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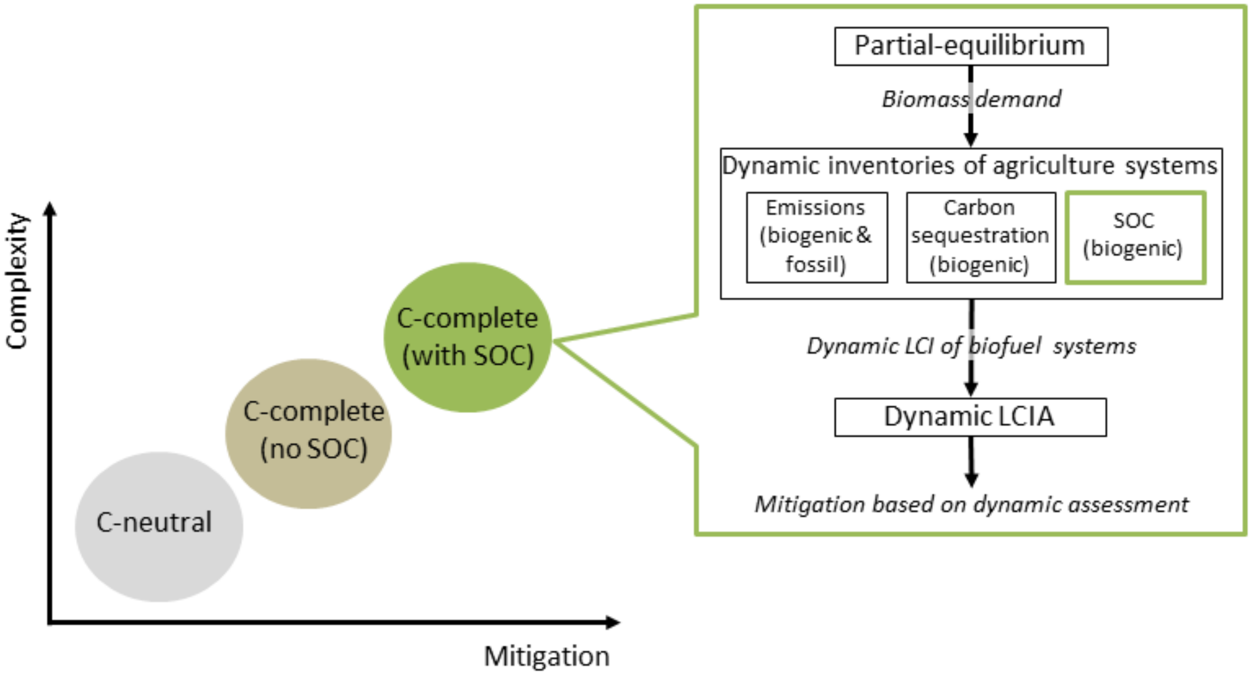
Graphical abstract



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Highlights

- Dynamic accounting of SOC from land use activities linked with energy crops for transport biofuels
- The modelling framework contributes to complete GHG inventories including biogenic C and SOC
- Mitigation potentials are sensitive to residue management (C inputs to the soil vs. removal rates)
- Temperature affects organic matter decay and thus mitigation effects
- Soil C sequestration from perennial is higher than that from annual crops

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Abstract

Low carbon strategies recently focus on soil organic carbon (SOC) sequestration potentials from agriculture and forestry, while Life Cycle Assessment (LCA) increasingly becomes the framework of choice to estimate the environmental impacts of these activities. Classic LCA is limited to static carbon neutral approaches, disregarding dynamic SOC flows and their time-dependent GHG contributions. To overcome such limitation, the purpose of this study is to model SOC flows associated with agricultural land use (LU) and the provision of agricultural substrates to transport biofuels, thus generating dynamic inventories and comparatively assessing energy policy scenarios and their climate consequences in the context of dynamic LCA. The proposed framework allows computing SOC from annual and perennial species under specific management practices (e.g. residue removal rates, organic fertiliser use). The results associated with the implementation of three energy policies and two accounting philosophies (C-neutral and C-complete) show that shifting energy pathways towards advanced biofuels reduces overall resource consumption, LU and GHG emissions. The French 2015 Energy Transition for Green Growth Act (LTECV) leads towards higher mitigation targets compared with business-as-usual (BAU) and intermediate (15BIO) policy constraints. C-neutral results show reduced radiative forcing effects by 10% and 34% for 15BIO and LTECV respectively, but not for BAU. C-complete (i.e. dynamic assessment of all biogenic- and fossil-sourced C flows) results reveal further mitigation potentials across policies, whereof 50%-65% can be attributed to temporal C sequestration in perennial rhizomes. A sensitivity analysis suggests important SOC variations due to temperature increase (+2°C) and changes in residue removal rates. Both factors affect mitigation and the latter also LU, by a factor of -0.56 to +5. This article highlights the importance of SOC modelling in the context of LU in LCA, which is usually disregarded, as SOC is considered only in the context of land use change (LUC).

Keywords:

Biofuels; dynamic life cycle assessment; energy policy scenarios; land use; residue management; SOC modelling

1 Introduction

1.1 Energy policies and low carbon mitigation strategies

Greenhouse Gas (GHG) emissions need to be reduced by 60% until 2050 (EC, 2018a; UNFCCC, 2018). Between 1990 and 2016, GHG emissions of EU-28 showed a relative reduction by 22% in most economic sectors, due to efficiency increases and changes in the energy mix, however, for the transport sector, including international aviation, they have increased by 26% (Eurostat, 2019). In France, 70% of GHG emissions are attributed to fuel combustion, of which about 30% derive from the transport sub-sector (SDES, 2019). Climate-energy policy targets promote a shift towards renewable energy (RE) and advanced biofuels. French policy formulates increasing RE-shares in the energy mix and transport sectors, by 32% and 15% (from a 2012 baseline (MTES, 2018)) respectively, as well as reducing GHG emissions by 40% (from a 1990 baseline (IPCC, 2006)).

Low carbon strategies include the use of energy crops for producing transport-biofuels, as they are RE carriers considered as carbon neutral GHG inventories. Most of these feedstock consist of dedicated food-crop based annual species (e.g. rapeseed, wheat), as well as lignocellulosic dedicated perennial species and residual matter, among other non-food crop derived biomass such as algae. Advanced second generation (2G) biofuels, i.e. based on perennial grasses, woody residues, and agricultural straw, are increasingly encouraged, as they do not displace food production, regardless of their alleged potential contribution to indirect LUC (Harvey and Pilgrim, 2011).

Additional mitigation strategies focus on the potential of carbon sequestration in soils through agricultural practices (Goglio et al., 2015), promoted for instance under the “4 per mille Soils for Food Security and Climate” initiative presented at the 21st Conference of the Parties of the UNFCCC, which resulted in the 2015 Paris Climate Agreement (CGIAR, 2018; INRA, 2019; Minasny et al., 2017; Zanella et al., 2018). This initiative faces nonetheless some criticism on the extent to which soil can sequester carbon (e.g. White et al. 2018) and the concept of soil carbon sequestration itself, as the release of nutrients is one of the key functions of soil organic matter (SOM) (Lehmann and Kleber, 2015). Therefore, the dynamic of soil organic carbon (SOC), as influenced by biomass production and use, needs further research when modelling climate benefits of future energy scenarios.

Prospective bottom-up energy system models are instruments assessing policy scenarios and their effects on a (sub-)sector, by means of linear programming and optimisation (Loulou et al., 2016). Scenario simulations from these models are built on least cost and low carbon energy pathways, involving technological innovation, efficiency and RE from fossil and biomass sources. The dynamic of SOC and LU are however not considered in energy system models (Frank et al., 2015).

1.2 Soil organic carbon modelling and applications in life cycle assessment

SOC is the main component of SOM, accounting for 55-60% by mass, divided among three pools: fast/labile/active (turnover time of 1-2 years), intermediate (turnover time of 10-100 years), and slow/refractory/stable (turnover time of >100 years) (FAO, 2017). The turnover rate plays a key role in the functioning (e.g. health) of the soil ecosystem, as well as on climate change, as C is eventually released to the atmosphere, as it undergoes continuous decomposition in the soil under influence of soil fauna activity (Kwiatkowska-Malina, 2018; Lehmann and Kleber, 2015; Campbell and Paustian, 2015; FAO, 2017). Several physical and biochemical mechanisms may influence the decomposition rate, and these mechanisms can be in turn influenced by management (e.g. to increase C sequestration) (Wiesmeier et al., 2019; Zomer et al., 2017).

In general, SOC models take into consideration soil temperature, water, and clay content; as main drivers for changes in C stocks (Bockstaller and Girardin, 2010; Ci et al., 2015; FAO, 2017; Han et al., 2018; Zhong et al., 2018). They are usually based on the assumption that SOM decomposes following first order kinetics (Luo et al., 2016; Smith et al., 2012), initially proposed in the 1945 pioneering model from Hénin and Dupuis (Henin and Dupuis, 1945; Shibu et al., 2006), where the decomposition rate constant corresponds to the pedoclimatic condition-dependent annual mineralisation rate. Mineralisation coefficients can be estimated from measured data (e.g. Delphin 2000) or modelled (Benbi and Richter, 2002; Bockstaller and Girardin, 2010), and are often available in the literature (e.g. Gobin et al. 2011).

SOC modelling in agriculture, livestock, climate mitigation and LCA are carried out by means of different methods, depending on the purpose of the study, data availability and spatial scales (i.e. site-specific, site-dependent or site-generic variables). Common classifications involve three levels of complexity (Bolinder et al., 2006; Campell and Paustian, 2015; FAO, 2018; Goglio et al., 2018, 2015; Shibu et al., 2006; Smith et al., 2012): i) analytical/empirical models, mostly based on the factors from IPCC Guideline for National GHG Inventories (IPCC, 2006), ii) process-oriented/conceptual models, with increasing complexity according with the number of pools considered, and iii) ecosystem/summary models, i.e. multi-compartment models involving sub-models such as plant growth, dynamic crop-soil-crop models etc.

Analytical modelling methods are based on two main rationales: gain-loss, where processes altering C content of pools are considered, and stock-difference, most common in LCA, where C stocks in pools are measured at two points in time (Benoist and Bessou, 2018; IPCC, 2006). Empirical models, such as the Campbell model (Campell and Paustian, 2015), use two functions to describe changes in SOC: one to model C dynamics associated with organic inputs (i.e. residues) and another for the decomposition of pre-existing SOC (Liang et al., 2005; Smith et al., 2012). These models have also been used to assess the C sequestration potentials of specific crops, such as the one proposed in Grogan and Matthews (2002) for energy crops (short rotation coppice willow). Other analytical models include the two-compartment (i.e. active and stable) Introductory Carbon Balance Model (ICBM) (Andrén and Kätterer, 1997) and variations of the three-compartment model first presented by Andriulo et al., (1999a), such as the AMG model (Clivot et al., 2019; Duparque et al., 2013; Saffih-Hdadi and Mary, 2008). The use of such models requires site-dependent coefficients (e.g. degradation rates; effects of clay, humidity and temperature). Complex dynamic models, on the other hand, aim at answering questions beyond C or N sequestration: their goal is to predict the performance of specific agricultural systems involving site-specific (i.e. local) calibrations.

LCA generally requires simple, site-generic models, which are useful under a variety of conditions and require a minimal amount of input data. Two models widely used in LCA, the monthly time-stepped C-TOOL (Petersen, 2003) and the daily to annually time-stepped RothC (Coleman and Jenkinson, 2014), demand a larger number of input parameters than ICBM or AMG models (Campell and Paustian, 2015; Goglio et al., 2015). Complex agro-ecosystem models such as CANDY, CENTURY, CERES-EGC, DAYCENT, DAISY, DNDC and STICS have been occasionally used in LCA (Brilli et al., 2017; Campbell and Paustian, 2015; Goglio et al., 2015; Gueudet, 2012), but the required level of expertise and data hinder their widespread applicability.

1.3 Land activities in the context of soil organic carbon modelling

In LCA, two types of activities are modelled in relation with SOC, namely LUC and LU, the latter referring to use of a land over time not involving LUC. LUC is associated with “transformation” and LU to “occupation”, two keywords used in LCA software to identify these two elementary flows. Depending on methods and data availability, land management changes (LMC) can be modelled as either transformation or occupation processes (Benoist and Bessou, 2018). LMC-related agricultural practices potentially affecting SOC dynamics include management of agricultural residues, organic fertilisation and the selection of high-biomass crops and rotations (Goglio et al., 2015, 2014).

The original ILCD handbook (EC-JRC, 2010) recommended a widely used single-indicator model for calculating the impacts of transformation and occupation, based on changes in soil quality, expressed in terms of SOM (Milà i Canals et al., 2007a, 2007b). More recently, the Product Environmental Footprint (EC, 2018b; Sala S. et al., 2019) suggested the multi-indicator models LANCA (Bos et al., 2016) and latest LANCA v2.5 (Horn and Maier, 2018). Regarding SOC modelling itself, mostly characterisation factors and simple models are used in LCA, yet no recommended or consensus model exists (Goglio et al., 2018, 2015). For instance, the PEFCR guidelines (EC, 2018b) recommend the PAS 2050 approach (BSI, 2011) to be used for all C emissions and removals arising from LUC, but PAS 2050 does in turn recommend using IPCC methods (for LCIs) and reporting SOC-related results separately. The IPCC approaches for SOC modelling (Tiers 1 and 2, and characterisation factors), include only the topsoil (first 30 cm), thus disregarding intermediate and stable pools.

The UN Environment (formerly UNEP-SETAC) Life Cycle Initiative recommends the same SOM-based approach to occupation and transformation of land as IPCC, yet it also recommends a specific method for SOC impacts on

C sequestration and climate change (Koellner et al., 2013). This method, described in Müller-Wenk and Brandão (2010), provides factors for C losses to air, from an initial stock in soil (estimated per biome), associated to various types of occupation and transformation. It is one of the few approaches, together with Schmidinger and Stehfest (2012), a method under development (Benoist and Cornillier, 2016), and project-oriented methods based on IPCC (e.g. under the Kyoto Protocol's Clean Development Mechanism, https://cdm.unfccc.int/methodologies/index.html), considering the impacts on climate change via C sequestration and release of both transformation and occupation of soils (Benoist and Bessou, 2018). Table 1 summarises the features of some of these modelling approaches used in LCA.

Table 1. Comparison of recommended static modelling approaches for calculating soil quality SOM/SOC changes associated with LU (occupation) and LUC (transformation) in LCA

Method	Recommending guideline	Land activities included	Usefulness for LCIA	Notes
SOM/SOC change (Brandão and Milà i Canals, 2013; Milà i Canals et al., 2007a, 2007b)	International Reference Life Cycle Data System (EC-JRC, 2010)	T+O	CF available, limited linking to AoP	Informing soil quality, site-dependent or -generic, but not climate change
LANCA (Beck et al., 2010; Bos et al., 2016; Horn and Maier, 2018)	Product Environmental Footprint Category Rules (EC, 2018b)	T+O	CF available	Informing soil functions, data intensive, suitable for site- dependent or generic assessment
SALCA-SQ (Oberholzer et al., 2012, 2006)	ecoinvent v2 (Nemecek et al., 2011; Nemecek and Kagi, 2007)	O	CF available, limited linking to AoP	Informing soil properties and treats, site-dependent or site-specific (plot level)
Müller-Wenk and Brandão (2010)	UNEP-SETAC (Koellner et al., 2013)	T+O	CF available	Informing climate change, site-generic (6 biomes over the world)
PAS 2050 standard (BSI, 2011) and IPCC Guideline for National GHG Inventories (IPCC, 2006)	Product Environmental Footprint Category Rules (EC, 2018b)	T	N/A	Dynamic modelling in the context of CDM methodologies, but site-dependent

Acronyms. AoP: Area of Protection, SOC: Soil Organic Carbon, SOM: Soil Organic Matter, T: Transformation; O: Occupation, LCIA: Life Cycle Impact Assessment, CF: characterisation factors, GHG: Greenhouse Gas, CDM: Kyoto Protocol's Clean Development Mechanism
Sources: Benoist and Bessou (2018)

Regarding biofuels, the effect of LU and LUC on soil C dynamics, as well as that of residue management practices (i.e. removal rates of residues exploited as RE carriers), are of key interest (Brandão et al., 2011; Caldeira-Pires et al., 2018; Smith et al., 2012). The overall potential C sequestration of energy crops has been computed, and estimated to be positive (Lemus and Lal, 2005; Mi et al., 2014; Zang et al., 2018). Moreover, the need for time dynamic SOC modelling in LCA has been highlighted (Brandão et al., 2013, 2011; Sommer and Bossio, 2014). A first effort in that direction is the approach to include SOC changes in LCA proposed by Petersen et al. (2013), which relies on the Bern Carbon Cycle Model to determine degradation curves, the superposition of which allows, by mass-balance, to estimate the amount of C remaining in soils by the end of the assessment time horizon (TH).

1.4 Goal and scope of the study

Based on such environment of evolving SOC modelling approaches and applications in LCA, the goal of this work is to propose a dynamic SOC modelling approach for life cycle inventories associated with LU and agricultural substrates to biofuels. The proposed approach would contribute to overcoming identified gaps of SOC modelling in LCA, namely, the consideration of: SOC associated with LU, SOC dynamic within a given reference TH, and the need for accessible SOC models in LCA. Furthermore, the resulting dynamic SOC inventories are integrated into a dynamic model-coupling framework with a partial-equilibrium model (PEM) as proposed in Albers et al., (2019a), to comparatively assess future energy-transport scenarios and climate change consequences associated with SOC. A key aspect of the proposed approach is its dynamic representation of SOC associated with the dynamic technical flows of the system, to more accurately estimate climate change impacts.

The functional unit in this study represents the annual energy demand, in MJ, over the prospective PEM simulation period (2019 to 2050), defined per policy constraint, here to satisfy the energy consumption of transport end-users, in this study referring to bioethanol and biodiesel from agricultural energy crops.

2 Material and methods

The construction of dynamic SOC inventories associated with energy policy scenarios and LU, follows the model-coupling framework specified in Fig. 1. The framework allows computing dynamic SOC flows from agricultural annual and/or perennial energy crops under specific (yet variable) management practices (e.g.

residue removal, or organic fertiliser use). The SOC model includes C inputs to the soil stemming from aboveground (AG) and belowground (BG) plant compartments, as well as from exogenous (EX) sources (i.e. organic fertilisers). Site-dependent coefficients, such as temperature and soil characteristics, relate to the crop cultivation in France, except for soybean, which is assumed to be imported from Brazil.

Firstly, the technical flows obtained from the energy system model (it could have been any other demand model) are exported to a) inform SOC modelling on the biomass commodity supply, b) compute LU requirements, and c) represent the results specific to two selected transport-biofuel (bioethanol and biodiesel) pathways per biomass commodity. Secondly, annualised “C-complete” balances are built by combining dynamic accounting of biogenic- (here referring to SOC flows) and fossil- (referring to C neutral flows without biogenic flows) sourced CO_2 elementary flows, which are subsequently assessed with time-dependent characterisation factors in the context of dynamic LCA (Levasseur et al., 2010). This study does not represent a complete LCA, as it solely focuses on modelling dynamic life cycle inventories of SOC and their climate change consequences.

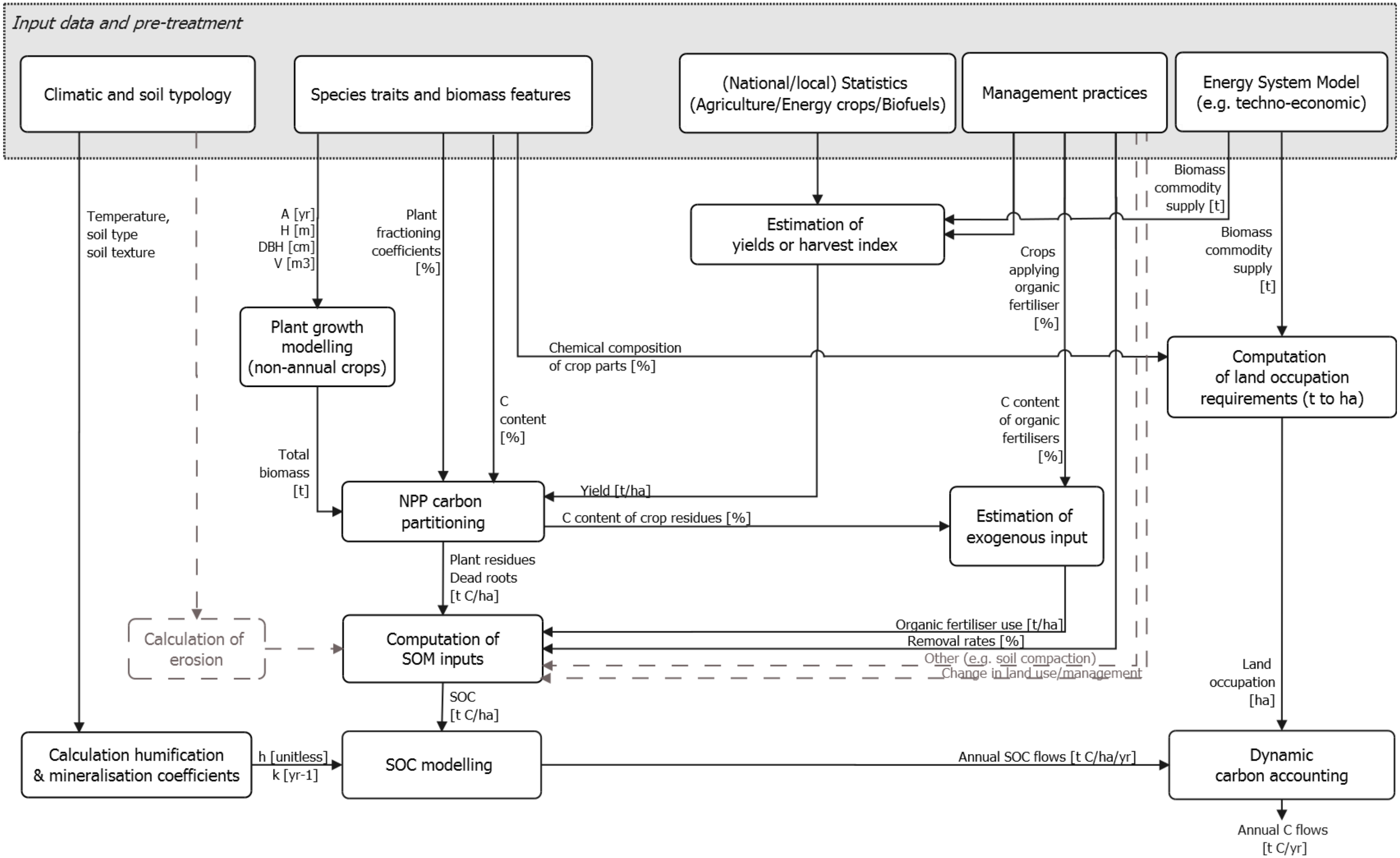

Fig. 1. Coupling diagram of energy system and soil organic carbon modelling for dynamic carbon accounting (Acronyms: A: Age, C: Carbon content, DBH: Diameter Breast Height, H: Height, h: Humification coefficient, k: Mineralisation coefficient, NPP: Net Primary Productivity, SOC: Soil Organic Carbon, V: Volume)

2.1 Processing model outputs from the energy system model

2.1.1 Demand model informing policy scenarios for the transport sub-sector

For this study, we exported energy crop commodity outputs from the TIMES-MIRET partial-equilibrium energy system model (Lorne and Tchung-Ming, 2012), over the simulation period 2019 - 2050. TIMES-MIRET is a bottom up PEM, also referred to as techno-economic model, covering the energy-transport sector of metropolitan France. Further specifications on the model were previously introduced in Albers et al. (2019a).

The TIMES-MIRET calibration is based on the 2009 EU Directive and National Energy Plan, with climate targets by 2020 serving as a reference in the business-as-usual (BAU) policy scenario. BAU is contrasted with new targets by 2030 from the 2015 French Energy Transition for Green Growth Act for the transport sub-sector. The new constraints are a 15% renewable energy share in the transport-subsector and a maximum of 7% 1G biofuels (here analysed with the 15BIO scenario), as well as a 30% reduction of fossil fuel and intermediate targets for advanced biofuels (here analysed in the LTECV scenario) (MTES, 2018).

2.1.2 Biomass-to-biofuel commodities and land use

Biomass-to-biofuel pathways, retrieved from the PEM, depend on the policy constraints given to the model. The following biomass commodities flows [kt] were considered: first generation (1G) crop-based starch (wheat, rapeseed, maize and triticale), oil (rapeseed, sunflower and soybean), sugar (sugar beet), as well as second generation (2G) residual lignocellulosic straw (wheat, rapeseed, maize and triticale) and dedicated lignocellulosic perennial grasses (miscanthus and switchgrass as a proxy for dedicated lignocellulosic biomass). Other commodities (e.g. algae, yeast, palm oil, sewage sludge, and spent cooking oil) are excluded due to their comparatively low to null contributions to the overall biofuel transport sector in the three analysed policy scenarios. The biofuel pathways included in this study refer to transport bioethanol and biodiesel.

We computed the LU requirements [ha yr^{-1}] in terms of the equivalent agricultural area. Such conversion is based on statistics and literature on agricultural data of potential yields per area [$t \cdot ha^{-1}$] revealing the amount of crop product that is exported from the field and the chemical composition of the harvested crop product, determining its starch, sugar or oil contents [%]. Residues (straw) are computed based on the residue yield of the whole plant times the residue removal rate (if any), while dedicated perennials represent 100% of the lignocellulosic commodity. Detailed specification on the computation and methods used for biomass-to-biofuel, LU and GHG emission conversion are provided in the Supplementary Material.

2.2 Dynamic soil organic carbon modelling

We adapted the relatively simple, yet appropriate for modelling dynamic inventories, SOC model of Hénin and Dupuis (1945). The model runs with a time step of one year compatible with the time-dependent climate change characterisation. Hénin and Dupuis' model is based on the interaction of C between two soil compartments: i) fresh organic matter input from AG (crop residues) and BG plant parts (dead roots and rhizomes), as well as exogenous organic inputs (e.g. soil amendments/fertilisers), and ii) the active pool (soil layer up to 30 cm depth) (see Supplementary Material). The C balance represents the difference between the dynamic C input [$t\ C \cdot ha^{-1}$] from a flow of organic matter (*m*) entering the active pool at a given time (t_0), as well as the losses from C output flows (here as CO_2 flows) determined by instant releases determined by the isohumic coefficient (*h*) and the gradual decay determined by the mineralisation coefficient (*k*). The model has been developed into a long-term SOC model, referred to as the AMG model (Andriulo et al., 1999), undergoing continuous refinements (latest version introduced in Clivot et al. (2019)). AMG accounts for C stocks in the upper layers (≤30 cm) and stable deeper layers (>30 cm). It has been integrated in the STICS model (Saffih-Hdadi and Mary, 2008) and implemented into the SIMEOS-AMG tool (Bouthier et al., 2014).

For the model coupling (here with an energy model), it is required to assess the technical flows of a product system (here biofuels) for any given calendar simulation year, independent from C stocks or C losses from previous LU or LUC. In contrast to the long-term AMG model, we aim at modelling the added C to the soil given by the technical flows and its time-dynamic decay within the active pool (i.e. the annual difference between the remaining C from a single-year input and the C releases over time until the SOC balance equals zero). Thus, initial stable C stocks from long-term crop cultivation systems associated with the same LU over several consecutive years are not modelled and it is assumed that the stable pool does not change over several centuries (Kwiatkowska-Malina, 2018; Shibu et al., 2006).

The modelling of the soil C balance is computed with Eq. 1 , according with Hénin and Dupuis (1945), however fractioning the C input from *m* into AG (crop residues including exogenous matter) and BG (root system) compartments. The integral for the net annual flows for *AG* and *BG* are given in Eq. 2 and

Eq. 3 respectively:

$$C_{AP} = C_{AG} + C_{BG} \qquad \text{Eq. 1}$$

$$C_{AG}(t_0) = m_{AG}h \qquad \text{Eq. 2}$$

$$\frac{dC_{AG}}{dt} = -kC_{AG}$$

$$C_{BG}(t < t_{RL}) = m_{BG} \qquad \text{Eq. 3}$$

$$\frac{dC_{BG}}{dt} = \begin{cases} 0, & when\ t < t_{RL} \\ -k\ C_{BG}, & when\ t \geq t_{RL} \end{cases}$$

where C_{AP} [t C·ha^{-1}] is the carbon content in the active pool from AG and BG compartments, *m* is the added carbon at time *t* [yr]*,* *RL* the rotation length [yr], *h* [unitless] is the humification coefficient, and *k* [yr^{-1}] the mineralisation coefficient. The rationale behind dividing C_A into *AB* and *BG* is the dynamic character of perennial grasses, as the rhizomes remains in the soil in the long-term (i.e. C is stored over the entire cultivation/RL period), while *AG* residues contribute to annual C inputs (i.e. *AG* biomass is harvested every year like annual crops) (Beuch et al., 2000). The long-term model, on the other hand, does not allow assessing perennial species (Clivot et al., 2019).

2.2.1 Humification coefficient

The isohumic coefficient *h* (by some authors also referred to as k_1) represents the ratio between the added SOM contributing to SOC increase and the total amount of the added SOM (Hénin and Dupuis, 1945). It thus represents the fraction of SOM transformed into humified C (i.e. available to plants), while the remaining C is released to the atmospheric pool, via mineralisation (Kwiatkowska-Malina, 2018). High *h* values mean that the organic matter decomposes easily (e.g. 15% for straw compared with up to 70% for some soil amendments) (Le Villio et al., 2001). For this study, *h* values and C contents per crop type and EX matter were taken from the literature (Supplementary Material).

2.2.2 Mineralisation coefficient

The initial SOC stock is continuously reduced by mineralisation, over time (i.e. a flow, represented by positive emissions), until the net balance reaches zero. The mineralisation coefficient k (also referred to as k_2 by some authors) represents the annual decay of SOM as GHG emissions, such as CO_2, and the release of nutrients into plant-assimilable forms, and depends heavily on soil type, soil characteristics, and other pedoclimatic conditions. Saffih-Hdadi and Mary (2008) demonstrated that C mineralisation of crop residues (and by extension of any exogenous organic matter) is driven by the substrate quality rather than by the soil type (under the same humidity and temperature conditions). The C:N ratio also plays a key role in SOM mineralisation (Nicolardot et al., 2001), but this parameter is not directly used in this model, as its influence is captured in the humification coefficient.

In France, the mean annual mineralisation constant rate is often estimated at 2% (Frisque, 2007; Le Villio et al., 2001; UNIFA, 1998). A review (see the Supplementary Material) of several site-specific studies (with k calibrated to specific locations) indicated a range between 0.7% and 9%, with mean values at 4%. For computing k, the updated method proposed in the AMGv2 model (Clivot et al., 2019), takes under consideration soil mean temperature, clay and calcium carbonate ($CaCO_3$) contents. Our k estimates excluded soil moisture, pH and C/N ratio, as the scope of the study disregards site-specific parameters, focusing primarily on the C flows. Soil temperature, clay and $CaCO_3$ content are the key parameters in this study, providing close approximations for a usable mineralisation rate. We computed k for eight climate types in France, referring to the classification by Joly et al. (2010), for which a dominant soil type can be roughly assigned. For the model coupling, we chose climate Type 3 (Central France) featuring a mean temperature of 11°C and mean clay content of 16.8%, as this climate type represents an important agricultural area for cereals and oil crops. For the imported soybean, we used the same method, based on the reference soil temperature of 27°C, representing about 2°C higher for surface soils in soybean cropland in Mato-Grosso, Brazil (Nagy et al., 2018). All specifications are provided in the Supplementary Material.

2.3 Modelling carbon inputs from aboveground, belowground and exogenous matter

The net C inputs to the soil dependent on management practices defining removal/export rates from the AG compartment (crop products, residues) and BG compartment (rhizomes and roots), as well as the incorporation of non-mineral exogenous matter (organic fertiliser). Therefore, methods were adapted to model the partitioning of C in the different crop fractions, to determine what proportion of AG and BG plant are incorporated in the soil and whether EX matter is added.

2.3.1 Rhizomes growth and carbon fixation of perennial grasses

Dynamic growth and carbon sequestration of annual crops are commonly excluded from dynamic carbon modelling, as their C fixation and release flows occur within one year, equivalent to carbon neutrality (Guest et al., 2013). The same applies to the AG perennial grasses, harvested annually. However, growth dynamics of the BG biomass fraction require an additional modelling step, given that the C fixation in the rhizomes occurs over several years, in contrast to annual crops.

We considered the miscanthus (*Miscanthus x giganteus*) and switchgrass (*Panicum virgatum*), which are perennial rhizomatous C4 grasses. These grasses have extensive root systems, which may increase in the long-term (Agostini et al., 2015). However, dynamic growth models for root system are not accessible, as they tend to be very complex and species-specific (Dupuy et al., 2010). A meta-analysis by Agostini et al. (2015) highlighted that the biomass growth from the BG compartment and the C inputs to the soil are mainly based on several single observations with variable stand age, depths and sampling frequencies, making it difficult to model the time series of the root system. Yet, it has been demonstrated that the C fixation increase with increasing cultivation period (Arevalo et al., 2011; Rehbein et al., 2015).

Rehbein et al. (2015) calculated the miscanthus-derived C for different soil depths/layers up to 100 cm and showed that the C stock increased linearly with increasing time ($R^2 = 0.8$, $P < 0.001$) in the top soil (≤10 cm) and deeper soil layers (0-100 cm), whereas 60 to 80% of the C is associated to the top soil. Based on the results from Rehbein et al. (2015) and meta-analysis from Agostini et al. (2015), we distributed the total C over the entire rotation length linearly to represent the rhizomes growth and C fixation in the biomass. Consequently, the time-dependent C_{BG} inputs to the soil (Eq. 3) from miscanthus and switchgrass take place after the end of the rotation length at 20 and 15 years respectively. Both C fixation and SOC release flows are allocated accordingly.

2.3.2 Plant fractioning and carbon partitioning

For computing the C inputs to the soil from AG and BG compartments, the approach of Bolinder et al. (2007), applied in other studies (Clivot et al., 2019; Wiesmeier et al., 2014), was adopted. The authors conceptualise the C input to the soil as a proportion of net primary productivity (NPP), summing up four plant fractions per unit of area [t C·ha^{-1}]:

- C_P: the C in the agricultural product (*P*) in the AG (e.g. seed, grain, perennial grasses, and forage crops) or BG (e.g. tuber) compartments, representing the primary economic value, not incorporated into the soil.
- C_S: C in the residual (*S*) AG fraction (e.g. straw, stover) incorporated into soil after harvest.
- C_R: C in root (*R*) BG tissue (rhizome), physically recoverable plant materials (excluding products such as tubers from sugar beet), mostly incorporated in the soil after harvest.
- C_E: C in extra-root (*E*) matter (rhizome deposition), involving root exudates and plant materials physically not easily recoverable, mostly incorporated in the soil after harvest.

C partitioning per plant fraction and per crop follows the method from Bolinder et al., (2007), including data from the literature (mean annual yield per crop and relative C allocation coefficients), both presented in the Supplementary Material. The C inputs to the soil depend on the annual yield estimates at field scales, obtained from statistics and literature. These values can be adapted to site-specific evaluations.

2.3.3 Estimation of exogenous inputs

Exogenous C inputs consist of added organic matter, under the form of amendments and fertilisers (Saffih-Hdadi and Mary, 2008). Based on French statistics on crop production (surfaces, yields) and organic fertiliser use (AGRESTE, 2019, 2014, 2011), as well as on the composition of French organic fertilisers (Avadí, 2019), average French fertilisation practices for each crop of interest were constructed. For Brazilian soybean, data was retrieved from FAO (2004).

2.4 Variations of carbon inputs to the soil

Not all the C embedded in plant fractions is returned to the soil. The net C inputs from AG, BG and EX matter depend on agricultural management practices. Consequently, four different scenarios are analysed and contrasted in this study, which could eventually be associated with residue management practices**:**

- Scenario S1_TOT: Total C inputs to soil (aboveground + belowground + exogenous carbon)
- Scenario S2_AG: C from aboveground plant residues
- Scenario S3_BG: C from belowground plant residues
- Scenario S4_EX: C from exogenous matter

The resulting scenarios are based on the origin of C from different plant fractions (AG and BG) and EX matter, whereas S1_TOT represents the sum of all added C to the soil. These scenarios represent highly contrasted extremes of management practices. In reality, these practices are likely to be more nuanced (e.g. partial combinations of AG, BG, EX added to the soil). The high contrast allows identifying the origin of C and their proportional contributions to the total SOC input.

We assumed that the total C_p is harvested. However, C_S, C_R and C_E inputs are adjusted with correction factors ranging between 0 (no C input) and 1 (100% C input) to specify the C plant proportion added to the soil (more details provided in the Supplementary Material). In France, common C_S removal rates from cereals and oily seeds are in the order of 0.5, while for vegetables, protein crops and perennials they are in the order of 1, whereas C_S from switchgrass is zero (ADEME, 2017). C_R and C_E are assumed to be wholly incorporated into the soil (except for sugar beet root, which is exported from the fields).

3 Results and discussion

3.1 Policy scenario simulations from the partial-equilibrium with static GHG emissions

Fig. 2 shows a comparative overview of the three analysed policy scenarios (BAU, 15BIO and LTECV) of the transport sub-sector from 2019 to 2050, analysed with the PEM, denoting LU requirements [ha], biomass commodity supply [kt], final energy supply [MJ], and associated GHG emissions [kt CO_2-eq] of the simulations represent the pathways of bioethanol and biodiesel demand only.

A general comparison among the three policy scenarios shows a clear shift from 1G to 2G energy carriers for the transport sub-sector, particularly evident for the LTECV scenario. The shifting energy-pathways reduce the overall resource consumption and LU demand, particularly for 1G energy crops, that consequently reduce the GHG emissions to meet the mitigation targets. It is noticeable that the prospective evaluations assume increased number of passengers per km driven per transport means, and thus reduced future fuel demand. The 15BIO scenario shows sudden increases between the years 2030 and 2040, responding to the constraint of limiting 1G share to 7% from 2020, remaining effective in the 2030s, concerning the multi-annual energy program in the transport sector. The scenario simulations return to a new equilibrium, as no further constraints are specified for advanced biofuels, yet the values remain under BAU evaluations. In contrast, LTECV takes into account all policy constraints from the French law for the transport sub-sector, such as intermediate targets for advanced biofuels and 30% reduction of fossil fuels in the final net energy share.

Results for LU requirements (Fig. 2a), reveal the equivalent agricultural area requirements associated with the biomass commodity supply of 1G and 2G transport biofuels. A comparison with BAU, shows that while LU for 1G decrease, they increase for 2G due to the shifting energy pathways towards more advanced biofuels. Yet, the overall LU decreases per policy scenario with 50%, 41% and 9% for BAU, 15BIO and LTECV respectively. The proportion of the derivative commodities (starch, sugar, oil) to the equivalent harvested energy crop yields vary considerably between 18% and 64%, and therefore represent higher equivalent agricultural area demand, compared with the residual and dedicated lignocellulosic commodities.

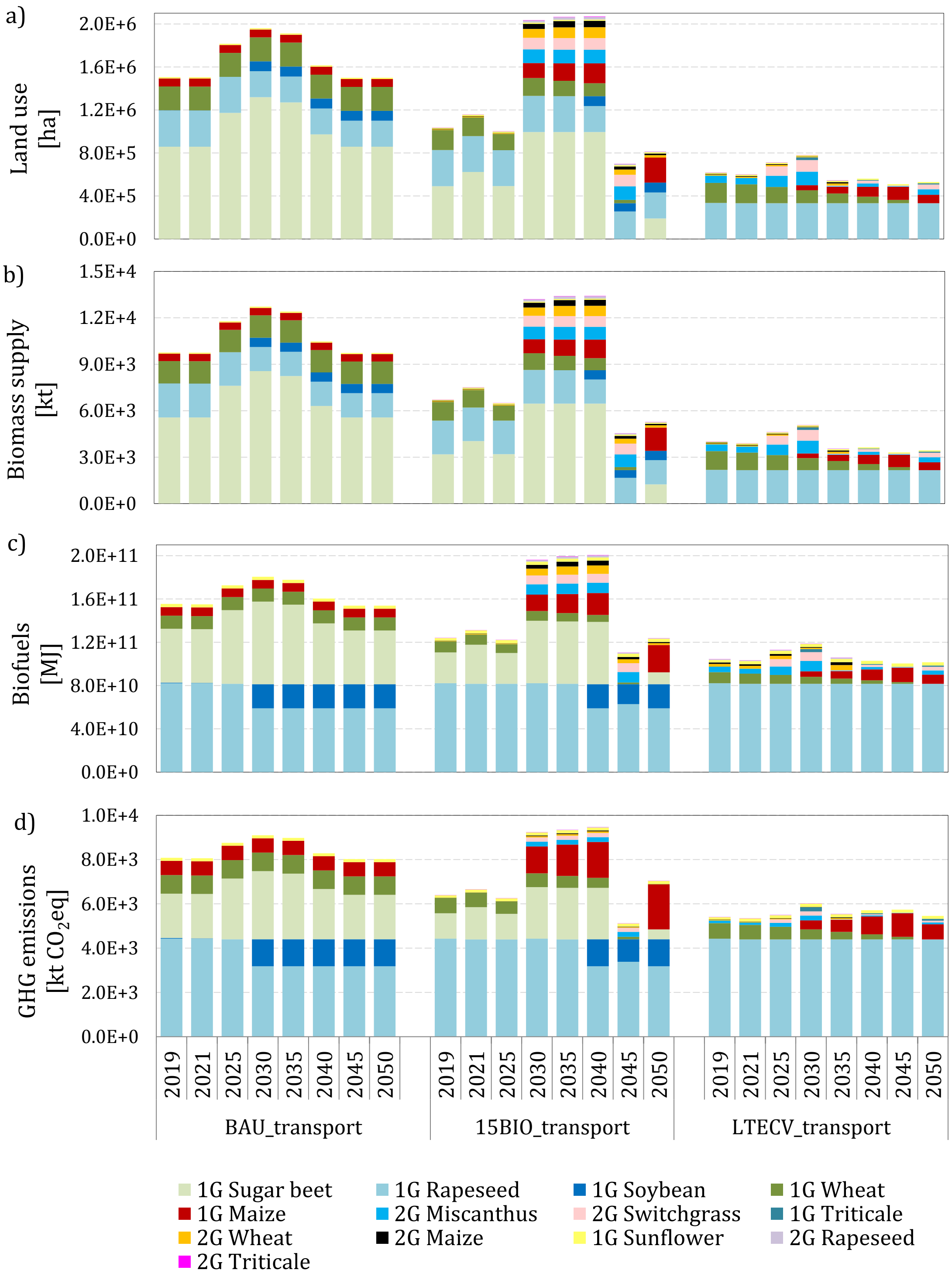

Fig. 2. Policy scenario simulations (BAU, 15BIO, LTECV) linked with first (1G) and second (2G) generation bioethanol and biodiesel pathways in terms of a) land use requirements in ha, b) biomass commodity supply in kt, c) equivalent energy supply in MJ, and d) associated Greenhouse Gas emissions in kt CO_2-eq

The biomass commodity supply (Fig. 2b) in the BAU policy —which does not follow the multi-annual energy program for the transport sub-sector— accounts for dedicated 1G annual crops only, dominated by sugar beet (60%), rapeseed (17%), and wheat (13%). 15BIO policy increases the 2G-share by 15%, yet sugar beet (44%), rapeseed (22%) and wheat (9%) remain the main supply sources. The LTECV policy further increased the 2G-share up to 17%, of which perennial grasses (miscanthus and switchgrass) contribute to 90%. 1G soybean and 1G sugar beet would be displaced completely; yet 1G rapeseed (55%) and wheat (17%) will remain the main supply sources.

The net final energy supply (Fig. 2c) represents the bioethanol and biodiesel yield per dry matter of the commodity. Conversion efficiencies vary strongly among the different renewable energy carriers, whereby oleaginous crops have higher yield efficiencies. The main contributor to the net biodiesel supply will increasingly be rapeseed oil with up to 41%, 49% and 77% for BAU, 15BIO and LTECV respectively, and for bioethanol sugar beet with up to 36% and 23% in BAU and 15BIO respectively (yet 0% for LTECV). With the upcoming technological innovation for advanced biofuels, LTECV scenarios showed that advanced biofuels (involving synthetic biofuels) will play a major mitigation role, with up to 10% share in the net final energy.

The GHG emission estimates (Fig. 2d) linked with fossil fuels only are based the EC JRC well-to-wheel method (Edwards et al., 2014), for bioethanol and biodiesel and the static IPCC GWP metric. The highest mitigation targets are achievable by means of the LTECV scenario. All emissions in the BAU scenario derive from 1G biofuels, whereas 4% and 3% originate from 2G in 15BIO and LTECV respectively. 1G source are the main contributors to GHG emissions, particularly rapeseed oil (up to 43%, 53% and 73% for BAU, 15BIO and LTECV respectively) and sugar beet (up to 28% and 19% in BAU and 15BIO respectively). The lower impact contributions from 2G biofuels are due to reduced emission factors in g of $CO_2eq \cdot MJ^{-1}$, as compared with conventional fuels and 1G biofuels.

3.2 Parameters for soil organic carbon computation

Table 2 provides an overview of data and coefficients used to compute the C inputs to the soil, associated with crop C content, humification coefficients, yields, carbon partitioning per relative plant fraction, NPP, and exogenous inputs, per ha, at field scales. C fractioning among plant parts and C partitioning from NPP are calculated here from annual yield estimates at field scales, per ha. For miscanthus, for which few data is available, dry matter yields range between 16.1 and 28.5 in France (AGRESTE, 2019; Strullu et al., 2014) and globally between 14.8 and 33.5 (Rehbein et al., 2015). We used the mean 22.8 t DM ha^{-1} based on measured values by Strullu et al. (2014). EX matter represents mean French agricultural practices regarding fertilisation of cultivation of energy crops. The mineralisation coefficients resulted in 0.1176 for French cereals and oily seeds and 0.0733 for Brazilian soybean, based on the regional mean temperature estimated at 25°C and a clay content of about 43%. The computation, underlying data and assumptions are further detailed in the Supplementary Material.

Table 2. Isohumic coefficient (h), carbon (C) content, carbon partitioning from net primary productivity (NPP), and mean French agricultural practices regarding fertilisation of energy crops and exogenous inputs

Crops and residues	Yields		Isohumic coefficient (*h*)		C content		Carbon partitioning per plant fraction (calculated)				NPP		Fertilisation of cultivation of energy crops (calculated)					
							C_P	C_S	C_R	C_E			Mineral N	Cattle effluents	Poultry effluents	Swine effluents	Compost	
	[t·ha^{-1}]		[unitless]		[t·t^{-1}]		[t C·ha^{-1}]	[t C·ha^{-1}]	[t C·ha^{-1}]	[t C·ha^{-1}]	[t C·ha^{-1}]		[kg·ha^{-1}]	[t·ha^{-1}]	[t·ha^{-1}]	[t·ha^{-1}]	[t·ha^{-1}]	
Maize	11.980	a	0.193	e	0.414	i	4.957	5.369	2.959	1.967	15.251	l	133	11.069	0.519	1.513	1.410	m
Rapeseed	3.655	a	0.244	f	0.502	i	1.901	10.231	3.393	2.238	17.763	l	169	3.989	0.187	0.545	0.508	m
Wheat	6.408	a	0.193	f	0.475	i	3.046	4.354	1.697	1.124	10.220	l	169	0.819	0.038	0.112	0.125	m
Triticale	5.501	a	0.125	e	0.475	i	2.615	5.088	1.428	0.925	10.056	l	107	5.265	0.247	0.720	0.671	m
Sunflower	2.720	b	0.200	e	0.440	i	1.197	1.795	0.330	0.000	3.322	l	123	2.843	0.133	0.389	0.362	m
Sugar beet	9.540	b	0.126	e	0.467	i	4.459	0.245	0.245	0.164	5.114	l	56	9.516	0.446	1.301	1.212	m
Soybean	3.479	c	0.230	g	0.440	j	1.531	2.291	0.735	0.478	5.035	l	8	0.000	0.000	0.000	0.000	m
Miscanthus	22.788	d	0.126	f	0.475	j	10.835	12.218	12.995	4.332	40.379	l	52	1.505	0.071	0.206	0.192	m
Switchgrass	15.714	a	0.126	e	0.497	k	7.805	0.000	5.451	3.54	16.796	l	65	0.983	0.046	0.134	0.125	m
Cattle effluents	N/A		0.558	h	0.055	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	
Poultry effluents	N/A		0.308	h	0.154	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	
Swine effluents	N/A		0.462	h	0.083	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	
Other soil amendments (proxy compost)	N/A		0.670	h	0.130	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	

Sources: a (AGRESTE, 2019), b (Besnard et al., 2014), c (Cattelan and Dall'Agnol, 2018), d (Strullu et al., 2014), e (Duparque et al., 2013; Irizar et al., 2015; Moreno et al., 2016; Saffih-Hdadi and Mary, 2008) , f (UNIFA, 1998), g (Irizar et al., 2015; Moreno et al., 2016), h (Agro-Transfert, 2019; Bouthier et al., 2014), i (PHYLLIS 2 database, 2019), j (Ma et al., 2018), k (Avadí, 2019), l (Bolinder et al., 2007; Carvalho et al., 2017; Richter et al., 2016; Strullu et al., 2014), for miscanthus aboveground inputs between 40% and 67% (Carvalho et al., 2017; Strullu et al., 2014) and perennial belowground proportions of rhizomes 75% and roots 25% (Agostini et al., 2015), m (AGRESTE, 2019, 2014, 2011; Avadí, 2019; FAO, 2004). "Effluents" refers to average values from manures, slurries and droppings (poultry). Modelling details of specific crops: maize (as a mean of grain and fodder), miscanthus (as permanent prairie), switchgrass (as temporary prairie), wheat (as a mean of hard and soft).

Descriptions of sub-indices: P - agricultural aboveground product, S - residual aboveground compartment, R - root/rhizome tissue, E - extra-root material.

3.3 Carbon inputs to the soil

Fig. 3 shows the relative C added to the soil per energy crop in proportion to the AG and BG plant fractions, as well EX matter. The C inputs vary considerably among the different energy crop types, yet BG and AG have highest contributions to SOC, as compared with organic fertilisers.

In this study, the comparatively higher C contributions are associated with BG (Fig. 3), ranging (from smaller to higher) between 20% and 30% for sunflower and sugar beet, between 35% and 45% for soybean and triticale, between 50% and 60% for rapeseed, wheat, maize and miscanthus, and up to 100% for switchgrass. Switchgrass has no residues (except for a disregarded minor amount of stubble), while the AG proportion of other crop types range between 16% and 31% for sugar beet and maize, between 40% and 50% for miscanthus, wheat, rapeseed and triticale, and the highest contribution from sunflower (60%) and soybean (65%). The remaining proportions associated with EX is rather low, yet with considerable differences per crop type, highest for sugar beet (57%), sunflower (17%), maize (12%) and triticale (9%). Note that the inputs are rather case- and site-specific, management practices may involve higher EX inputs due to displacement of inorganic fertilisers or higher/lower removal rates for AG/BG matter.

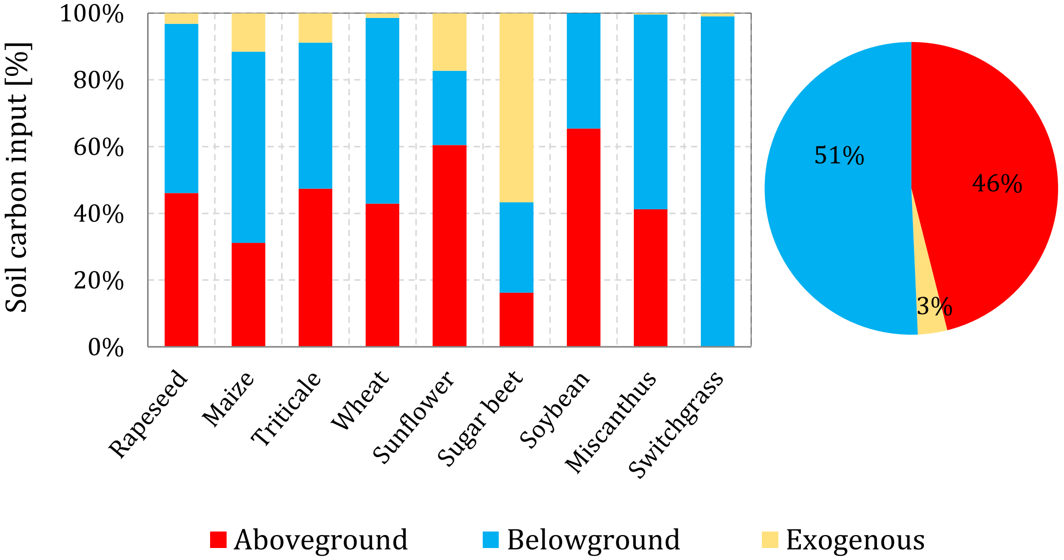

Fig. 3. Soil carbon inputs per biomass commodity from above- and belowground plant compartments, including exogenous matter. Pie chart represents the average proportions

Fig. 4 shows the dynamic SOC inventories associated with policy and C input scenarios. It represents the dynamic elementary flows resulting from the coupling with the PEM biomass commodity outputs (technical flows) per policy scenario, i.e. BAU (Fig. 4a), 15BIO (Fig. 4b) and LTECV (Fig. 4c). The flows are expressed in t CO_2 according to the C content in the compound (44/12 g $CO_2.g^{-1}$). Other GHG emissions from decay, such as methane, are not accounted for, but should be considered in future studies.

The net annual SOC balance adds up all C inputs (negative values) per simulation year and the subsequent gradual releases (positive values) from decay of all previous and consecutive years. The end-year 2050 shows an “artificial cut-off” due to the ending of the prospective assessment of the PEM with no further biomass mobilisation. Therefore, the year 2050 reveals peaking positive values.

For this study, the selected TH projects the last year of the PEM simulation period over an additional century, that is to say from 2050 to 2150. The TH generally defines the length of time over which the GHG emissions are integrated (Levasseur et al., 2016) (in static methods fixed to 20 or 100 years), however is flexible in dynamic LCA (Levasseur et al., 2010) and can be adapted to any dynamic inventory TH, as discussed in (Albers et al., 2019b). The determination of a TH remains subjective, as no theoretical foundation has been identified, but only a political one (the widely accepted IPCC 100 years TH). The chosen TH over 100 years is valid here for the SOC inventory flows as well as for the subsequent impact assessment. The temporal cut-off for SOC inventories at year 2150 is justifiable: after the first century, the remaining SOC-sourced CO_2 range between 6E-5and 4E-5, assuming here at the given TH that an equivalent zero net C balance is reached (i.e. carbon neutrality). The first SOC input in the year 2019 represents the highest SOC sequestration potential, decreasing with increasing inventory time horizon (LCI TH).

A comparison among variations of TIMES-MIRET scenarios featuring the origin of different C inputs denotes a particular SOC dynamic associated with S3_BG in 15BIO and LTECV. Note that S3_BG has a longer sequestration curve and extended release flows, as compared with the S2_AG and S4_EX contributions. This phenomenon relates with the perennial grasses introduced for advanced biofuels to respond to the new policy constraints. This type of energy crop involves biomass growth and carbon fixation dynamic of rhizomes during the rotation length. Moreover, the proportions of the AG and BG SOC flows (S2_AG and S3_BG) in the first inventory year 2019, demonstrated that the two input variations contribute to SOC in similar proportions for BAU (32% and 38%, 15BIO (36% and 41%) and LTECV (44% and 49%). In contrast, S4_EX considerably decreases for 15BIO (22%) and LTECV (7%) compared with BAU (29%). The cumulative sum of all C inputs (referring to S1_TOT) represented SOC contributions of about 40%, 34%, and 26% for BAU, 15BIO and LTECV scenarios respectively.

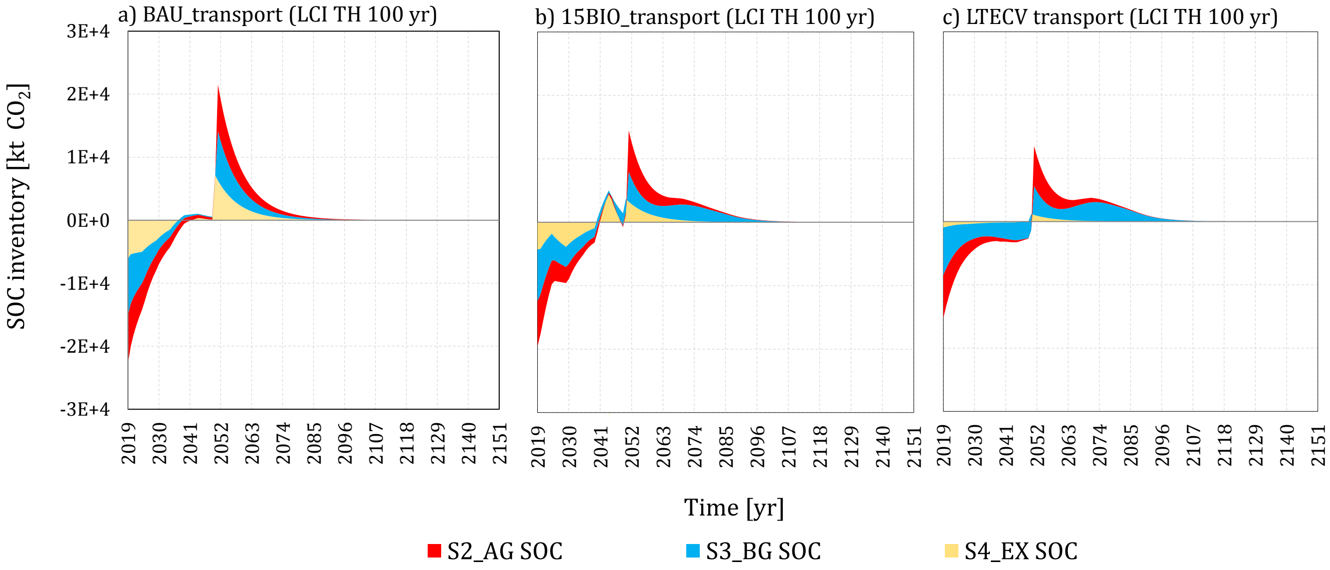

Fig. 4. Soil organic carbon inventories over a time horizon of 100 years [kt CO_2] per TIMES-MIRET (BAU, 15BIO, LTECV) and C input (S2_AG, S3_BG, S4_EX) scenarios

3.4 Dynamic impact assessment: Radiative forcing effects per policy and management scenario

Fig. 5 shows the instantaneous [in $W\cdot m^{-2}$] and cumulative [$W\cdot yr\cdot m^{-2}$] radiative forcing (RF) effects per policy and C input scenarios over a 100-year LCIA TH. The 100-year reference is recommended by the IPCC guidelines (Myhre et al., 2013) and most commonly used in LCA, yet any future reference year could be chose with dynamic LCA (Levasseur et al., 2016, 2010). The RF effects are given for SOC (i.e. biogenic-sourced), C-neutral (i.e. fossil-sourced), as well as the C-complete (i.e. SOC + C-neutral). The overall results show considerable variations between C-neutral and C-complete effects, due to SOC accounting.

Instantaneous RF (Fig. 5a, b, and c) refers to the GHG concentrations and their induced net concentration change (Myhre et al., 2013). It allows describing the net changes through time. The “artificial cut-off” at year 2050 is evident. For SOC emissions, it means that no further inputs are computed and therefore the positive emissions outrange the negative ones until equilibrium is reached and all emissions are returned back to the air (referred here as a net zero C-balance). The annual cumulative RF effect (Fig. 5d, e, and f) of a pulse emission is given by integrating the instantaneous forcing, allowing a direct comparison among scenarios. Firstly, it is identifiable that the C-neutral effects are considerably lower for LTECV than for BAU and 15BIO. It reveals that the constraints lead towards higher climate mitigation targets. Secondly, the annual negative effects from SOC-CO_2 flows further reduce the C-neutral results in all analysed policy scenarios within the first century, contributing to climate mitigation. The mitigation is higher for S3_BG (and consequently S1_TOT) in 15BIO (Fig. 5b) and LTECV (Fig. 5c).

A quantitative comparison of the cumulative RF of C-neutral and C-complete results per policy scenario can only be undertaken by selecting an end-year of the impact assessment (reference year), here 2150. The C-neutral results of 15BIO (2.5E-8 $W \cdot yr \cdot m^{-2}$) and LTECV (1.8E-8 $W \cdot yr \cdot m^{-2}$) show reduced forcing effects by about 10% and 34% respectively compared with the BAU reference (2.8E-8 $W \cdot yr \cdot m^{-2}$). The accounting of SOC flows further reduce the cumulative RF effects, as highlighted with C-complete results. S1_TOT (S2_AG + S3_BG + S4_EX) represents the highest reduction potentials for 15BIO (2E-8 $W \cdot yr \cdot m^{-2}$) and LTECV (1.4E-8 $W \cdot yr \cdot m^{-2}$) versus BAU (2.5E8_$W \cdot yr \cdot m^{-2}$), whereof 50% and 65% are BG contributions given in 15BIO and LTECV scenarios respectively (see also the Supplementary Material).

However, SOC benefits decrease with increasing LCIA TH, that is to say, the more into the future the reference end-year is set, the lower are the contributions to climate mitigation. Firstly, this is due to the artificial cut-off associated to the PEM analysis. Secondly, in the long-term (beyond a 100-year LCIA TH), all SOC-sourced CO_2 emissions converge to equilibrium, reaching a steady state, as all emissions return to the air. Yet, without the consideration of SOC emissions, the negative RF (cooling effects), and thus the temporary climate benefits, are not account for, leading to biased net C balance results over time.

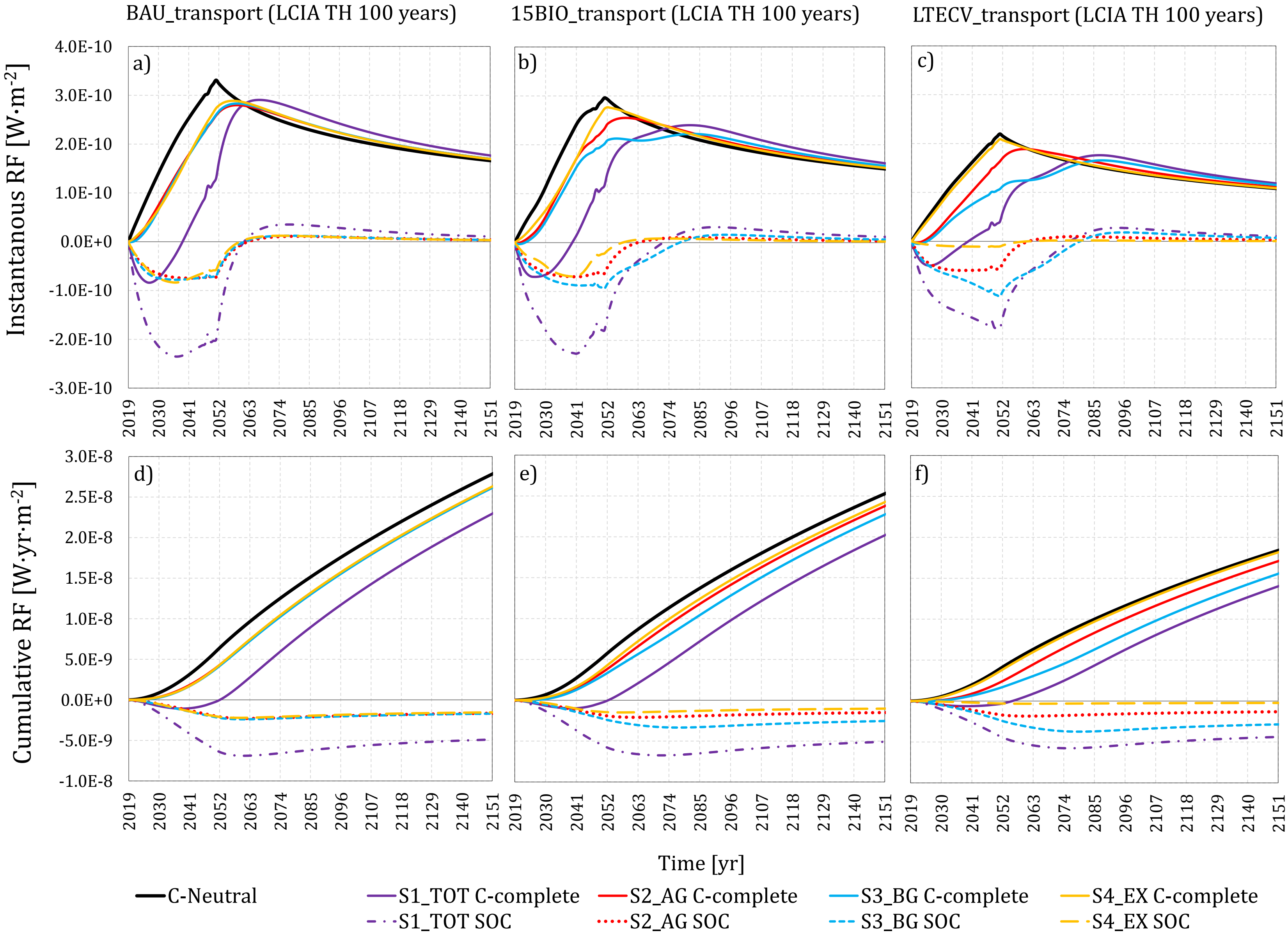

Fig. 5. Instantaneous [W·m^{-2}] and cumulative [W·yr·m^{-2}] radiative forcing per policy (BAU, 15BIO and LTECV) and C input (S1_TOT, S2_AG, S3_BG, S4_EX) scenarios, denoting the dynamic impacts from biogenic- (here SOC flows) and fossil- (C neutral) sourced emissions, as well the sum of both in C-complete

The forcing contribution of the different SOC compartments become more evident by taking a closer look into the cumulative RF effect of AG (Fig. 6a), BG (Fig. 6b) and EX (Fig. 6c) per policy constraint. The highest contributions to climate mitigation are associated with S3_BG in both 15BIO and LTECV, reducing BAU by 150% and 170% respectively. This is due to biomass growth of rhizomes of perennial grasses that are not incorporated into the soil until the end of the rotation length, and thus represent temporal C-stock delaying degradation emissions. Consequently, the temporary sequestration and storage has climatic benefits due to postponement of positive RF (warming effects). The negative RF effects from perennial grasses and their derivative biofuels may represent a better alternative to annual crops in terms of climate change mitigation.

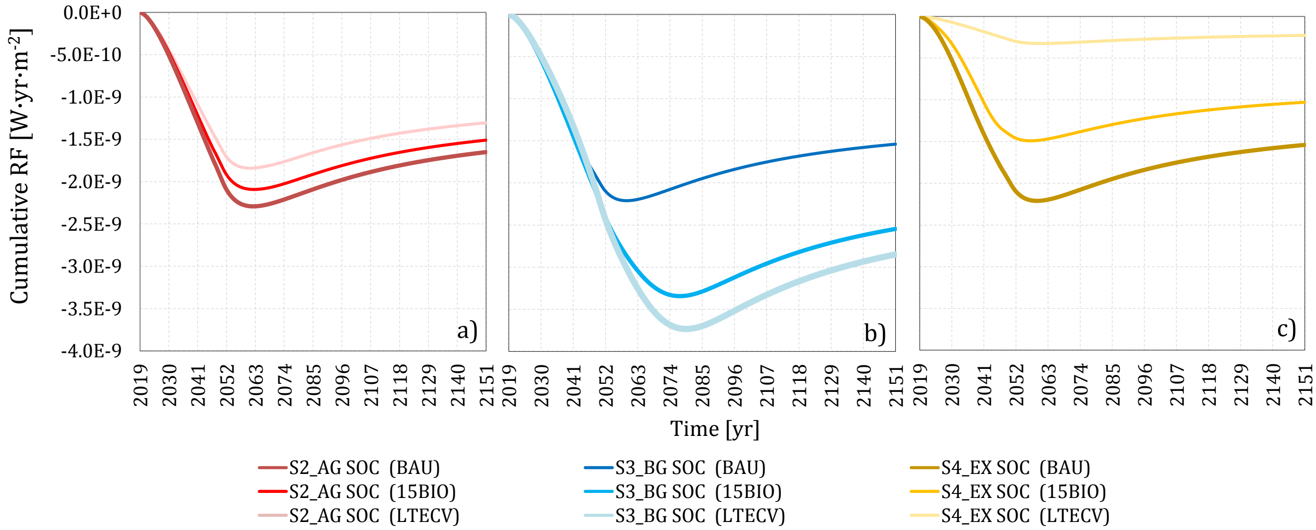

Fig. 6. Cumulative radiative forcing [W·yr·m^{-2}] per policy (BAU, 15BIO and LTECV) and C input (S2_AG, S3_BG, S4_EX) scenarios

3.5 Sensitivity analysis

We conducted a sensitivity analysis for the LTECV policy scenario concerning i) the SOC model *k* coefficient (uncertainty due to site-dependent pedoclimatic conditions), and ii) the C inputs to the soil (variations in residue removal rates from the field). Therefore, *k* for type 3 pedoclimatic conditions were recalculated, assuming a temperature increase of 2°C (referred to as SOC K+2°C) due to climate change, resulting in 0.1485, similar to *k* for oceanic climate type 5. *k* for SOC K +2°C in Brazil is 0.0924, yet soybean is excluded in the LTECV simulations. The removal rates concerned the S2_AG compartment (and consequently S1_TOT), for which we run the SOC simulations, assuming two variations equally applied to all energy crops, namely 90% (referred to as SOC_AG 90%) and 10% (referred to as SOC_AG 10%) C input to the soil.

The cumulative RF results from 2019 to 2150 (in Fig. 7a), demonstrate significant variations between model parameter and C input to the soil. A quantitative comparison at year 2150 (in Fig. 7b) per C input scenario, shows a difference between the original values and SOC K+2°C results by 122%, 127%, 119% and 127% for S1_TOT, S2_AG, S3_BG, and S4_EX respectively. Two major interpretations are drawn. Firstly, SOC benefits decrease with increasing temperature (climate change), because the decay rate increases with temperature and thus C releases to the atmosphere occur over a shorter TH. Secondly, exogenous inputs (S4_EX) are more affected by temperature changes, because they already have high *h* values and thus lower initial SOC. Regarding the C input variations from SOC_AG residues at year 2150 (in Fig. 7c) S1_TOT original values increase with SOC_AG 90% (due to S2_AG benefit contribution by almost 60%) and decrease with SOC_AG 10% (due S2_AG deficit contributions by about 500%). Fig. 7b and c additionally show the minimum attainable values, representing the peak sequestration potential attributable to the year 2074 (Fig. 7a). This sensitivity is given due to the selected end-year 2150, which results in lower climatic benefits than the year 2074, linked with the artificial cut-off of the PEM simulation at year 2050.

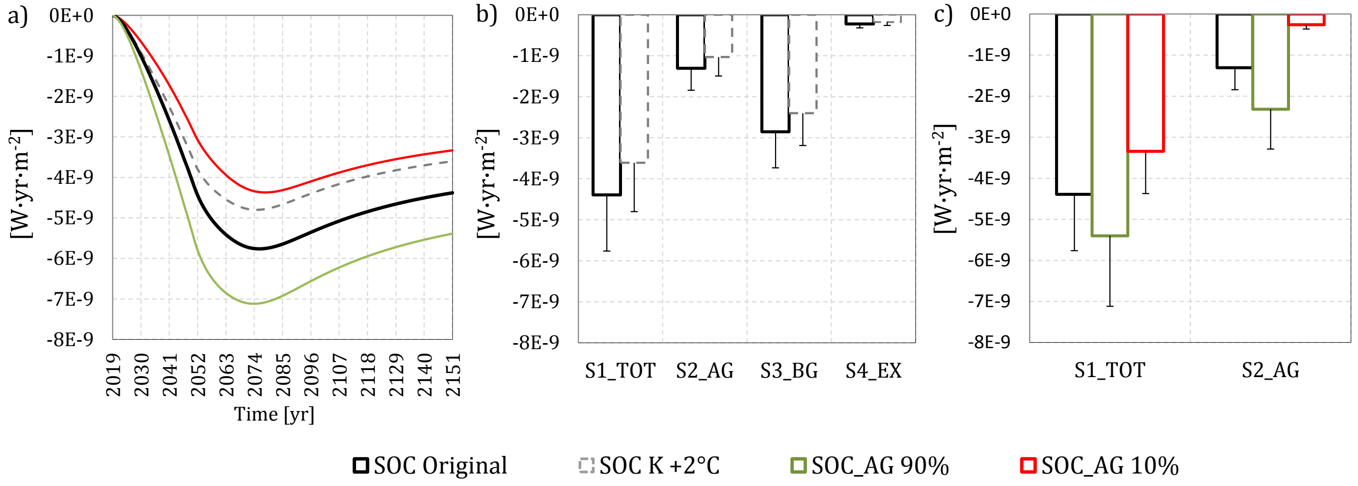

Fig. 7. Cumulative radiative forcing [W·yr·m^{-2}] from the sensitivity analysis results a) over the time horizon 2019 to 2119, b) quantitative uncertainty concerning k coefficient and temperature variations, and c) effect from changes in C inputs. b) and c) represent the year 2019 including uncertainty (error bar represent the minimum attainable value)

The variations of residue removal rates have significant consequences on the LU requirements (see Sensitivity analysis on LU in the Supplementary Material). The residue removal rate for energy is an important consideration, as it defines the equivalent agricultural area requirements to meet the energy demand of 2G biofuels. SOC_AG 90% represent minimum and SOC_AG 10% maximum values in terms of residue export from the fields and the inverse for C inputs to the soil. The higher the residue removal rate for energy the higher per unit of area demand: for SOC_AG 10% (i.e. 90% removal rate) LU requirements increase by a factor of 5, while for SOC_AG 90% (i.e. 10% removal rate) decrease by a factor of 0.56. Consequently, trade-off results for the same unit of energy [MJ] produced between higher removals rates versus climate benefits from C inputs to the soil. Note that other relevant factors (e.g. effects on biodiversity, N-mineralisation, yields) —not considered in this study— may play an essential role.

3.6 Limitations of the proposed approach

The coupling framework is generic enough to be used in combination with any demand model or life cycle inventory; however, other essential soil quality indicators and impacts from LUC are not included in the proposed SOC modelling approach. The dynamic of these indicators (e.g. the set of indicators included in LANCA) also needs to be developed to improve the results from soil activities modelling.

Furthermore, it is encouraged to use primary data when available to reduced uncertainties from averaged values. The use of secondary data may compound the overall (data + model) uncertainty, yet it can in principle be reduced by data processing and model calibration. Model calibration in particular, which implies the selection of starting values, may nonetheless be biased, and thus self-starting models may be used to find initial conditions for the main models, or, even better, observations data should be used if available.

Data processing should aim to improve the statistical representativeness and coherence of the data. The presented SOC model could be replaced by or combined with alternative models with different structure, or contrasted with other models, for ultimately more robust findings and lower uncertainty in predicting C dynamics in the soil (Shi et al., 2018).

4 Conclusions

The overall comparison among the policy and C input scenarios to the soil shows achievable climate mitigation targets in the transport sub-sector by means of shifting 1G-biomass share towards 2G (advanced) biofuels, particularly given the LTECV policy. Dynamic SOC accounting makes a considerable difference in the C-complete assessment. Without its modelling, temporary mitigation is ignored, thus biasing GHG emission results. Highest mitigation contributions are attributed to perennial grasses, further delaying radiative forcing due to C sequestration in the rhizomes fraction during the entire rotation length. Yet, cooling effects from SOC decrease with increasing LCIA TH, as all emissions return to the atmospheric pool in the long-term. A sensitivity analysis confirmed the SOC variability due to temperature (+2°C increase) and residue removal rates changes. Both affect climate mitigation and the latter also LU by a factor of -0.56 to +5. In the context of LCA, the consideration of other direct and indirect impacts associated with changes in LU, management (e.g. tillage and land preparation, fertiliser use, crop and yield protection, erosion measures) and LUC, including biodiversity should follow suit to better understand trade-offs.

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Figure captions

Fig. 1. Coupling diagram of energy system and soil organic carbon modelling for dynamic carbon accounting (Acronyms: A: Age, C: Carbon content, DBH: Diameter Breast Height, H: Height, H: Humification coefficient, K: Mineralisation coefficient, NPP: Net Primary Productivity, SOC: Soil Organic Carbon, V: Volume)

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Modelling dynamic soil organic carbon flows of annual and perennial energy crops to inform energy-transport policy scenarios in France

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Tables

Table 1. Comparison of recommended static modelling approaches for calculating soil quality SOM/SOC changes associated with LU (occupation) and LUC (transformation) in LCA

Method	Recommending guideline	Land activities included	Usefulness for LCIA	Notes
SOM/SOC change (Brandão and Milà i Canals, 2013; Milà i Canals et al., 2007a, 2007b)	International Reference Life Cycle Data System (EC-JRC, 2010)	T+O	CF available, limited linking to AoP	Informing soil quality, site-dependent or -generic, but not climate change
LANCA (Beck et al., 2010; Bos et al., 2016; Horn and Maier, 2018)	Product Environmental Footprint Category Rules (EC, 2018b)	T+O	CF available	Informing soil functions, data intensive, suitable for site- dependent or generic assessment
SALCA-SQ (Oberholzer et al., 2012, 2006)	ecoinvent v2 (Nemecek et al., 2011; Nemecek and Kagi, 2007)	O	CF available, limited linking to AoP	Informing soil properties and treats, site-dependent or site-specific (plot level)
Müller-Wenk and Brandão (2010)	UNEP-SETAC (Koellner et al., 2013)	T+O	CF available	Informing climate change, site-generic (6 biomes over the world)
PAS 2050 standard (BSI, 2011) and IPCC Guideline for National GHG Inventories (IPCC, 2006)	Product Environmental Footprint Category Rules (EC, 2018b)	T	N/A	Dynamic modelling in the context of CDM methodologies, but site-dependent

Acronyms. AoP: Area of Protection, SOC: Soil Organic Carbon, SOM: Soil Organic Matter, T: Transformation; O: Occupation, LCIA: Life Cycle Impact Assessment, CF: characterisation factors, GHG: Greenhouse Gas, CDM: Kyoto Protocol's Clean Development Mechanism

Sources: Benoist and Bessou (2018)

Table 2. Isohumic coefficient (h), carbon (C) content, carbon partitioning from net primary productivity (NPP), and mean French agricultural practices regarding fertilisation of energy crops and exogenous inputs

Crops and residues	Yields		Isohumic coefficient (*h*)		C content		Carbon partitioning per plant fraction (calculated)				NPP		Fertilisation of cultivation of energy crops (calculated)					
							C_P	C_S	C_R	C_E			Mineral N	Cattle effluents	Poultry effluents	Swine effluents	Compost	
	$[t \cdot ha^{-1}]$		[unitless]		$[t \cdot t^{-1}]$		$[t\ C \cdot ha^{-1}]$	$[t\ C \cdot ha^{-1}]$	$[t\ C \cdot ha^{-1}]$	$[t\ C \cdot ha^{-1}]$	$[t\ C \cdot ha^{-1}]$		$[kg \cdot ha^{-1}]$	$[t \cdot ha^{-1}]$	$[t \cdot ha^{-1}]$	$[t \cdot ha^{-1}]$	$[t \cdot ha^{-1}]$	
Maize	11.980	a	0.193	e	0.414	i	4.957	5.369	2.959	1.967	15.251	l	133	11.069	0.519	1.513	1.410	m
Rapeseed	3.655	a	0.244	f	0.502	i	1.901	10.231	3.393	2.238	17.763	l	169	3.989	0.187	0.545	0.508	m
Wheat	6.408	a	0.193	f	0.475	i	3.046	4.354	1.697	1.124	10.220	l	169	0.819	0.038	0.112	0.125	m
Triticale	5.501	a	0.125	e	0.475	i	2.615	5.088	1.428	0.925	10.056	l	107	5.265	0.247	0.720	0.671	m
Sunflower	2.720	b	0.200	e	0.440	i	1.197	1.795	0.330	0.000	3.322	l	123	2.843	0.133	0.389	0.362	m
Sugar beet	9.540	b	0.126	e	0.467	i	4.459	0.245	0.245	0.164	5.114	l	56	9.516	0.446	1.301	1.212	m
Soybean	3.479	c	0.230	g	0.440	j	1.531	2.291	0.735	0.478	5.035	l	8	0.000	0.000	0.000	0.000	m
Miscanthus	22.788	d	0.126	f	0.475	j	10.835	12.218	12.995	4.332	40.379	l	52	1.505	0.071	0.206	0.192	m
Switchgrass	15.714	a	0.126	e	0.497	k	7.805	0.000	5.451	3.54	16.796	l	65	0.983	0.046	0.134	0.125	m
Cattle effluents	N/A		0.558	h	0.055	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	
Poultry effluents	N/A		0.308	h	0.154	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	
Swine effluents	N/A		0.462	h	0.083	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	
Other soil amendments (proxy compost)	N/A		0.670	h	0.130	k	N/A	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	N/A	

Sources: a (AGRESTE, 2019), b (Besnard et al., 2014), c (Cattelan and Dall'Agnol, 2018), d (Strullu et al., 2014), e (Duparque et al., 2013; Irizar et al., 2015; Moreno et al., 2016; Saffih-Hdadi and Mary, 2008) , f (UNIFA, 1998), g (Irizar et al., 2015; Moreno et al., 2016), h (Agro-Transfert, 2019; Bouthier et al., 2014), i (PHYLLIS 2 database, 2019), j (Ma et al., 2018), k (Avadí, 2019), l (Bolinder et al., 2007; Carvalho et al., 2017; Richter et al., 2016; Strullu et al., 2014), for miscanthus aboveground inputs between 40% and 67% (Carvalho et al., 2017; Strullu et al., 2014) and perennial belowground proportions of rhizomes 75% and roots 25% (Agostini et al., 2015), m (AGRESTE, 2019, 2014, 2011; Avadí, 2019; FAO, 2004). "Effluents" refers to average values from manures, slurries and droppings (poultry). Modelling details of specific crops: maize (as a mean of grain and fodder), miscanthus (as permanent prairie), switchgrass (as temporary prairie), and wheat (as a mean of hard and soft).

Descriptions of sub-indices: P - agricultural aboveground product, S - residual aboveground compartment, R - root/rhizome tissue, E - extra-root material.

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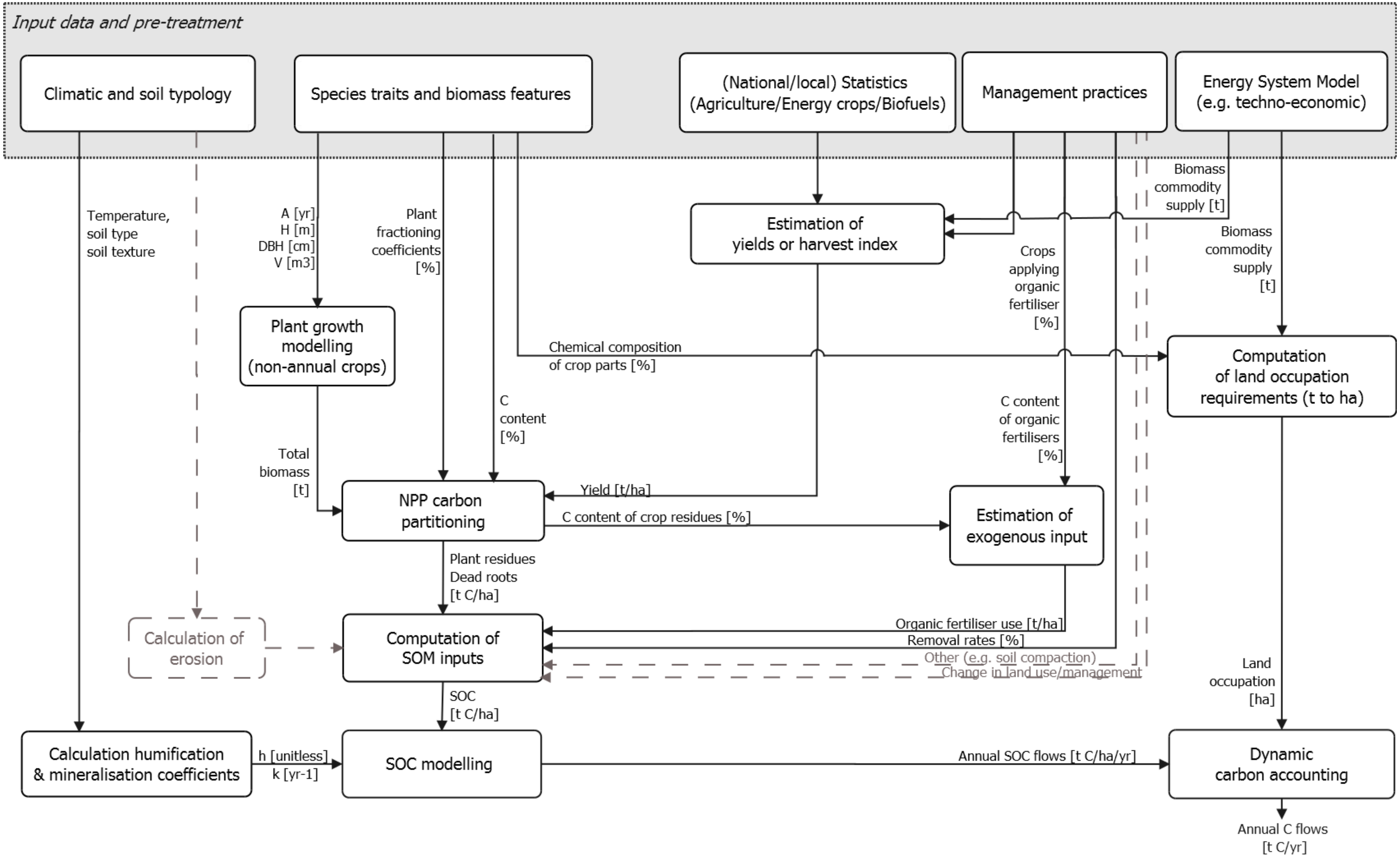
Figures



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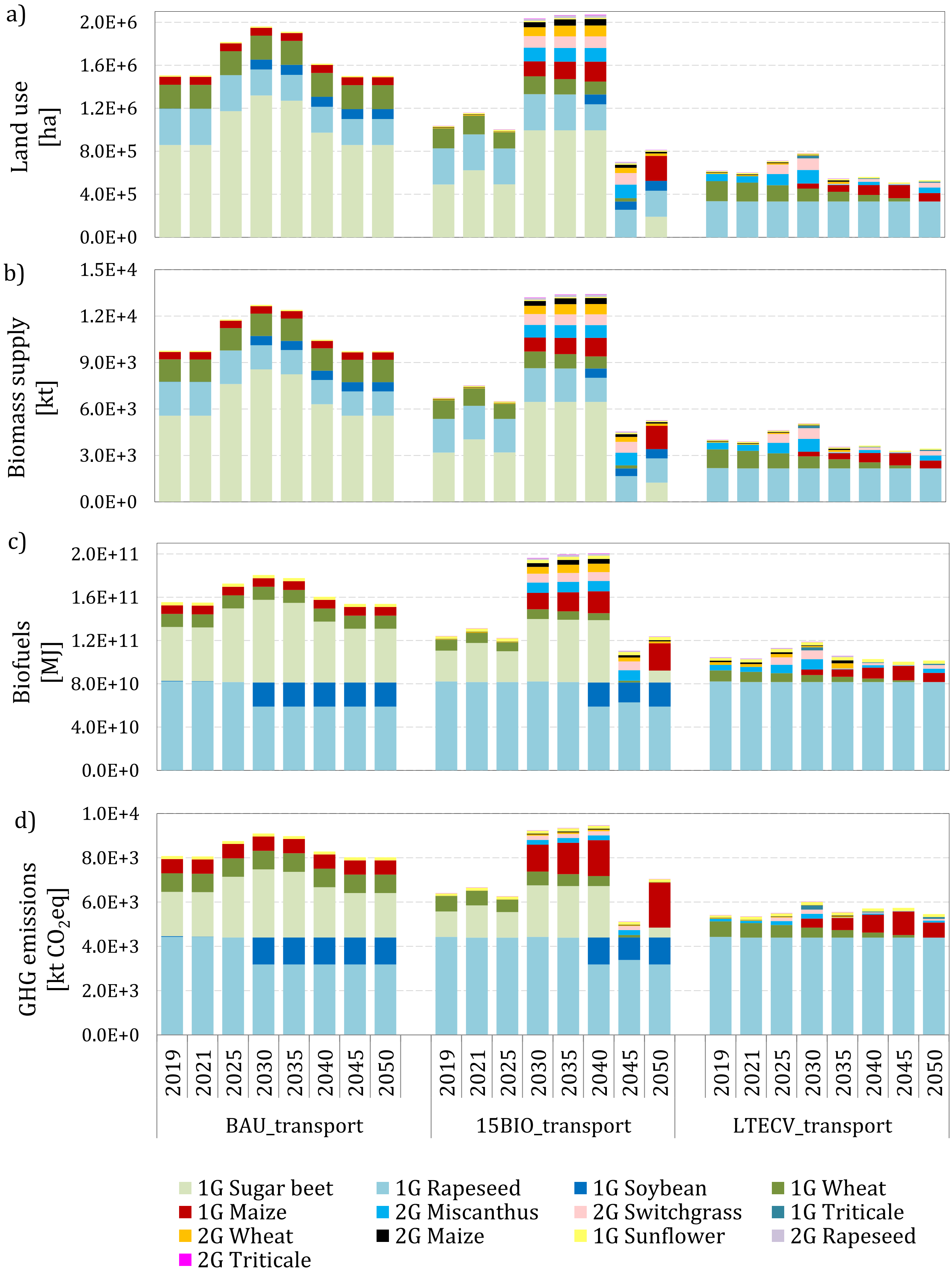

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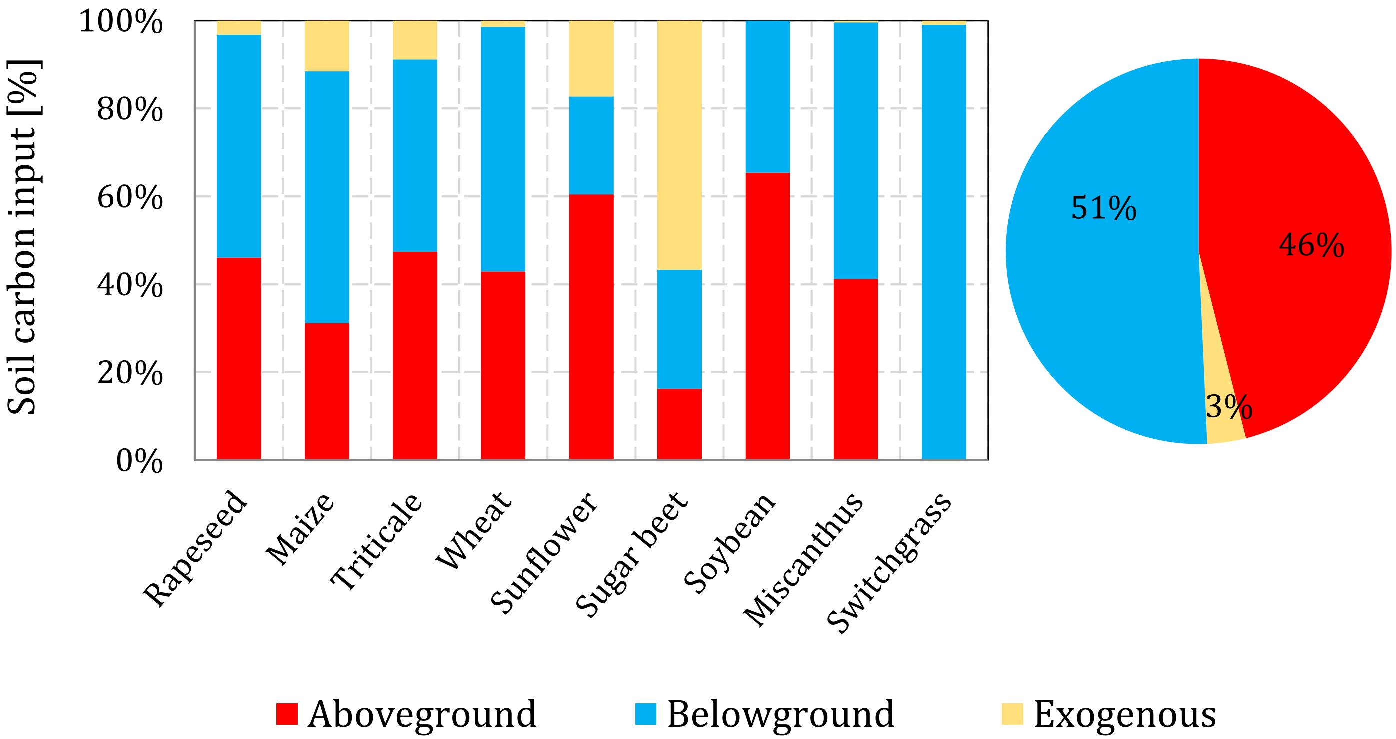

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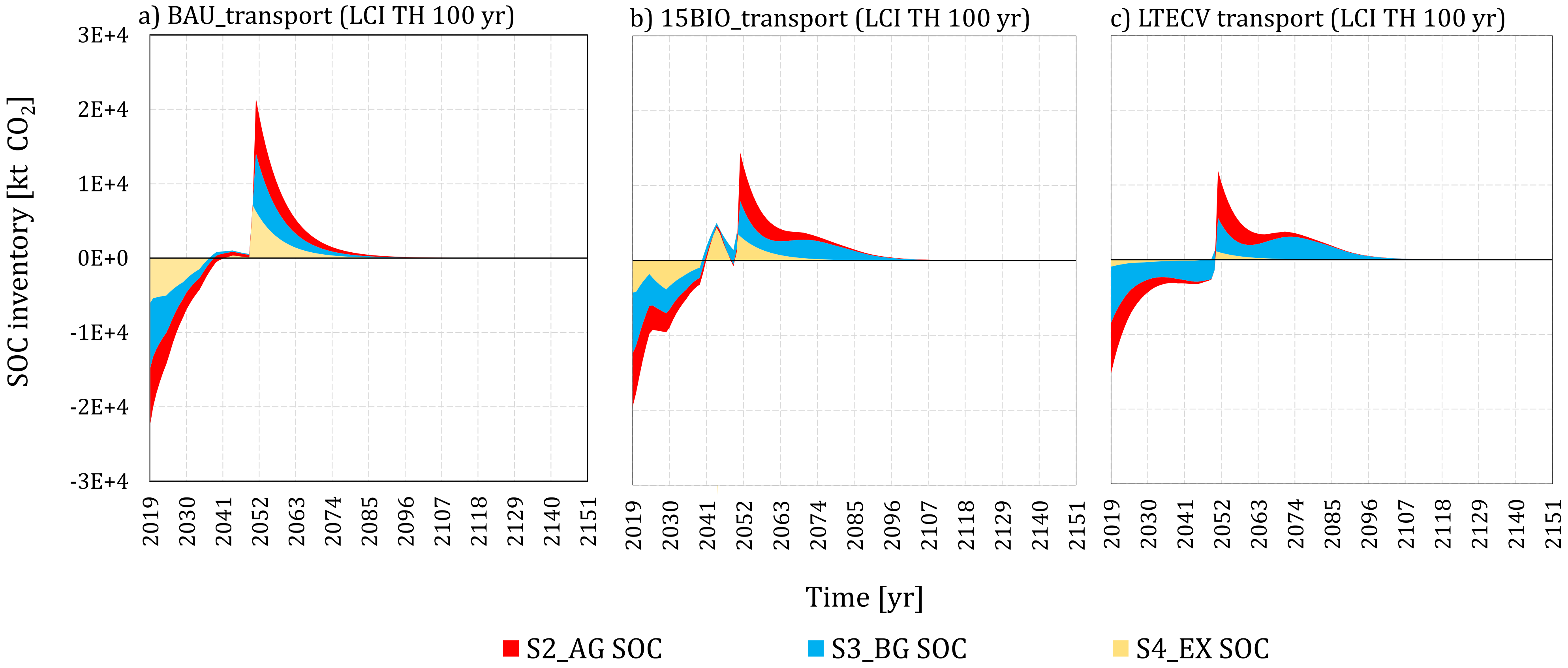

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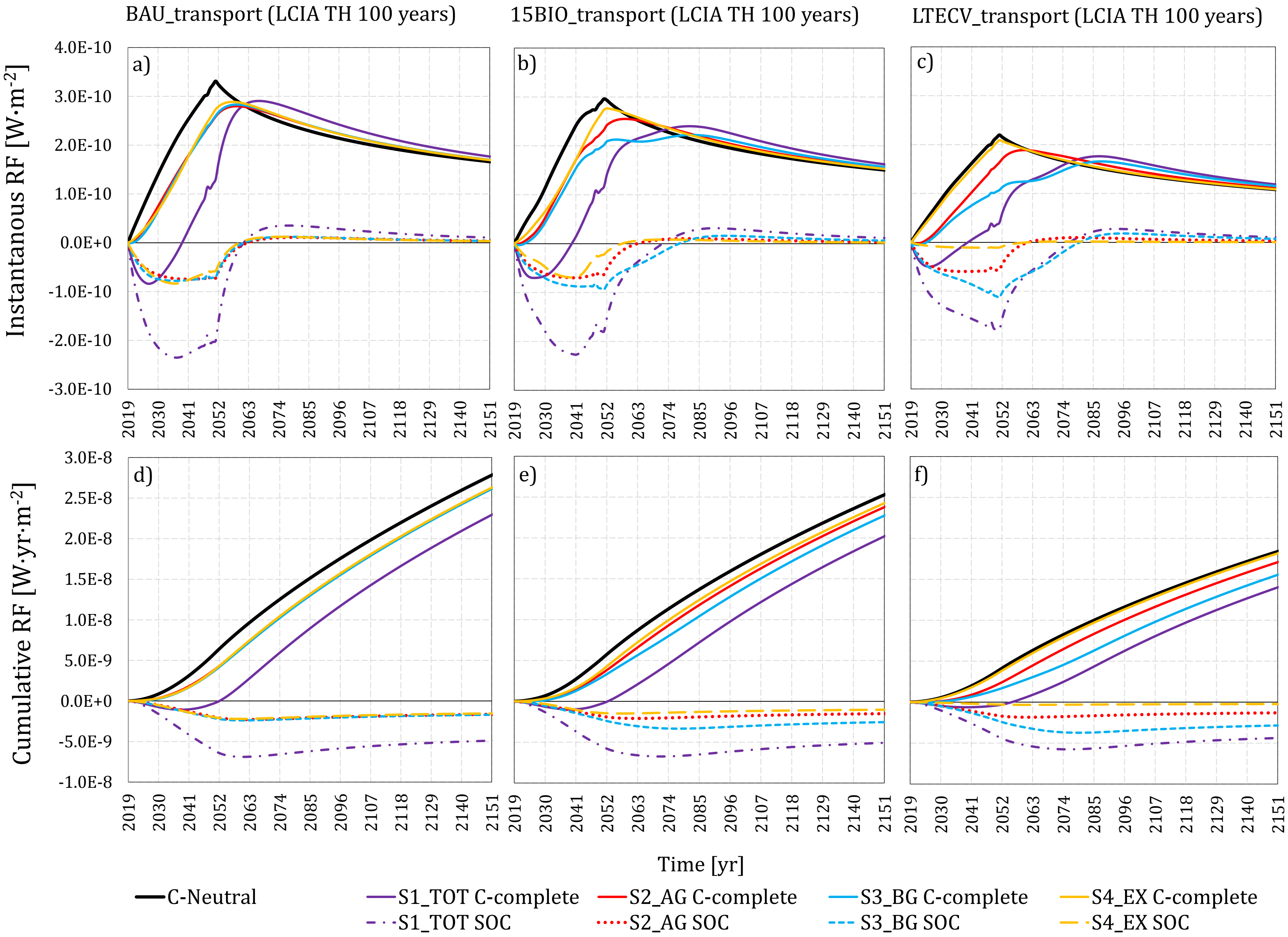

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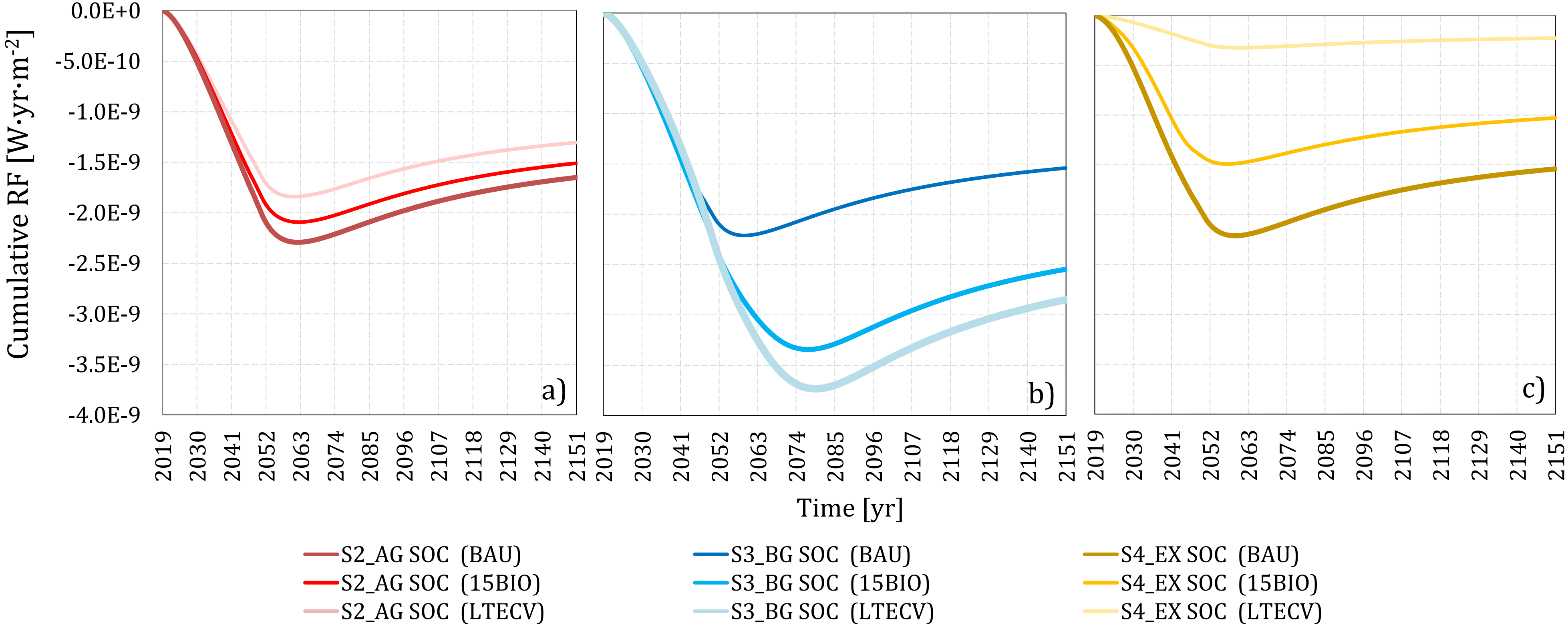

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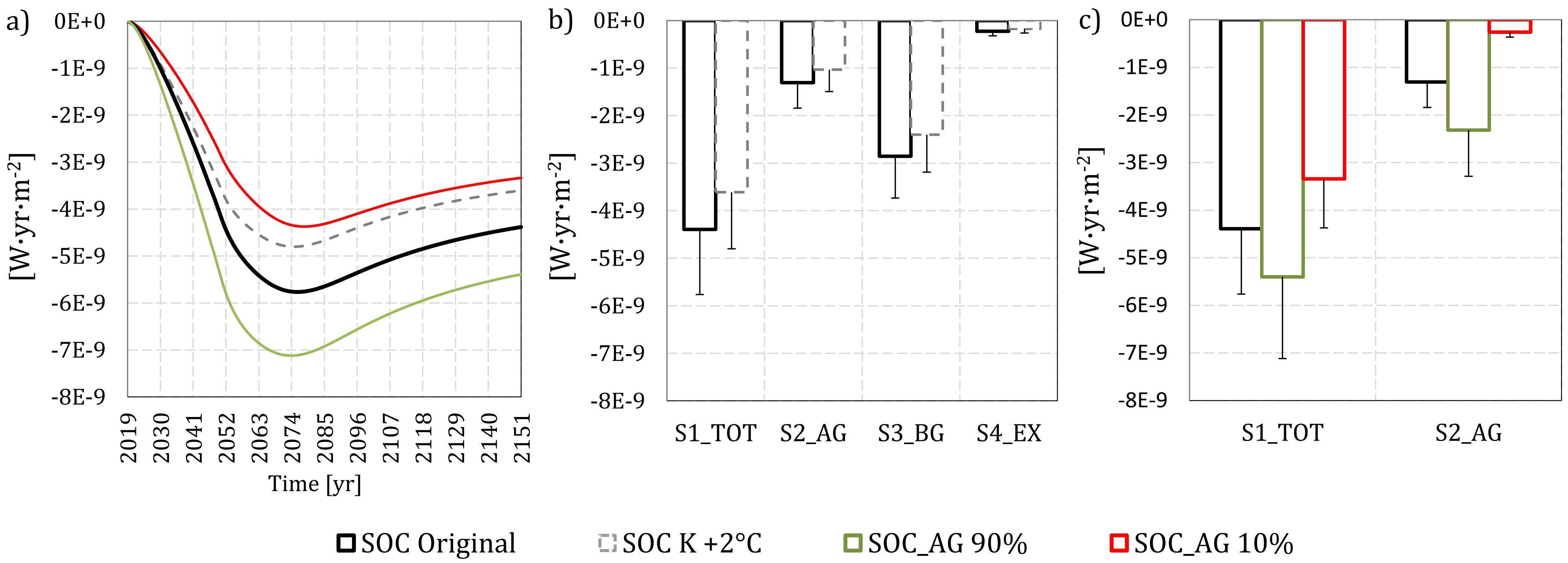

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