of 200 years and 131 years for a) transport sub-sector and b) bioethanol system. The first year of the 200-year rotation length is 1819, and for the 131-year it is 1888

3.5 Overall discussion

The comparison between TIMES-MIRET PEM scenarios revealed relevant insights into the changes of energy-transport dynamics induced by new policy constraints associated with climate change mitigation and low-carbon energy strategies. Consequences from the 15Bio policy —limiting 1G biofuel share to 7% and increasing the renewable energy share by 15% by 2030— are shown through the changes in the new biomass commodity and energy pathways for the production of advanced biofuels. Non-food crop-based biomass resources (i.e. FoWooR, agricultural residues and dedicated LGC material) were introduced to the transport sub-sector as renewable resources linked with competitive biofuel processes. The mobilisation of FoWooR supply to the transport was linked to cellulosic bioethanol, the main 2G transport biofuel under the 15Bio scenario.

The dynamic accounting of C_{bio} allowed a complete assessment of both fixation and release flows of FoWooR over time. Dynamic C_{bio} modelling and coupling with the PEM (in principle replaceable with other economic models) demonstrated the relevance of including C_{bio} emissions in the assessment of bioenergy systems. The annual biogenic values are not carbon neutral and, therefore, not zero. The historic rotation length in this study was based on a 200-year period, which is the maximum sequestration period in the French forest wood supply chain. However, the sensitivity analysis has proven that the mitigation effect from sequestration is sensitive to chosen rotation length modelling. The shorter the length the lower is the difference between the C neutral and complete C estimates.

To date, no modelling consensus exists for the initial C_{bio} fixation flow when assessing forest wood use from managed or non-managed systems. The first year of the C_{bio} fixation flow confronts the so-called chicken-or-egg causality dilemma [99]. We accounted for historic C_{bio} flows, as practiced by other authors [66,95–99], following an economic point of view of the technosphere. The residues from logging operation are considered as a co-product from the forest wood supply chain, when collected for the energy sector. The co-product is thus destined to meet the raw material requirements of emerging 2G biofuels. The selection of the modelling perspective is thus based on the origin of a biotic resource. That is to say, to meet the market requirements for future advanced biofuel production, the biotic resource extraction (e.g. FoWooR) derives from "man-made controlled culture" and not from nature [100]. Controlled cultures are, for instance, agriculture, aquaculture and silviculture/forestry. These systems experience a higher level of human interventions to meet the requirements of the market demand, and are thus considered as a part of the technosphere. For valuing C_{bio} fixation and sequestration and appropriately assess climate change mitigation targets, the different modelling approaches should be further studied and contrasted.

Furthermore, the C_{bio} model relied on empirical data from long-term field studies, tabulated into yield tables, to predict the mean tree growth dynamic and carbon fixation. The sensitivity analysis has demonstrated the robustness and flexibility of the C_{bio} model tool developed for this study. It is operational for any type of wood-based products, also cross-sectoral (e.g. wood for construction or paper industry). However, the model did not consider site-specific parameters, such as unexpected losses (e.g. diseases, wildfires). Potential losses from mortality and diseases, for France, where taken into consideration in the input data of the PEM. However, for other case specific applications, these site-dependent parameters would further improve dynamic approaches and reduced uncertainties. Further studies should be conducted to extend C_{bio} modelling to other biomass types (e.g. short rotation coppice and perennial crops) and alternative EOL pathways.

The relative climate change results demonstrated that the substitution of fossil fuel feedstock by renewables contributes to climate change mitigation. The inclusion and assessment of the C_{bio} balance, further reduced the carbon neutral estimates. The mitigation effect of the bioethanol systems was significantly larger than that of the overall transport sub-sector: the 15Bio C neutral results would be lowered by 462% and 3% for bioethanol and transport respectively. The high mitigation effect for the bioethanol is explained by the relative contribution of the fossil sourced GHG emissions in the two systems, and the historic long-term sequestration period of wood. For bioethanol, fossil emissions represented only 5.4% of the total emissions. The negative impact, implying sequestration, gradually increases with projections beyond the end year 2119, as the they are reduced by the positive fossil and biogenic emissions from the release. In contrary, the hypothetical BAU* scenario with decay EOL revealed higher impact for the complete C, meaning that the C neutral estimates would be increased by 316%.

Moreover, for FoWooR-based 2G bioethanol, a dynamic emissions factor was computed and compared with the static EC-JRC emission factor. This representation requires careful interpretation. A direct comparison between the relative impact from static (GWP_{100}) and dynamic (time-dependent CFs) methods is not directly possible, as both have different impact representations. The main inconsistency lies between the different time horizons generated by the different emission years [47,50]. The static approach assigns the same impact characterisation to all emissions. That is to say, all inventoried GHG emissions are aggregated and characterised in the same way. The GWP_{100} results express the effects of all aggregate GHG emissions in year zero (in static inventories with no time consideration) and the year 100. The fixed TH ignores the temporal variability of the flows and their time-sensitive impact.

The dynamic method, on the other hand, has no fixed TH and is thus variable, representing the actual impact for any given characterisation TH. A reference year, or end year of the LCIA TH, needs to be defined to enable a comparison among different scenario results, as done in the present study. The end year of the assessment thus expresses the climatic effects between the year of each GHG emission and the chosen reference year. For instance, with the chosen end year 2119, the LCIA TH of the impact representation for the GHG emissions inventoried in the year 2019 is 100 years (2119 minus 2019), for those inventoried in the year 2050 is 69 years (2119 minus 2050), and so forth. Thus, the representation of the impact differs from that of static approaches.

For valuing the temporary C_{bio} fixation and sequestration in emerging bioenergy systems, the use of dynamic impact assessment approaches is more appropriate, as demonstrated with the model coupling. Recent studies [77,78] thoroughly discuss the shortcomings of using the single GWP metric and encourage the use of different metrics to more accurately assess climate change and mitigation efforts. We recommend the dynamic method to take into account the temporal GHG emission profiles of C_{bio} and fossil sources. If time is not taken into consideration, positive and negative impact contributions of biogenic emissions sum up to zero, thus yielding the same steady state result as carbon neutral estimates. Further research is needed to address the spatially-explicit dynamic impacts for forest bioenergy applications (e.g. concerning albedo effects, land-use change, soil organic carbon), as highlighted in various studies [15,53,63,114–116]. This implies the assessment of other impact categories, as intended by LCA.

Higher mitigation targets and restrictions of 1G biofuels may mobilise larger quantities of FoWooR or other biomass resources for the production of 2G biofuels. This raises the question: what would be the consequences of a demand change in other sectors or economies, if the demand for a specific biomass (e.g. energy crops, dedicated wood) increases significantly? Cross-sectoral interactions are not analysed in the PEM. This could be addressed by means of full CLCA, which intends to determine the biophysical changes that one life cycle could have on other life cycles (including indirect effects such as land use change) as a consequence of a decision [117]. Consequential approaches would further complement the analysis and provide meaningful insights into the shifting market- and macroeconomic dynamics (i.e. the effects that the substitution of fossil fuels by biofuels could have on other life cycles or sectors.

4 Conclusions

The proposed model coupling was successfully implemented, yielding meaningful information on how to assess biogenic carbon of bioenergy systems and emerging renewable energy pathways in response to any policy scenario. The coupled model combines crosscutting aspects of energy system analysis and forest carbon modelling in the specific context of dynamic LCA and climate change mitigation. The proposed strategy challenges the current static carbon neutral and renewable energy displacement approaches by means of dynamic assessment of biogenic carbon and time sensitive climate change impacts. The biogenic carbon models are applicable to specific cases and the parametrisation can be refined to site-specific conditions if needed. The Cbio modelling tool developed for this study is available upon request to the corresponding author.

Prospective models of emerging markets support policy-decision making of a specific sector by means of different scenario comparisons. The consideration of technological innovation and market dynamics in a transitioning energy system expands the assessment boundaries commonly used in attributional LCA. The PEM provides insights into economic optimisation of energy-transport pathways and climate change mitigation potentials. Studies should be further complemented with other environmental impact categories and other externalisations involving indirect effects (e.g. land use change and soil organic carbon). Future refinements of spatially-explicit dynamics and other impact categories should follow.

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Figure captions

Fig. 1. Conceptual diagram of the model coupling strategy of the TIMES-MIRET partial-equilibrium model with dynamic biogenic carbon modelling

Fig. 2. Diagram for coupling TIMES-MIRET partial-equilibrium model with dynamic biogenic carbon models

Fig. 3. TIMES-MIRET primary biomass supply from 2019 to 2050 per BAU and 15Bio scenarios of a) Energy mix (heat and electricity) and transport, and b) Transport sub-sector only.

Fig. 4. Final energy consumption in the transport sub-sector per energy carrier and per scenario

Fig. 5. Dynamic biogenic carbon (C_{bio}) balance of residual forest wood biomass [Mt $C_{bio}\cdot yr^{-1}$] in the transport sub-sector with historic fixation (positive) and EOL combustion (negative) flows of a) BAU scenario, and b) 15Bio scenario

Fig. 6. Carbon flows [Mt C] at year 2030, as Sankey-type diagrams, from biogenic and fossil sources of the transport sub-sector under a) BAU and b) 15Bio scenarios. Advanced second generation biofuels are not accounted for in the BAU scenario

Fig. 7. Relative climate change impact [Mt CO_2-eq], assessed by means of time-dependent characterisation factors based on the radiative forcing method for a) the transport sub-sector, and b) the bioethanol systems

Fig. 8. a) Dynamic biogenic carbon [Cbio] balance of forest wood residues [Mt Cbio·yr-1] with fixation and two EOL options concerning combustion (15Bio scenario) and decay (BAU* alternative scenario), and b) relative climate change impact [Mt CO2-eq] of the bioethanol system of both scenarios BAU* and 15Bio

Fig. 9. Sensitivity analysis of the 15Bio scenario concerning the full rotation lengths applied for modelling C_{bio} fixation. Compared are the climate change impact [Mt CO_2-eq] from the complete carbon [C] balance, involving a full rotation lengths of 200 years and 131 years for a) transport sub-sector and b) bioethanol system. The first year of the 200-year rotation length is 1819, and for the 131-year it is 1888