Measuring and modelling soil carbon stocks and stock changes in livestock production systems

A scoping analysis for the
Livestock Environmental Assessment and Performance (LEAP) Partnership
work stream on soil carbon stock changes

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AUTHORSHIP AND DEVELOPMENT PROCESS

Further to a request of the LEAP Partnership Steering Committee to prepare the work of the LEAP Technical Advisory Group (TAG) on soil carbon stock changes, this scoping analysis was drafted in 2016 by a task force composed of Guillermo Peralta (National Research Council of Argentina (CONICET), Argentina), Miguel A. Taboada (Institute of Soils, INTA-CIRN; National Research Council of Argentina (CONICET), Argentina), and Miguel Brandão (KTH – Royal Institute of Technology, Stockholm, Sweden). The task force carried out the background research and developed the core technical content of the scoping analysis. Adrian Leip (European Commission's Joint Research Centre, EC-JRC, Italy) peer reviewed the initial draft and provided substantial input in 2017. Once formed the TAG on soil carbon stock changes, additional feedback was provided by the LEAP Partnership Steering Committee, the Secretariat and the TAG in 2017.

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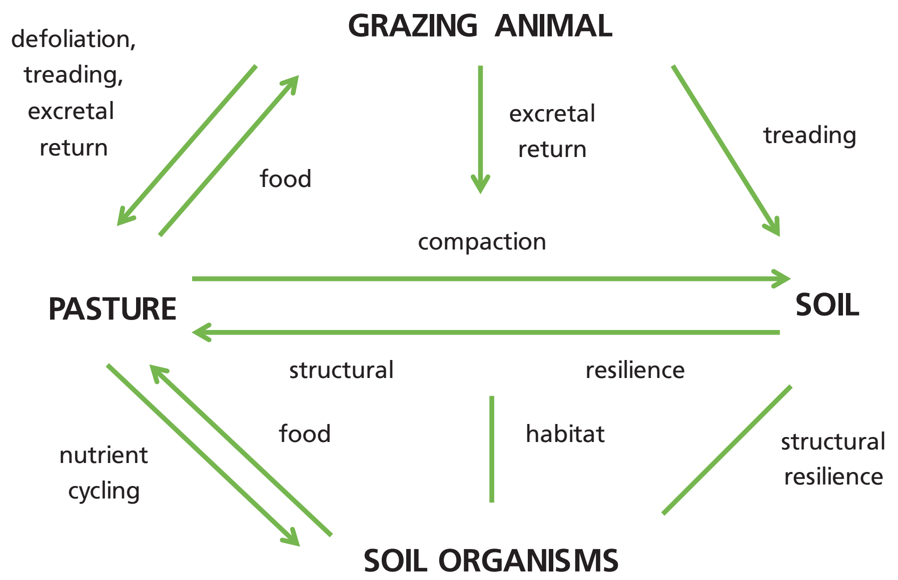
1. Introduction

Livestock production systems may be classified as intensive or extensive, depending on the level of technology applied and the way livestock is managed and fed throughout the year. Soil properties, particular soil organic matter (SOM) content, may be affected directly when livestock graze on grassland and/or pastures, or indirectly when land is used for fodder crops or forage production. Impacts on soil properties will differ greatly, depending on stocking rates, because of the myriad of effects in which grazing influences the soil properties. Grazing animals are typical in extensive livestock production systems (e.g. meat and dairy cattle, sheep, goats, etc.), which are mainly based on the direct grazing of grassland, pastures, fodder crops, and crop residues by livestock. As reviewed by Taboada *et al.* (2011), grazing effects on soil properties of forage production systems follow direct and indirect pathways. Direct effects relate to animal trampling and excretion, while indirect effects are mediated by changes in vegetation structure and function. Figure 1 shows a simplified model of a grazing system, integrating both direct and indirect effects of livestock on soil properties, as proposed by Greenwood and McKenzie (2001).

SOM plays a critical role in the physical, chemical and biological function of soils, in livestock and other land-production systems. SOM includes both living organisms and dead organic material at different stages of decomposition; it has a diverse composition and a complex origin and parts of it (such as humus) have a

Figure 1

Interactions among soil, vegetation, and livestock in grazing systems



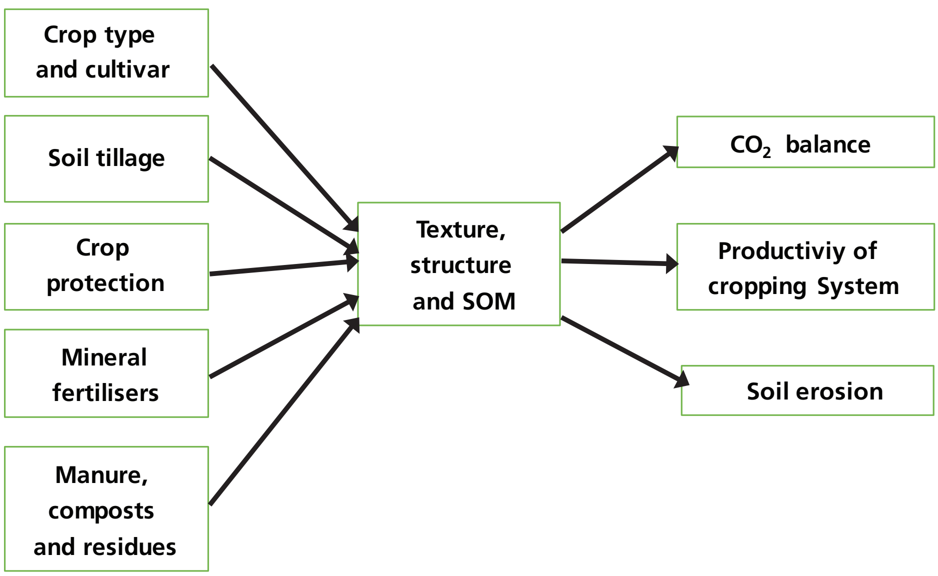
Source: modified from Greenwood and McKenzie, 2001.

structure that is still poorly understood (Van-Camp *et al.*, 2004). Despite the relatively minor quantity in soil (0.1 – 10 percent), SOM plays an important role as a soil constituent and as source of nutrients and energy for soil biota. In addition to influence soil structure and nutrient cycling, which together determine the general productivity of livestock and cropping systems, SOM is also important for the CO_2 balance between agroecosystems and the atmosphere (Christensen and Johnston, 1997) as displayed in Figure 2.

Before the invention and use of synthetic fertilisers, SOM was at the core of soil fertility for biomass production, which is still the case for low-input agriculture, forestry, husbandry and organic/ecological agriculture (Van-Camp *et al.*, 2004). Because SOM affects, either directly or indirectly, most of the chemical, physical and biological properties of soil, it is thought to be a good measure of soil quality, since its presence determines the conditions necessary for such functions and, due to its slow changes, it also captures the resilience of the ecosystem. The anthropogenic causes of SOM loss include land conversion, tillage, overgrazing, soil erosion, and fires (Van-Camp *et al.*, 2004).

Long-term experiments in Askov (Denmark) and in Rothamsted (England), from 1894 and 1843, respectively, showed the influence of land use and soil management on the quantity of SOM and its change over time (Christensen and Johnston, 1997). This, in turn, influences soil quality. However, not only the quantity of SOM is important for soil quality but also its quality, which is defined "in terms of bioavailability of carbon to decomposer populations and mineralizability of organically bound plant

Figure 2
Soil properties depend on soil management and influence other conditions



Source: Drawn from Christensen and Johnston, 1997.

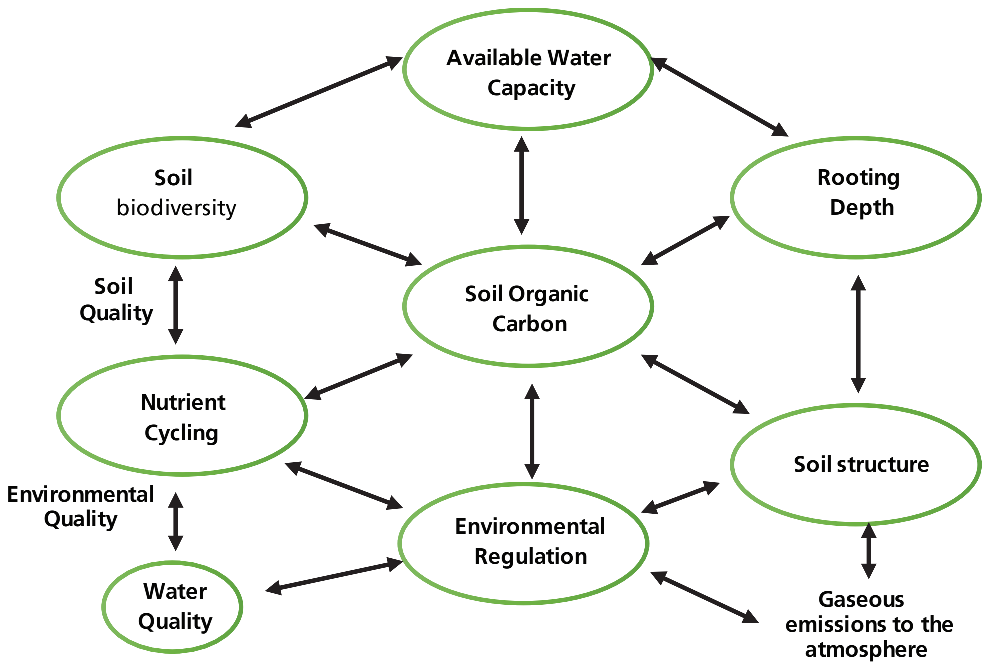
nutrients, and by the chemical nature (composition, reactivity, and mobility) of SOM. Soil biota also relates to the quality of SOM (Christensen and Johnston, 1997).

These long-term experiments have shown that SOM has a significant impact on yields. Indeed, "irrespective of the amount of N applied, yields (…) were larger on soils with extra SOM resulting from applications of FYM since 1843" (Christensen and Johnston, 1997). SOM can affect the yield of arable crops through mechanisms like nutrient release, improved soil structure, and improved water-holding capacity, "but these cannot be readily separated and quantified" (Christensen and Johnston, 1997), which indicates that soil quality is an emergent property of the whole system. The role of SOM in soil fertility can be summarised as (Milà i Canals *et al.*, 2007):

- Physical fertility: soil structure (formation of aggregates) enabling root penetration; contribution to erosion resistance and land stability; reduction of susceptibility to compaction; and soil aeration;
- Chemical fertility: nutrient pool; nutrient protection (cation exchange capacity) holds nutrients avoiding their loss through leaching); pH control (buffer capacity); and plant growth regulation; and
- Biological fertility: enhancing soil biota (food source); nutrient cycling (degradation capacity and nutrient availability); and microbial activity.

SOM is probably the most cited indicator of soil quality in soil science (Milà i Canals *et al.*, 2007a; Milà i Canals *et al.*, 2007). The reason why is that it influences a wide range of soil properties (e.g. Brussaard *et al.*, 2007) as identified in Figure 3. The value of this indicator lies in the fact that it is closely related to other soil quality indicators.

Figure 3
Soil Organic Carbon impact on soil and environmental quality



Source: Manlay *et al.*, 2007.

SOM is best measured as SOC, according to Reeves (1997). SOM content is measured as density of SOC, and SOC is usually considered to be 58 percent of SOM, giving a conversion factor of 1.72:1 (SOM: SOC) (Brady and Weil, 1999). The amount of SOC varies according to soil type and biome. Indeed, according to Watson *et al.* (2001), there is a strong negative correlation between land use intensity and SOC. Natural ecosystems, such as peats, bogs and grasslands have a higher SOC than semi-natural ecosystems (e.g. pastures, forest plantations and woodlands) and agricultural land has one of the lowest levels of SOC (IPCC, 2003). Within this last category, perennial crops show higher SOC levels than land under annual crops. Tillage, in particular, accelerates the oxidation/mineralisation of SOC. In more intensive uses, such as building, mining or transport infrastructures, soil is removed or sealed, and it can thus be argued that SOC has effectively disappeared.

Soils are the largest terrestrial sink of carbon. The global soil carbon (C) pool of 2500 gigatonnes (Gt[1]) includes about 1550 Gt of soil organic carbon (SOC) and 950 Gt of soil inorganic carbon (SIC) (Lal, 2008; Jansson *et al.*, 2010). The SOC pool represents a dynamic equilibrium of gains, such as carbon added from aboveground residues and root biomass, and losses as oxidized carbon dioxide (CO_2) to the atmosphere and soil erosion. Conversion of natural to agricultural ecosystems causes depletion of the SOC pool by as much as 60 percent in soils of temperate regions and 75 percent or more in cultivated soils of the tropics. When the depletion of the SOC pool is severe, soil quality and biomass productivity decrease, with adverse impacts on water quality and contribution to global warming (Lal 2004).

Managed grasslands with grazing animals are a main forage resource for livestock production systems globally (Conant *et al.,* 2001, Ni 2002). According to Taboada *et al.* (2011), grassland carbon stocks are primarily determined by climatic factors: total carbon increases with precipitation (as a result of increased primary production) and decreases with temperature (as a result of increased decomposition rates). More than two-thirds of the carbon stored in grasslands is located below ground in soil organic matter pools (Parton *et al.*, 1987; Burke *et al.*, 1989). Grazing exerts a major influence on grassland carbon cycling, affecting not only transfers among vegetation and soil compartments, but also ecosystem input and output flows as illustrated in Figure 4.

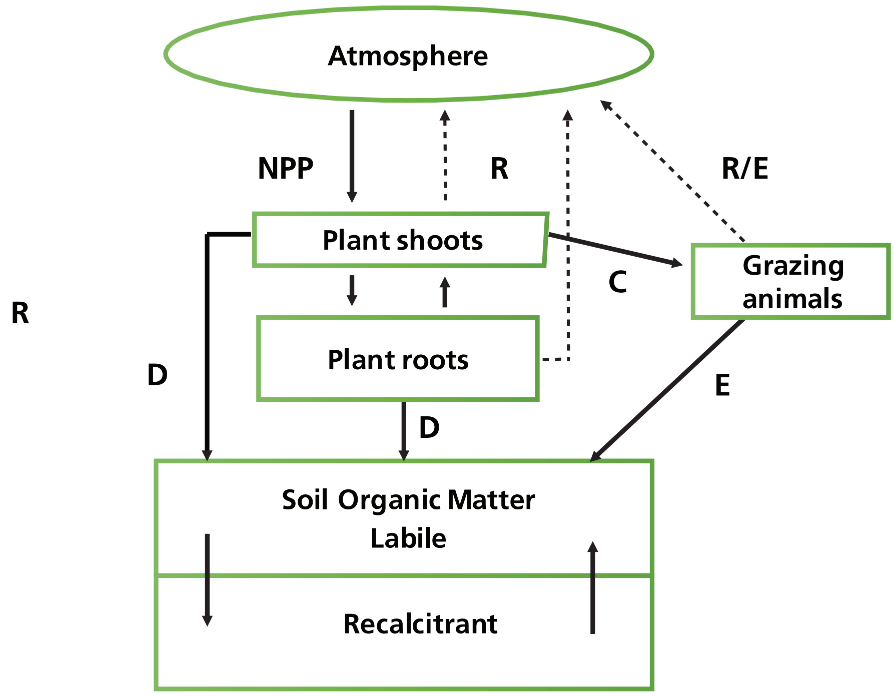
The amount of CO_2 fixed by plants through net primary production (NPP) can follow different pathways as illustrated in Figure 4. Carbon is translocated from above- to below-ground plant organs and back to shoots depending on the season and on grazing pressure. Herbivores consume a sizeable fraction of the aboveground NPP; the rest of the carbon is accumulated as plant biomass and eventually enters above- and below-ground detrital routes, undergoing decomposition by soil microorganisms. Grazers also transfer carbon into the soil organic matter via waste deposition. From the review carried out by Taboada *et al.* (2011), in which the comparison with grazing enclosures is used to analyse grazing impacts, it can be concluded that in mesic grasslands grazing decreases the amount of carbon stored in above-ground vegetation and there is variable impact on root mass. Conversely, livestock grazing has been reported to decrease, increase, or even produce no observable change in SOC.

Taboada *et al.* (2011) suggested that the relative effect of grazing on soil carbon may shift from negative in arid systems, to positive in mesic systems through humid habitats

[1] 1 Gt = 1 billion tonnes = 1 Pg

Figure 4
The carbon budget in a grazing system showing major carbon pools and transfer flows.

Microbial decomposers are included in the soil labile organic matter compartment.
Solid arrows depict ecosystem inputs and transfers among compartments; dashed arrows denote gaseous losses.
NPP = net primary production; R = respiration; C = consumption; D = detritus production; E = excretion.
Grazing may directly or indirectly control all these fluxes.



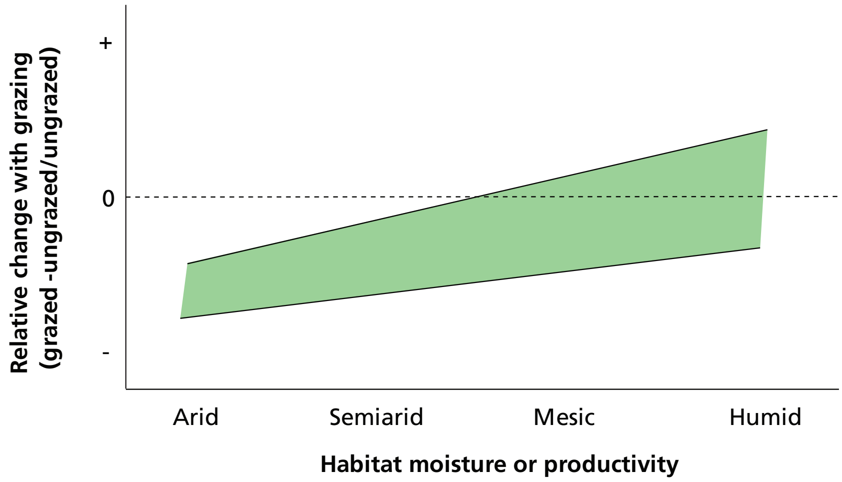
Source: Edrawn from Taboada *et al.*, 2011,

shown in Figure 5. In mesic-to-humid systems, soil carbon may be either increased or decreased, depending on the balance between root production (input) and above- and below-ground litter decomposition (output). At the opposite end of the gradient, negative grazing effects on soil carbon prevail. A large body of evidence suggests that reduced litter inputs from herbivores, increased erosion, and photodegradation of litter may lead to significant reductions in soil carbon stocks in arid rangelands.

Long-term changes in input and output fluxes may not only alter topsoil carbon content, but may also be transmitted to deeper layers, affecting storage in less active pools, and the grassland net carbon balance (Chapin *et al.*, 2002). To account for grazing impacts on whole-grassland carbon dynamics, a long-term (>100 year) perspective is needed as suggested by Piñeiro *et al.* (2006). Using the CENTURY model (Parton *et al.*, 1987, 1988), these authors simulated long-term dynamics of soil carbon and nitrogen pools for the Río de la Plata grasslands in southern South America. They found that, in the long term, grazing redistributed soil carbon from the slow organic carbon pool (turnover ~25 year) to the “passive” pool from 39 percent to 47 percent, reflecting in part the imbalance between input and output carbon fluxes.

Figure 5
Relative effect of grazing on SOC in the rooting zone, along a habitat moisture gradient from dry to humid grasslands.

Values above (positive) and below (negative) the dashed line indicate increases and decreases in soil carbon as a result of grazing, respectively. The stippled area represents cross-site variability in soil carbon response within habitat types.



Source: Redrawn from Taboada *et al.* (2011).

A considerable amount of land remains under managed grasslands and pastures in many world regions, such as the Loess Plateau of China (Ni 2002), the Rio de la Plata Grasslands (Piñeiro *et al.*, 2006, Taboada *et al.*, 2011), or the Brazilian Cerrado (Batlle-Bayer *et al.*, 2010). These areas could be the focus of potential strategies to mitigate climate change in the future. Such strategies could include emission reductions and activities that increase C sinks, including terrestrial sinks (Milne *et al.*, 2007). Grazing management is promising for mitigating climate change, particularly when the recommended management practices (RMPs) are followed, implying the transfer of atmospheric CO_2 into long-lived pools, to increase SOC levels and C sequestration. SOC stocks increase after land-use changes and adoption of RMPs, following a sigmoid curve. The rate of increase in SOC stocks attains its maximum 5 to 20 years after adoption of RMPs, and SOC levels increase until a new equilibrium is reached (Lal 2004). Attainable soil C sequestration in rangelands is 50-150 kg C ha^{-1}, as a function of ecosystem type and grazing management (Conant *et al.*, 2001). The restoration of grasslands and the de-intensification (or extensification) of intensive livestock systems are likely to provide opportunities of soil C sequestration in European livestock production systems (Soussanna *et al.*, 2004).

A robust estimation of SOC changes is crucial in the Life Cycle Assessment (LCA) of agricultural crop and livestock product systems. LCA is a tool that quantifies the environmental impacts of products, and has been applied extensively to agricultural systems. However, the estimation of SOC changes associated to land use and land use change have not been done consistently across different studies, leading to results that may be perceived as unrobust. Clearly, there is room for further harmonisation in the practice of estimating SOC changes from human activities on land, particularly in livestock systems. This is partly the aim of the Technical Advisory Group (TAG) on SOC changes, under the LEAP initiative of FAO, which is crucial in the carbon footprinting of livestock products.

To support farmers, policy makers and other stakeholders across the feed and livestock sectors in taking land use and management decisions that mitigate climate change, there is the need for a commonly agreed methodological system to estimate SOC stocks and stock changes in grasslands and rangelands, and to combine them with LCA. However, soils are extremely complex systems, spatially heterogeneous at different scales, and include biogeochemical processes with temporal dynamics that range from hourly responses to large time scales. Furthermore, estimating SOC in livestock systems have additional complexities. SOC levels tend to be highly variable due to the patchy distribution of the vegetation and animal excretal returns. Grazing animals affect not only aerial net primary productivity (NAPP) and litter inputs to the soil, but may also affect belowground production and C inputs, and these effects depend on the spatial distribution and intensity of the grazing regimes. As mentioned above, animal trampling may unevenly affect bulk density and other soil physical properties, which may in turn have an impact on soil water balance, NPP and carbon inputs. Finally, short-term changes in SOC are usually relatively small compared to the amount of C stored in grasslands soils (Conant and Paustian, 2002), and detecting these changes may encounter some limitations.

Taking these specificities into account, there are different direct and indirect approaches to account for SOC stocks and changes in livestock systems: soil sampling, eddy covariance, remote sensing, and modelling among others (Post *et al.*, 2001). Physical sampling and modelling have been the most common approaches. Spatial variability, minimum detectable changes, sampling depth, sampling frequency, and analytical methods to determine carbon content, should be taken into account when designing a sampling scheme. A sampling protocol for SOC estimations is beyond the scope of this document. For a review of sampling designs and considerations in grasslands and other livestock systems, refer to Ellert *et al.* (2001), Conant and Paustian (2002), De Gruijter *et al.* (2006), Allen *et al.* (2010), and Chappell *et al.* (2013).

Models have been developed since the 1930s, as simplified mathematical representations that quantitatively describe these processes (Manzoni and Porporato, 2009). Simulation models of SOC have played a crucial role in research, by providing a better understanding of soil processes, extrapolating or interpolating experimental results in time, space and to different environmental conditions, and providing scenarios and hypotheses that are beyond the realm of experimental work (Falloon and Smith, 2009; Campbell and Paustian, 2015). In the last decades, there has also been an expanding interest in SOC models for decision making (Manlay et al 2007; Taghizadeh-Toosi et al 2014; Campbell and Paustian, 2015).

A wide variety of SOC models have been developed, differing in their structure, mechanisms, purpose, scale and complexity. Manzoni and Porporato (2009) reviewed and classified about 250 different mathematical models developed over 80 years that describe biogeochemical processes in soils. Falloon and Smith (2009) mention that at least 98 agro-ecosystem models involving SOC processes were registered in CAMASE (Plentinger and Penning de Vries, 1996), while Campbell and Paustian (2015) listed 87 models where SOC or soil carbon dynamics were explicitly included in the model's foundational formulation.

The main objectives of the present study are to:

- Review and analyse the main approaches for modelling SOC stock changes, with special emphasis on grasslands and rangelands;
- Review how these approaches have been implemented in Life Cycle Assessment studies;
- Identify contentious issues where consensus is lacking in SOC modelling approaches; and
- Provide a suitable proposal within the technical boundaries of the TAG.

2. Types of SOC Models

2.1 EMPIRICAL, FUNCTIONAL AND MECHANISTIC MODELS

Agroecological models may be classified, according to the prevailing underlying mechanisms used to generate their results, as empirical, functional and mechanistic (Addiscott and Wagenet, 1985; O'Sullivan y Simota 1995; Passioura, 1996; Maraux *et al.*, 1998; Connolly, 1998; Doering, 2002; Wallach *et al.*, 2013). As found by several authors (McGill *et al.*, 1996; Manzoni and Porporato, 2009; Falloon and Smith, 2009; Batlle-Aguilar *et al.*, 2011), a precise classification of the different models is often difficult because they are based on a wide range of physical and biogeochemical descriptions of the processes and the underlying assumptions vary significantly. They differ in the way the mathematical description of the processes is framed, its structure, the number of variables used, and the spatial resolution (Manzoni and Porporato, 2009). A clear-cut classification of models is hard to achieve, and a given model could be functional or empiric at one scale, and mechanistic at another (Connolly, 1998). According to Christensen (1996), most of SOC turnover models essentially overlap empirical and mechanistic approaches. Moreover, at some level of analysis, all models may have empirical functions (Whistler *et al.*, 1986).

Empirical models represent observed relationships between SOC stocks or SOC changes or carbon fluxes and environmental variables, such as soil clay content, temperature, precipitation and land use (Grigal and Berguson, 1998; Davidson and Janssens, 2006; Milne *et al.*, 2007). There are several examples of studies that analyse factors controlling SOC levels in grasslands and other productive environments (Parton *et al.*, 1987; Alvarez and Lavado, 1998; Jobbágy and Jackson, 2000; Percival *et al.*, 2000), and examples of national and regional estimates of current SOC stocks and historical changes in SOC content (Arrouays *et al.*, 2001; Jones *et al.*, 2005; Bellamy *et al.*, 2005).

Smith *et al.* (2000; 2001), and Gupta and Rao (1994) used this type of empirical regressions of changes in SOC stocks under changes in land use or management based on long-term experimental data to calculate annual percent variations in SOC, and to extrapolate future changes in SOC stocks under different scenarios. A more complex regression approach, that takes account of local variability in soil and climatic conditions, uses functions based on spatially-explicit soil databases (Kern and Johnson, 1993; Kotto-Same *et al.*, 1997). One of the best-known empirical approaches is the computational method to estimate SOC stock changes developed by the Intergovernmental Panel on Climate Change (IPCC; 2004, 2006). The main limitation of this approach is that they assume a constant rate of SOC change throughout the time period of the scenario under study (Milne *et al.*, 2007). Regression-based estimates may also be limited in their ability to predict long-term soil C dynamics in a changing environment (Peng *et al.*, 1998).

Functional models are more complex than empirical models, and tend to use robust empirical functions, or functions based on general physical-chemical principles to simulate and integrate different processes (Maraux *et al.*, 1998; Doering, 2002). Many of these models can predict and integrate a variety of variables other than SOC, such as soil moisture, soil temperature, plant biomass production, crop yield, and nutrient leaching among others (Smith *et al.*, 1997). This approach takes account of the underlying dynamic processes and variables determining SOC stocks and changes, with turnover times ranging from days to centuries (Jenkinson, 1990). SOC stocks and rates of SOC changes in time can be modelled taking climatic and soil factors into account, together with land use and management variables.

Based on the characteristics summarized by Smith *et al.* (1997), known ecosystem and agricultural models that simulate SOC dynamics like CENTURY (Parton *et al.*, 1987; Parton, 1996), RothC/RothPC (Jenkinson *et al.,* 1990; Jenkinson and Coleman 2008), SOCRATES (Grace and Ladd 1995), CANDY (Franko *et al.,* 1995), SOMM (Chertov and Komarov 1997), DAISY (Hansen *et al.*, 1991), DSSAT (Hoogenboom *et al.,* 1994), NCSOIL (Hadas *et al.,* 1998), EPIC (Williams *et al.,* 1984, Jones *et al.,* 1984), ECOSYS (Grant *et al.,* 1993), among others, could be included under this classification. However, some of these models are often classified as mechanistic by some authors (Stockmann *et al.*, 2013).

Mechanistic models are the most complex and use mathematical functions that describe the physical and chemical processes involved in detail. They incorporate the most fundamental mechanisms of each process, as far as known at present. For example, a mechanistic approach is often needed for the simulation of microbial processes in natural systems, and some authors developed mechanistic models to describe the interrelations between C, N and microbial populations (Knapp *et al.*, 1983; Maggi et al, 2008). Researchers are also using more mechanistic approaches to describe temperature responses on SOM dynamics, based on the understanding of factors such as substrate diffusion, enzyme activity, membrane transport and microbial community dynamics (Grant *et al.*, 2003; Davidson *et al.,* 2006, 2012). INDISIM-SOM (Ginovart *et al.*, 2002; 2005) and ENZModel (Allison, 2005) are known examples of this type of modelling approximations.

There has also been more frequent use of this mechanistic kind of approach to estimate fluxes and emissions of nitrous oxide in specific grassland environments (Müller *et al.*, 1997). However, this kind of model is generally used for the investigation of a particular process and usually predicts short-term and small-scale changes (Campbell and Paustian, 2015). Researchers argue that a greater inclusion of more mechanistic representations of microbial growth, microbial enzyme kinetics and stoichiometric constraints may derive a 'first principle' approach to soil organic matter (SOM) dynamics and would improve other types of model predictions (Todd-Brown *et al.,* 2012; Xu *et al.*, 2014). However, these efforts could be hampered by greater model complexity and data availability (Campbell and Paustian, 2015).

2.2 PROCESS-ORIENTED, ORGANISM-ORIENTED AND COHORT MODELS

Batlle-Aguilar *et al.* (2011) and Stockmann *et al.* (2013) have recently divided SOC models according to their internal structure: process-oriented compartment models; organism-oriented (food-web) models; and cohort models. Process-oriented models are built considering the processes involved in the transfer of SOC across the soil profile and its transformations (Smith *et al.*, 1998). They are generally used to predict SOC dynamics based on different conceptual C pools or compartments that alter in size via decomposition rates and stabilization mechanisms (each compartment or pool being a fraction of SOC with similar chemical and physical characteristics; Stockmann *et al.*, 2013). Models belonging to this class can potentially have a variable degree of complexity, from one compartment to multiple compartments (Jenkinson *et al.*, 1990). Early models simulated SOC as one homogeneous compartment (Jenny, 1949). Beek and Frisel (1973) and Jenkinson and Rayner (1977) proposed two-compartment models, and as computational tools became more accessible, multi-compartment models were developed (McGill, 1996).

According to Falloon and Smith (2009), decay rates (k) are usually expressed in this type of models by first-order kinetics with respect to the concentration (C) of the pool:

Equation 1

$$dC/dt = -kC$$

The flows of carbon within most models represent a sequence of carbon going from plant and animal debris to the microbial biomass and then, to soil organic pools of increasing stability. The output flow from an organic pool is usually split. It is directed to a microbial biomass pool, another organic pool and, under aerobic conditions, to CO_2. This split simulates the simultaneous anabolic and catabolic activities and growth of a microbial population feeding on one substrate. Two parameters are generally required to quantify the split flow, often defined as a microbial (utilization) efficiency and a stabilization (humification) factor, which control the flow of decayed carbon to the biomass and humus pools, respectively.

Process-oriented multicompartment SOC models have been dominant in efforts to simulate changes in SOC in grasslands and other environments (Stockmann *et al.*, 2013). CENTURY (Parton *et al.*, 1987; Parton, 1996), RothC/RothPC (Jenkinson et al 1990; Coleman and Jenkinson, 1996), SOCRATES (Grace *et al.*, 2006), DNDC (Li, 1996), CANDY (Franko *et al.,* 1997), DAISY (Hansen *et al.*, 1991), NCSOIL (Hadas *et al.,* 1998) and EPIC (Williams *et al.,* 1983; 1984) are known examples of this kind of process-oriented multicompartment models. They have been developed and tested using long-run data sets, and in general they show a good ability to predict SOC dynamics over decades across a range of land uses, soil types and climatic regions (Smith *et al.*, 1997). Nevertheless, model calibrations play a major role in influencing their predictive ability. Process-oriented models can be combined with GIS software, giving a modelling platform well suited for regional scale studies. Examples of successful coupling between soil turnover and GIS software are CANDY (Franko, 1996), CENTURY (Schimel *et al.*, 1994), RothC (Post *et al.*, 1982; Jenkinson *et al.*, 1991), and the inclusion of CENTURY, RothC and the IPCC methodology into the Global Environment Facility Soil Organic Carbon (GEFSOC) Modelling System (Easter *et al.*, 2007; Milne *et al.*, 2007; Kamoni *et al.*, 2007; Falloon *et al.*, 2007).

In **organism-based models** the SOM flows from one organism pool to another, which are classified depending on their taxonomy or metabolism (Batlle-Aguilar *et al.*, 2011). They provide understanding of C and N flows through food webs and explore the role of soil biota in C and N mobilization (Smith *et al.*, 1998). In these models, C and N fluxes are simulated through functional groups based on their specific death rates and consumption rates, applying energy conversion efficiencies and C:N ratios of the organisms (Stockmann *et al.*, 2013). They also enable analysis of environmental risks and provide a guide to above and below-ground linkage of food webs (Brussaard, 1998; Smith *et al.*, 1998; Susilo *et al.*, 2004). The main advantage of organism-oriented models is that the main drivers of SOC fluxes and transformations are explicitly accounted for (Hunt *et al.*, 1991; de Ruiter *et al.*, 1993; Moore *et al.*, 2005). However, there is no general acceptance of the existence of a relation between soil biota abundance and degradation rates (Post *et al.*, 2007). Although they have been applied to arable land and grasslands alike, they usually work in a small-plot scale and with daily basis time steps. Site-specific calibration of organism-oriented models involves the characterization of the soil microbial consortia and therefore requires more complex techniques (Stockmann *et al.*, 2013). Nevertheless, organism-oriented models have been proposed by several authors, including Moore *et al.* (2005), Kuijper *et al.* (2005), Zelenev *et al.* (2006) and Cherif and Loreau (2009).

Cohort models divide SOM into cohorts (McGill, 1996), which are further divided into different pools (Batlle-Aguilar *et al.*, 2010). Such models consider one SOM pool that decays with a feedback loop into itself. In models like Q-SOIL (Bosatta and Ågren, 1995a), for example, SOM is represented by a single rate equation. The SOC pool is divided into an infinite number of components, each characterized by its "quality" with respect to degradability, as well as impact on the physiology of the decomposers (Smith *et al.*, 2008). Exact solutions to the rate equations are obtained analytically (e.g. Bosatta and Ågren, 1995b). In analytically-solved models, such as ICBM (e.g. Kätterer and Andrén, 2001), the "model" can be restricted to the equations describing soil carbon transformations and other functions (e.g. weather-top-soil-climate) can be made external to the model (but they can be included in the model package). These models have usually a prevailing mechanistic approach. An example of a cohort model was proposed by Furniss *et al.* (1982), where SOM was divided into three cohorts considering age, origin and size, with each cohort subdivided into a number of chemical constituents. Gignoux *et al.* (2001) developed soil organic matter cohort (SOMKO), where SOM is divided into different cohorts in a demographic sense, meaning that a cohort is a set of items of the same age. At each time step a new cohort is defined and its fate is followed until its relative amount to total SOM becomes negligible. Other examples of models belonging to this class are those of Pastor and Post (1986), Bosatta and Ågren (1991, 1994) and Frolking *et al.* (2001).

2.3 DETERMINISTIC VS STOCHASTIC MODELS

Models may also be classified as deterministic or stochastic, according to the nature of their results (Addiscott and Wagenet, 1985; O'Sullivan and Simota 1995; Manzoni and Porporato, 2009). Deterministic models presume that a system or process operates in such a way that the occurrence of a given set of events leads to a uniquely-definable outcome, while stochastic models presuppose the outcome to be uncertain, and are structured to account for this uncertainty (Addiscott and Wagenet, 1985). According to these and other authors (Manzoni and Porporato, 2009), every real system must be considered subject to uncertainties of some kind, but they are ignored in the formulation of a deterministic model. Such a model can therefore only simulate the system's response to a single set of assumed conditions, and whether these predictions are of practical use must depend on the nature and extent of the variability within the system of physical, chemical and biological processes. This inherent variability has promoted the development of models that can consider the statistical variability of both input conditions and model predictions. Stochastic models may therefore generate probabilities linked to random elements or the variability of the analysed system.

Due to the existence of many internal processes and of uncertainty in structure as well as spatial heterogeneity, a detailed description of the soil system would require the use of an extremely high number of variables. However, given the impossibility of achieving such a detailed modelling, it is highly desirable to shift from high-dimensional models to a suitable combination of deterministic variables and random functions or stochastic processes, providing a more parsimonious and balanced representation of the soil system (Katul *et al.*, 2007). A stochastic representation could also assess the role of climatic variability and quantify uncertainties in soil carbon projections. The Q-model, for example, employs a statistical description of the substrate quality (Bosatta and Ågren, 1995). The quality of the degraded substrate is considered as an internal random variable described by a probability density function, evolving in time according to dynamic interactions of the substrate with biotic and abiotic factors (Ågren and Bosatta, 1996), and evolving in space along the soil profile according to convective and dispersive mechanisms (Bosatta and Ågren, 1996). The use of a probability function substitutes the common compartmental deterministic structure. Some approaches account for soil heterogeneity at the field- to the landscape-scale based on distributed parameters (Walter *et al.*, 2003). A few SOC models address the stochastic nature of the climatic variables, which affects, through soil moisture and temperature, the rates of soil biogeochemical fluxes (Porporato *et al.*, 2004; Daly *et al.*, 2008; Wang *et al.*, 2009). However, despite the need for a stochastic approach, only a few soil models employ stochastic components, and most of them use a deterministic approach (Manzoni and Porporato, 2009).

3. Frequently used models and their characteristics

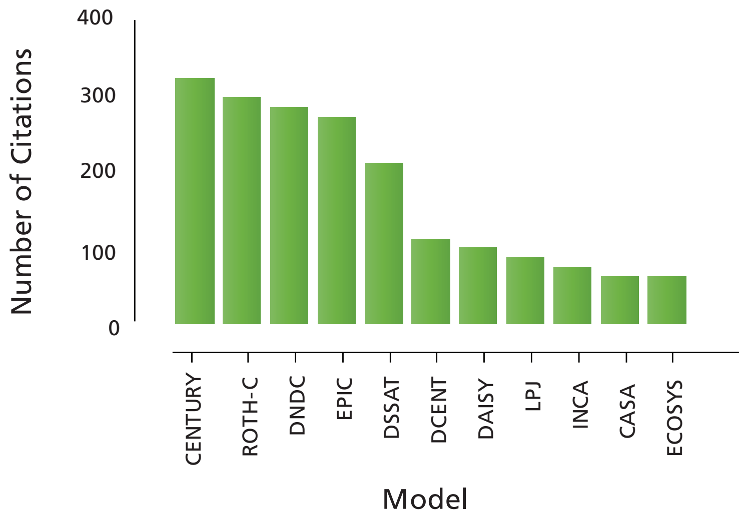
The most widespread SOC simulation models are functional (though classified as mechanistic by some authors), process-oriented and deterministic, because they represent a compromise solution between their relative simplicity and their robustness to explain the workings of the most important processes of the system. Campbell and Paustian (2015) undertook a quantitative review to evaluate SOC model "use" in scientific literature from 1930 to 2015, recording the number of citations of over 70 named models. Their analysis suggests that a relatively small subset of SOC known models shown in Figure 6 dominate SOC simulations in the scientific literature. Moreover, the top five cited models (CENTURY, ROTH-C, DNDC, EPIC, DSSAT) account for 61 percent of the total citations. Other models may be widely and successfully used for some specific environments or for the simulation of particular processes, but their spread is relatively limited.

This report emphasizes the fact that among these known models, no particular one clearly outperforms the others. According to Campbell and Paustian (2015), there has even been an increase in multi-model comparison publications in the last decades, which shows the lack of consensus in SOC modelling approaches. It is also noteworthy that among these comparisons, there was no single model identified with conclusively higher performance capacity. Some models though, performed better than others for specific components or locations within the comparative analyses. Therefore, we summarize the main characteristics of five well-known,

Figure 6

Total citations for different SOC models in Web of Science literature

(for named models with over 50 citations).



Source: Redrawn from Campbell and Paustian (2015).

recognized and used approaches in grasslands ecosystems, including the four most cited models mentioned in the previous analysis (without considering DSSAT, which has recently included a CENTURY sub-routine), and the relatively recent but well-recognized IPCC methodology (IPCC, 2004; 2006).

3.1 INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE (IPCC) COMPUTATIONAL METHOD

This empirical approach computes projected net stock changes of C over a given period of time (namely 20 years), in a one-step process. The approach estimates change in SOC stocks by assigning a reference C stock (total C stock in soil), which varies depending on climate, soil type and other factors and then by multiplying that value by factors representing the quantitative effect of changing management on SOC storage. The method can use default climatic, soil and land use/management information given by the IPCC or, if available, country-specific data. The approach enables the estimation of annual carbon stock change in different carbon pools (aboveground biomass, belowground biomass, dead wood, litter and soils), subdivided as necessary to capture differences between ecosystems, climatic zones and management practices. Net stock changes in a given pool are computed as a function of gain and losses:

Equation 2

$$\Delta C = \Sigma ijk\ [Aijk\ (CI - CL)ijk]$$

where:
ΔC = carbon stock change in the pool, tonnes C yr^{-1}
A = area of land, ha
ijk = corresponds to climate type i, land type j, management practice k
CI = rate of gain of carbon, tonnes C ha^{-1} yr^{-1}
CL = rate of loss of carbon, tonnes C ha^{-1} yr^{-1}

In order to enable the estimation of annual rates of soil carbon change for different land uses and different specified management practices, the IPCC complemented the Computational Method methodology by multiplying SOC reference level by factors reflecting land use, land management, and carbon inputs in 2006. Using this type of approach and an extensive database from Europe, South America and North America, Ogle *et al.* (2004) estimated C sequestration potentials for rangelands and pastures and analysed the potential effects of medium- and high-input management practices. A recent study adapted the IPCC method to estimate SOC stock changes and to assess C sequestration potentials in soils, at a regional scale, in five contrasting eco-regions: South Eastern Australia, Northern Kazakhstan, the Indian Indo-Gangetic Plains, Sweden and Uruguay (Grace *et al.*, 2004). Using a global map of estimated organic SOC at a resolution of 1 by 1 km at the equator, in conjunction with other global data and bibliographic information on stock change factors, Petri *et al.* (2010) estimated C sequestration potentials for grasslands by the IPCC methodology on a global scale. The IPCC methodology has been linked to spatial GIS databases, enabling the estimation of SOC stocks and SOC changes at national and sub-national scales (e.g. Global Environment Facility Soil Organic Carbon-GEFSOC Modelling System, used in studies such as Easter *et al.*, 2007; Milne *et al.*, 2007; and Kamoni *et al.*, 2007).

One main drawback of the IPCC approach is that it considers, as do other regression approaches, SOC changes linearly (Milne *et al.*, 2007). Another drawback is that much of the data available for deriving the empirical factors in the IPCC default approach are from studies in North America and Europe, and that there is a significant lack of data for unmanaged grasslands, which may result in bias (Petri *et al.*, 2010). While the IPCC approach showed to be a useful tool to assess C sequestration potential in grassland soils and the economic cost associated with that sequestration at a regional scale, the method may have limitations for sub-national or sub-regional assessments (Milne *et al.*, 2007).

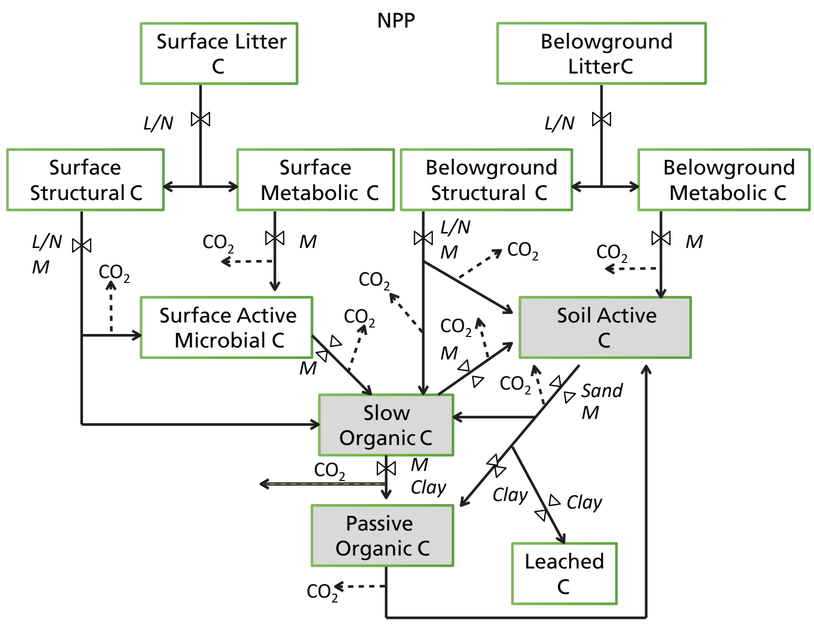
3.2 CENTURY - SOIL ORGANIC MATTER MODEL

The model simulates SOM dynamics, plant growth and the flow of C, N, P, and S through plant litter and the different inorganic and organic pools in the soil. As described by Metherell *et al.* (1993) and Parton (1996), the model includes; three soil organic matter pools (active, slow and passive) with different potential decomposition rates; above and below-ground litter pools; and a surface microbial pool which is associated with decomposing surface litter. Above and below-ground plant residues and organic animal excreta are partitioned into structural and metabolic pools as a function of the lignin to N ratio (L:N) in the residue (as the ratio increases, more of the residue is partitioned to the structural pools which have considerably

Figure 7

Structure, pools, and flows of Carbon in the CENTURY model, including major factors controlling the fluxes

(M=multiplier for effects of moisture, temperature and cultivation; L:N = lignin to nitrogen ratio).



Source: Redrawn from Parton (1996) and Falloon and Smith (2009).

slower decay rates than the metabolic pools). Figure 7 displays the structure, pools and flows of the Century model.

The decomposition of both plant residues and SOC are assumed to be microbially mediated with an associated loss of CO_2 as a result of microbial respiration. Decomposition products flow into a surface microbe pool or to one of three SOC pools, each characterized by different decomposition rates. The potential decomposition rate is reduced by multiplicative (M) functions of soil moisture and soil temperature and may be increased as an effect of cultivation. The decomposition rate of the structural material is a function of the fraction of the structural material that is lignin (L:N). The active pool represents soil microbes and microbial products and has a turnover time of months to a few years, depending on the environment and sand content. Soil texture influences the turnover rate of the active SOM (highest rates for sandy soils) and the efficiency of stabilizing active SOM into slow SOM (highest stabilization rates for clay soils). The surface microbial pool turnover rate is independent of soil texture, and it transfers material directly into the slow SOM pool. The slow pool includes resistant plant material derived from the structural pool and soil-stabilized microbial products derived from the active and surface microbe pools. Its turnover time is from 20 to 50 years. The passive pool is very resistant to decomposition and includes physically and chemically stabilized SOM with a turnover time of 400 to 2,000 years. The proportions of the decomposition products entering the passive pool from the slow and active pools increase with expanding soil clay content. A fraction of the products from the decomposition of the active pool is lost as leached organic matter.

The CENTURY model has N, P, and S pools analogous to all the C pools. It includes a simplified water budget model, which calculates monthly evaporation and transpiration water loss, water content of the soil layers, snow water content, and saturated flow of water between soil layers. The relevant (crop, grass or forest) plant-growth model determines plant carbon inputs. The model simulates net primary production (NPP), controlled by moisture, temperature and nutrient availability. The model is intended to simulate the monthly dynamics of grasslands, agricultural crops, forests, and savanna (tree-grass) systems, including management options. One major improvement has been the ability to simulate full greenhouse gas dynamics for agricultural, forest and grassland systems (Stockmann *et al.*, 2013). For example, DayCent (daily version of CENTURY) can simulate soil CH_4, N_2, N_2O and NO_x gas fluxes, plant production dynamics, soil N dynamics, soil NO_3 leaching and SOM dynamics using daily time steps. DayCent is also considered to be sufficiently well calibrated to project future changes in GHG dynamics (Del Grosso *et al.*, 2009; De Gryze *et al.*, 2010). A more extensive review of the model variables, inputs, sub-models and processes can be found in Parton (1996), Smith *et al.*, (1997), and Falloon and Smith (2009).

CENTURY was originally developed for the grassland systems of the Central Great Plains and then extended to arable ecosystems, savannas and forests (Parton, 1996; Smith *et al.*, 1997). Multiple studies have used the CENTURY model in livestock systems around the world. For example, Parton *et al.* (1993) tested the ability of the model to simulate patterns of living biomass, NPP and soil C and N levels in temperate and tropical grasslands, ranging from the continental plains of the United States, the Russian Federation, and Arid central Asia, to natural and converted grasslands in wet and dry regions of the tropical region (the Caribbean, Northern Africa, Southern and Eastern Africa, and the tropical Asian Monsoon Region). Using CENTURY, Parton *et al.* (1995) estimated the impact of climate change and increasing atmospheric CO_2 on NPP and SOC stocks for similar temperate and tropical grasslands. Ardo and Olsson (2003) combined CENTURY with GIS and estimated SOC changes in grasslands and savannas of semi-arid Sudan, under different grazing intensities and fire frequencies. Piñeiro *et al.,* (2006) analysed the impacts of 370 years of livestock grazing on SOC contents of grasslands in Uruguay and Argentina using this model. Cerri *et al.* (2007) evaluated CENTURY's accuracy in estimating changes under forest-to-pasture conditions in the Brazilian Amazon and suggested that modelling techniques can successfully be used to monitor soil C stocks and stock changes in this type of environment. The model has also been linked to spatial GIS databases, integrated into the Global Environment Facility Soil Organic Carbon (GEFSOC) Modelling System (Easter *et al.*, 2007; Milne *et al.*, 2007; Kamoni *et al.*, 2007).

The CENTURY model has recently been integrated into other methodologies to estimate GHG emissions and mitigation potentials. Using remote sensing data, national statistics databases, and a surrogate model for CENTURY's soil organic C dynamics submodel, Kwon *et al.* (2013) estimated the forward change in soil C and associated CO_2 emissions for the 2011 to 2040 period for the conversion of croplands, grasslands, pastures and forests to biofuel feedstock production systems. Henderson *et al.* (2015) estimated the net GHG mitigation potential of a selected range of management practices in the world's native and cultivated grazing lands. Changes in soil carbon stocks, soil N_2O emissions and forage removals by ruminants associated with these practices were estimated using the CENTURY model.

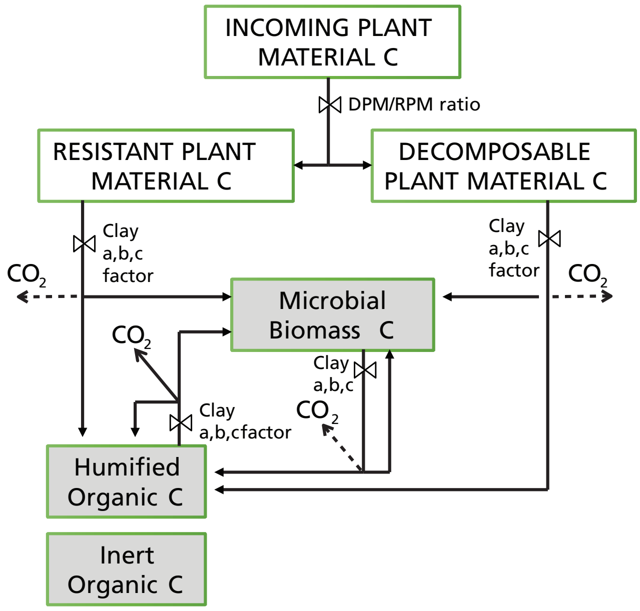
3.3 ROTHC – ROTHAMSTED C MODEL

RothC is a model for the turnover of organic carbon in non-waterlogged topsoils that enables the inclusion of the effects of soil type, temperature, moisture content and plant cover on the turnover process, with a monthly time step (Coleman and Jenkinson, 1996). RothC only deals with soil processes, and is not linked to a plant production model like CENTURY (instead it is the user who defines the carbon inputs to the soil). SOC is split into four active compartments and a small amount of inert organic matter (IOM, comparable to CENTURY's "Passive organic C" pool). The four active compartments are Decomposable Plant Material (DPM, comparable to CENTURY's "Belowground metabolic C" pool), Resistant Plant Material (RPM, comparable to CENTURY's "Belowground structural C" pool), Microbial Biomass (BIO, comparable to CENTURY's "Soil Active C" pool), and Humified Organic Matter (HUM, comparable to CENTURY's "Soil Slow Organic C" pool). The IOM compartment is resistant to decomposition. The structure of the model is shown in Figure 8.

Incoming plant carbon is split between DPM and RPM, depending on the DPM/RPM ratio of the particular incoming plant material. All incoming plant material passes through these two compartments only once. Both DPM and RPM decompose to form CO_2, BIO and HUM. The proportion that goes to CO_2 and to BIO + HUM is determined by the clay content of the soil. The BIO + HUM

Figure 8
Structure pools, and flows of Carbon in the RothC model, including major factors controlling the fluxes.

(a = multiplier for effects of temperature, b = multiplier for effects of moisture, c = multiplier for effects of soil cover; DPM/RPM = Decomposable/resistant plant material ratio).



Source: Redrawn from Coleman and Jenkinson (1996) and Falloon and Smith (2009).

is then split into 46 percent BIO and 54 percent HUM. BIO and HUM both decompose to form more CO_2, BIO and HUM. Each compartment decomposes by a first-order process with its own characteristic rate. If an active compartment contains Y t C ha^{-1}, this declines at the end of the month to:

Equation 3

$$Y e^{-abckt} \, t \, C \, ha^{-1}$$

where:
a is the rate-modifying factor for temperature
b is the rate-modifying factor for moisture
c is the soil cover rate-modifying factor
k is the decomposition rate constant for that compartment
t is 1/12, since *k* is based on an annual decomposition rate. Y $(1 - e^{-abckt})$ is the amount of the material in a compartment that decomposes in a particular month.

RothC has also been adapted to simulate N and S dynamics (Falloon and Smith, 2009), where nutrient and C dynamics are not interconnected. RothC was originally developed and parameterized to model the turnover of organic C in arable topsoils, and it was later extended to model turnover in grasslands, savannas and woodlands, and to operate in different soils and under different climates (Coleman and Jenkinson, 1996).

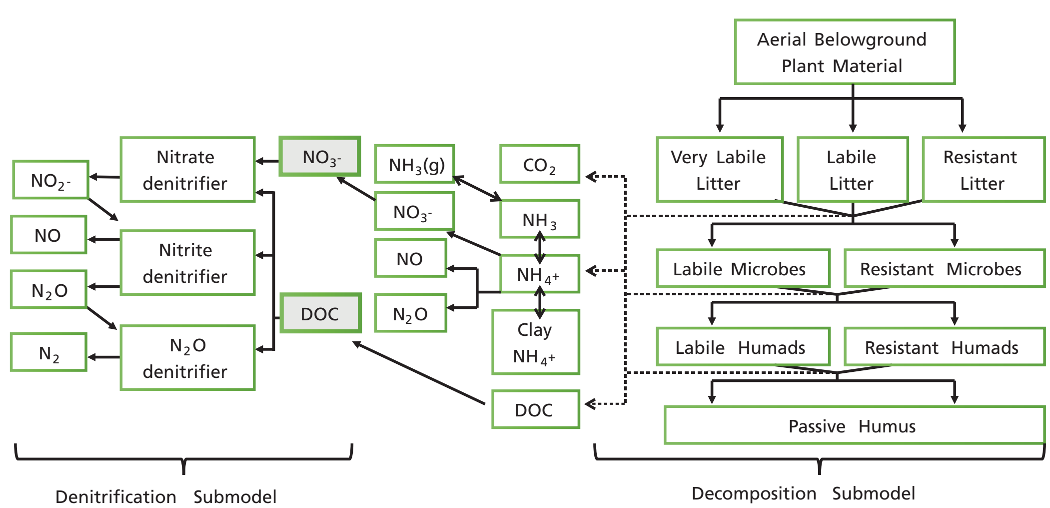
Like CENTURY, RothC has been used to simulate C dynamics in grasslands and other productive environments from small plot-paddock scale to regional-country states (Falloon and Smith, 2009). For example, Cerri *et al.* (2003) used RothC to model SOC changes associated to changes in land use (tropical forests to pastures) in the Western Amazon. Martí-Roura *et al.* (2011) used the model to estimate abiotic effects, such as droughts and fire in grasslands and shrublands of the Mediterranean basin, while Liu *et al.*, (2011) simulated SOC dynamics under different pasture management regimes in Australia. Linking RothC to spatially explicit soils and climate data via GIS, Falloon *et al.*(1998) used it to estimate SOC changes and C sequestration potentials in grasslands and other land uses, at a regional scale in Central Europe. RothC has also been applied to 1 km-level databases of soil and land use, and coarser resolution databases of climate in the United Kingdom (Falloon *et al.*, 2006). Smith *et al.* (2005) used RothC to estimate land-use change scenarios and climatic effects in grasslands and croplands across Europe, while Wan *et al.* (2011) projected climatic and anthropic effects in SOC levels in China. The model has been also linked to GIS data and integrated into the Global Environment Facility Soil Organic Carbon (GEFSOC) Modelling System (Easter *et al.*, 2007), and used to predict SOC stocks and SOC changes in grasslands, savannas and other land uses from different soils and climates in Kenya, Jordan, India and Brazil (Kamoni *et al.*, 2007; Falloon *et al.*, 2007; Milne *et al.*, 2007). RothC has been also coupled with other modelling approaches to estimate the GHG balance for different land use change transitions at a national scale (Hillier *et al.*, 2009).

3.4 DNDC - DENITRIFICATION AND DECOMPOSITION MODEL

DNDC is a process-oriented simulation model of soil carbon and nitrogen biogeochemistry and is intended to be used to estimate effects of climate change, land use, agricultural management, soil properties, and atmospheric nitrogen deposition on soil C and N dynamics (Li, 1996). DNDC contains four interacting submodels of soil climate, decomposition, denitrification, and plant growth. The soil climate submodel calculates soil temperature, moisture profiles, and soil water flow over time based on soil physical properties, air temperature, precipitation, and water uptake by plants; information is fed into either decomposition or a denitrification submodel. The plant growth submodel calculates daily water- and N-uptake by plants, plant growth, root respiration, and biomass partitioning to grain, stalks and roots. Effects of cropping practices including tillage, fertilization, manure application, and irrigation, are incorporated into the model. The decomposition submodel calculates daily decomposition, nitrification, movement of nitrate and ammonium along soil profile, ammonia (NH_3) volatilization, and carbon dioxide (CO_2) and other trace gases emissions. The denitrification submodel calculates nitrous oxide (N_20), nitric oxide (NO) and dinitrogen (N_2) production during wet periods. A simplified structure of the Decomposition and Denitrification submodels is shown in Figure 9.

According to Li (1996) and Li *et al.* (2012), four major pools reside in DNDC SOC: plant residue (i.e. litter), microbial biomass, humads (i.e., active humus), and passive humus. These pools are similar to the ones mentioned in CENTURY and RothC. Each pool consists of two or three sub-pools with different specific decomposition rates. Daily decomposition rate for each sub-pool is regulated by the pool size, the specific decomposition rate, soil clay content, N availability, soil temperature, and soil moisture. Clay adsorption of humads permits some soil-specificity. When SOC in a pool decomposes, the decomposed carbon is partially lost as CO_2

Figure 9
Simplified Structure of Denitrification and Decomposition Submodels in DNDC.



Source: Rredrawn from Li (2012).

while the rest is allocated into other SOC pools. Dissolved organic carbon (DOC) is produced as an intermediate during decomposition and can immediately be consumed by the soil microbes.

During the processes of SOC decomposition, the decomposed organic nitrogen partially transfers to the next organic matter pool and is partially mineralized to ammonium (NH_4^+). The free NH_4^+ concentration is in equilibrium with both the clay-adsorbed NH_4^+ and the dissolved ammonia (NH_3). Volatilization of NH_3 to the atmosphere is controlled by NH_3 concentration in the soil liquid phase and subject to soil environmental factors (e.g. temperature, moisture, and pH). A kinetic scheme "anaerobic balloon" in the model predicts the soil aeration status by calculating the content of oxygen or other oxidants in the soil profile. Based on the predicted redox potential, the soil in each layer is divided into aerobic and anaerobic parts, where nitrification and denitrification occur, respectively. When the anaerobic balloon swells, more substrates (e.g. DOC, NH_4^+, and N oxides) will be allocated to the anaerobic microsites to enhance denitrification. When the anaerobic balloon shrinks, nitrification will be enhanced due to the reallocation of the substrates into the aerobic microsites. NO and N_2O gases produced in either nitrification or denitrification are subject to further transformation during their diffusion through the soil matrix. Long-term (e.g. several days to months) submergence will activate fermentation, which produces hydrogen sulphide (H_2S) and methane (CH_4) driven by decreasing of the soil pH. The time step is hourly for the soil climate and denitrification submodels, and daily for the decomposition and plant growth submodels.

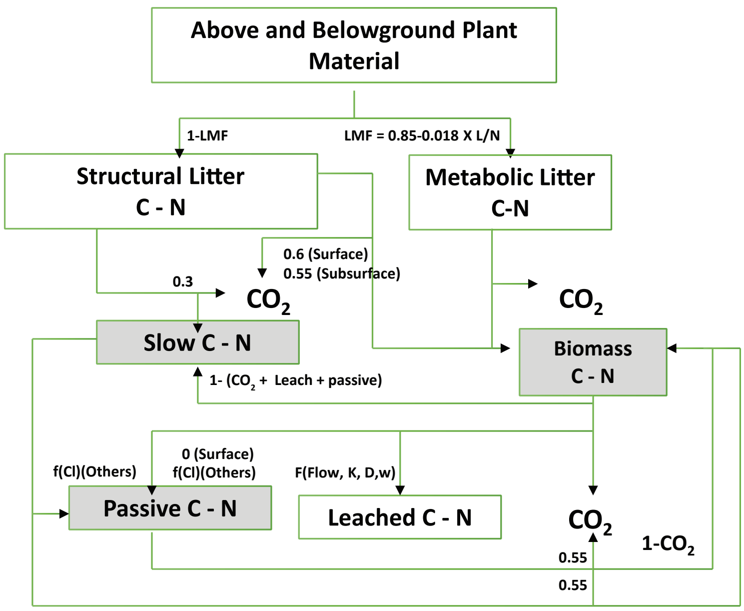
DNDC was initially developed to predict emissions of CO_2, N_2O and N_2 from agricultural soils (Smith *et al.*, 1997), but it was later used to simulate long-term changes in SOC stocks in grasslands and croplands in specific sites in the United Kingdom and Australia (Li *et al.*, 1997). Frolking *et al.* (1998) used the model to simulate N_2O emissions in grassland sites in the United Kingdom, the United States and in Germany. Introducing specific input data to DNDC's database and modifying its ability to simulate daily C and N inputs from grazing animals, Brown *et al.* (2002) used the modified DNDC model to estimate N_2O emissions for grasslands and croplands of the United Kingdom on a national scale. Using a modified DNDC model, Xu-Ri *et al.* (2003) estimated N_2O fluxes from semi-arid grasslands in Northern China, from plot to regional scales. Saggar *et al.* (2004, 2007) modified the DNDC model to simulate the year-round grazed pastures better and applied it to New Zealand's systems. Tang *et al.* (2006) used the model to estimate SOC storage, changes, and emissions at a national scale in China. Levy *et al.* (2007) combined IPCC and DNDC estimations to simulate CH_4, N_2O and CO_2 fluxes in European grasslands at a regional scale. In general, the use of DNDC in livestock systems has been less widespread than other SOC models, and generally oriented to the estimation of gas fluxes.

3.5 EPIC - ENVIRONMENTAL POLICY INTEGRATED CLIMATE (FORMER EROSION PRODUCTIVITY IMPACT CALCULATOR)

EPIC was developed to assess the effect of erosion on productivity (Williams, *et al.*, 1984). Later developments extended EPIC's scope to encompass aspects of agricultural sustainability, including changes in soil quality and estimations of the effects of global climate/CO_2 change (Wang *et al.*, 2012). The major components in EPIC

Figure 10
Simplified Structure of Carbon Submodel in EPIC.

LMF = fraction of litter that is metabolic; L/N = lignin: nitrogen ratio; Cl = clay fraction; K = distribution coefficient of organic compounds between soil solid and liquid phases; D = Bulk density; w = soil water content.



Source: Redrawn from Izaurralde et al. (2006).

are weather simulation, hydrology, erosion-sedimentation, nutrient cycling, pesticide fate, crop growth, soil temperature, tillage, economics, and plant environment control. The model can be used to compare management systems and their effects on N, P, SOC, pesticides and sediments. The SOC submodel is based on concepts used in the CENTURY model (Parton *et al.,* 1996). EPIC simulates carbon and nitrogen compounds stored in and converted between biomass, slow, and passive soil pools. Carbon leaching from surface litter to deeper soil layers and the effect of soil texture on organic matter stabilization are also modelled as illustrated in Figure 10. However, EPIC includes different equations to account for soil erosion: USLE (Wischmeier and Smith, 1978), MUSLE (Williams and Berndt, 1977) and USLE yet again, modified by Onstad and Foster (1975). These modified equations include runoff variables into the formulation of erosive energy, thereby increasing the accuracy of erosion prediction, and SOC loss estimations (Polyakov and Lal, 2004).

Simulations of sites in the US and Canada showed EPIC satisfactorily replicated the soil carbon dynamics over a range of environmental conditions and cropping/vegetation and management systems (Izaurralde *et al.,* 2006; 2007). EPIC performed robustly for simulations of deforested conditions, cropping systems, and native vegetation in Argentina (Apezteguía *et al.,* 2009). Billen *et al.* (2009) calibrated the EPIC model to estimate Carbon sequestration in arable and grassland soils affected by agricultural management in Germany. By combining land use classification and soil maps with EPIC, Causarano *et al.* (2010) studied the impacts of land use changes and management practices on SOC in the native rangeland ecosystems of Central Asia. However, EPIC has generally been oriented towards erosion studies, and its use to simulate SOC dynamics in grasslands and rangelands has been relatively limited compared to the previously mentioned models.

Table 1 summarizes the main inputs and characteristics of the 5 previously mentioned models.

Table 1. Main characteristics of some of the most-frequently used SOC models.

Model	Type	Minimum Weather variables/Inputs	Minimum Soil variables/ inputs	Minimum Management variables/inputs	Factors affecting decaying constants	Time Scale Use	Spatial Scale Use
IPCC	Empirical, process-oriented (one compartment), deterministic.	Climatic type (defines Reference SOC)	Soil type (defines Reference SOC)	Land use factor (type of activity. E.g. grassland, cropland).	Management factor (e.g. degraded, improved)	Years	Regional/ Global
CENTURY	Functional, process-oriented (multi-compartment), deterministic	Total Precipitation (Monthly) Mean Maximum Air Temperature (Monthly) Mean Minimum Air Temperature (Monthly)	Sand (%) Silt (%) Clay (%) Bulk Density SOC content Nitrogen content pH Water constants (FC, PWP)	Residue Lignin/N Rotation Tillage Fertilizers Manure Irrigation Residue management Atmospheric N inputs	Temperature Water Nitrogen Clay	Months to years (although DAYCENT uses daily steps)	Plot to national/ Regional
ROTH C	Functional, process-oriented (multi-compartment), Deterministic	Total Precipitation (Monthly) Mean Air Temperature (Monthly) Total evaporation (Monthly)	Clay (%) SOC content Inert C (can be estimated)	Residue quality (DPM/RPM) Manure Residue management/ Soil cover	Temperature Water Clay Soil cover	Months to years	Plot to national/ Regional
DNDC	Functional (partly mechanistic), process-oriented (multi-compartment), deterministic	Precipitation (Monthly or Daily) Air Temperature (Monthly or Daily)	Clay (%) Bulk Density SOM content pH	Residue Lignin/N Rotation Tillage Fertilizers Manure Irrigation Residue management	Temperature Water Nitrogen Clay Tillage	Days to years	Plot to national/ Regional
EPIC	Functional, process-oriented (multi-compartment), deterministic		Clay (%) Bulk Density SOC content Nitrogen content pH CEC Water constants (FC, PWP)	Rotation Tillage Fertilizers Manure Irrigation Residue management/ Crop cover	Temperature Water Nitrogen Clay Crop cover Cation exchange capacity	Days to years	Plot to national/ Regional Widely used for Landscape scales

Source: Adapted from Falloon and Smith (2009).

4. Combining SOC models with Life Cycle Assessment

Life Cycle Assessment (LCA) is a tool that quantitatively estimates the impacts of product systems on a range of environmental categories, such as climate change, soil quality, ecosystem services and biodiversity as well as resource depletion. LCA has been accepted as the appropriate tool for the comparison of alternatives that yield the same function (e.g. bioethanol vs gasoline, vegetarian diet vs meat-based diet, organic vs conventional crop production).

LCA has been applied to all sectors, including agriculture, such as crops and livestock products. For example, the debate over the perceived benefits of biofuels has made LCA the tool of choice to estimate the relative impacts of plant-derived fuels against the use of their fossil-based counterparts. In this case, the need for the proper accounting of C stocks and flows associated with land use and land-use change in a robust manner soon became apparent, but the interest from the LCA community on SOC changes first arose when attempts were made to include land use impacts in the LCA methodology.

The inclusion of SOC changes in the LCA of agricultural systems has largely not taken place before 2011 (Brañdao *et al.,* 2011). SOC changes are important because their exclusion may completely negate any benefits occurring at other life cycle stages, as is the case with some biofuels. This necessarily affects the results of key impact categories, such as climate change and soil quality as well as associated decisions and policy implications.

4.1 JUSTIFYING SOC CHANGES AS AN INDICATOR FOR LAND USE IMPACTS ON SOIL QUALITY IN LCA

Different methods have been developed to assess soil quality in LCA, many of which highlight the role of SOC as a key indicator. The indicator for soil quality, or for life support functions of land, is not straightforward. Soil quality refers to the ability of soil to sustain life support functions, e.g. biotic production; substance cycling and buffer capacity; climate regulation (Milà i Canals, 2003; Milà i Canals *et al.*, 2007).

Despite the consideration of several indicators for soil quality (e.g. erosion, salinisation, exergy, soil microbial biomass), SOC content is at the heart of most ecosystem services. Milà i Canals and co-workers (2007) and others have argued that SOC can be used as an indicator for soil quality within the LCA of agricultural systems: an increase in SOC due to the soil management practices implies a benefit, whereas any decrease in SOC is accounted for as damage. Following the common LCA approach of "less is better", a lower SOC deficit is an indicator of reduced impact. The impact is measured as a carbon deficit (or credit, expressed by negative values) with the unit "kg C·year", referring to the amount of extra carbon temporarily present in or absent from the soil compared to a reference system (Milà i Canals *et al.*, 2007).

Despite the strength of this indicator, not all aspects of soil quality are captured by the SOC (Milà i Canals, 2003; Milà i Canals *et al.*, 2007). These include build-up of toxic substances, acidification and salinization. In addition, SOC is highly location-dependent, which affects its practical use because spatially differentiated soil databases are only now emerging. Nonetheless, SOC is an important indicator due to its close relationship with soil functions. In terms of applicability, the existence of several soil carbon databases at different regional scales (e.g. by CTCD, DEFRA, IES, IPCC, HWSD) and models (e.g. RothC, Century, Daisy, GEFSOC, SDGVM) enable the inclusion if SOC in LCAs.

4.2 ESTIMATING LAND-USE IMPACTS ON CLIMATE CHANGE USING LCA

SOC accounting is also relevant for LCA when making climate change calculations, particularly for studies on food, bioenergy and forest products. This section identifies the links between land use and climate change, and reports on the manner this has been dealt with under the Kyoto Protocol accounting and in LCA methodology. By recognising the importance of timing issues in the assessment of climate change impacts, this section also reviews existing approaches (e.g. PAS 2050) and the limitations of using relative Global Warming Potentials (GWPs) in assessing the contribution of GHG balances to climate change. Finally, different methods that address temporary SOC changes are reviewed, and an approach is proposed to that effect.

Since terrestrial ecosystems play an important role in the carbon cycle, the focus here is on land use impacts on climate change, through carbon emissions and sequestration in plants and soil as well as the importance of time as a parameter. This section, therefore, focuses on the carbon balance, its perturbation by humans, and the influence of land use on the exchange of carbon dioxide (CO_2) between the atmospheric and the terrestrial carbon pools; the latter including vegetation and soil.

Land use and land-use change influences the climate system in various ways, in particular by influencing radiative forcing through (Müller-Wenk and Brandão, 2010):

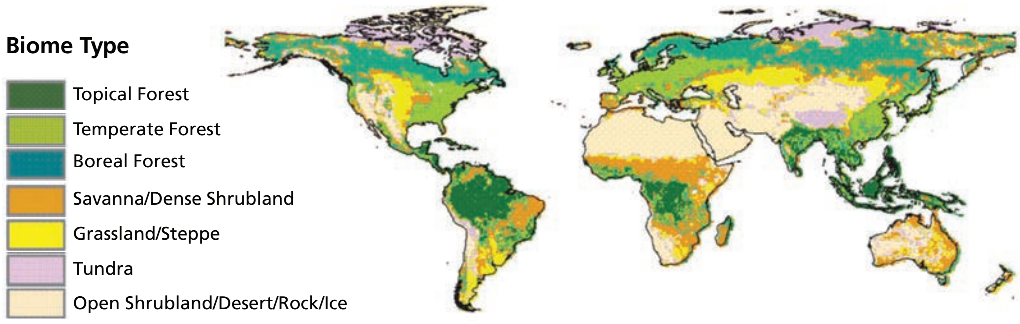
- Releasing GHGs that were previously stored in biomass and soil, and resulting in an increase in the concentration of GHGs in the atmosphere;
- Changing the albedo of the earth, influencing the absorption of solar radiation; and
- Changing the evapotranspiration rate, influencing the degree of cloudiness.

This section focuses on the first of these impact pathways.

To calculate the carbon flows associated with a particular land use and land-use change, it is necessary that the location is known as it determines potential vegetation and SOC levels. This potential land cover can serve as the reference land use against which other land uses are measured. Figure 11 shows a global map of Potential Natural Vegetation, which may help finding the biome corresponding to a given location where land use activity takes place. Each of these biomes is associated with a certain carbon stock, also displayed in numbers in Table 2.

The map of potential natural vegetation in Figure 11 may be compared with Figure 12, which displays the lands that have been changed by humans into cropland and pasture until year 1990. It is clear that temperate forest, grassland and savannas are the biomes which have suffered most change. The conversion of these areas was accompanied by a release of carbon from the biospheric pool and into the atmospheric pool, thereby increasing the atmosphere's concentration of CO_2. Unlike fossil fuels, the direction of the flow may be reversed in reasonably short time. Indeed, the natural

Figure 11
Global map of Potential Natural Veg



Source: Forster *et al.*, 2007.

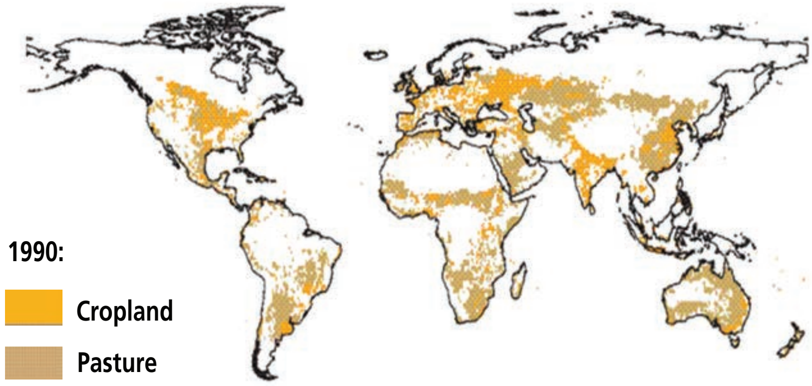
Table 2. Carbon stocks in vegetation and soils.

Biome	Area (10^9 ha)	Vegetation	Soils (3 m)	Total Global Carbon Stocks (GtC)
Tropical forests	1.75	340 (194)	692 (395)	1032 (590)
Temperate forests	1.04	139 (134)	262 (252)	401 (386)
Boreal forests	1.37	57 (42)	150 (109)	207 (151)
Mediterranean shrub lands	0.28	17 (61)	124 (443)	141 (504)
Tropical savannahs and grasslands	2.76	79 (29)	345 (125)	424 (154)
Temperate grasslands	1.50	6 (4)	172 (115)	178 (119)
Deserts	2.77	10 (4)	208 (75)	218 (79)
Arctic Tundra	0.56	2 (4)	144 (257)	146 (261)
Wetlands	0.35	15 (43)	450 (1286)	465 (1329)
Permafrost	2.55	0 (0)	2991 (1173)	2991 (1173)
Croplands	1.35	4 (3)	248 (184)	252 (187)
TOTAL	17.83	673 (38)	6177 (346)	6850 (384)

Note: numbers in parenthesis refer to average biome carbon stocks (t C per ha).
Source: extrapolated from Watson *et al.* (2000).

colonisation and succession of plants after a land disturbance would usually ensure that the Potential Natural Vegetation is re-established relatively rapidly following the end of human intervention. This regeneration is spontaneous and is assumed to develop towards a quasi-natural land state. Therefore, all land uses and land-use change, however extensive, have the potential to be reversed to a quasi-original state, depending on the amount of time they are left to regenerate.

Figure 12
Global map of areas converted into cropland or pasture until year 1990



Source: Forster *et al.*, 2007.

4.2.1 Accounting for terrestrial carbon stock changes: reconciling LCA with alternative approaches

The Kyoto Protocol (United Nations, 1998) and IPCC methodology
The now-defunct Kyoto Protocol permitted countries to meet their commitments not only by reducing emissions of greenhouse gases from combustion and similar processes, but also by inducing land-use changes with favourable carbon balances. Indeed, article 3.3 of the Kyoto Protocol states that "... the net changes in greenhouse gas ... resulting from direct human-induced land-use change and forestry activities, limited to afforestation, reforestation and deforestation since 1990 ... shall be used to meet the commitments...". In addition, article 3.4 states that "... the COP [Conference of Parties] ... shall decide upon … which additional human-induced activities related to changes in greenhouse gas emissions by sources and removals by sinks in the agricultural soils and the land-use change and forestry categories shall be added to, or subtracted from, the assigned amounts …" (Watson *et al.*, 2000). Although the precise meaning of these passages may not be fully clear, it is evident that the Kyoto Protocol:

- Includes credits for anthropogenic land-use activities that avoid or compensate for fossil greenhouse gas emissions;
- Adopts the status of the land in year 1990 as the reference land use; and
- Limits land-use activities to the agricultural and silvicultural sectors.

In contrast, LCA quantifies the different environmental impacts that arise from anthropogenic land use, and no credits for abstaining from executing an intervention are awarded. Furthermore, the arbitrary choice of the year 1990 as the reference land use is not obvious for LCA. LCA compares the land's environmental burdens, as caused by anthropogenic land-use activities, with those from one of the following four reference situations that would exist at that same location (See Soimakallio *et al.*, 2015; Koponen *et al.*, 2017):

- One consisting of a mix representing the current state of land;
- One which can consist of the most likely alternative land use (consequential perspective);
- One that can consist of the land use that develops without human influence and potentially achieves the natural land cover of that area (regeneration); or
- One consisting of the natural or a semi-natural land cover (i.e. Potential Natural Vegetation).

The IPCC methodology described in Section 3.1 is the basis for reporting terrestrial carbon stock changes from the Land Use, Land-Use Change and Forestry (LULUCF) sector. There is an important conceptual difference between the LCA and the national reporting under the Kyoto Protocol with respect to carbon accounting. Carbon accounting related to land use, in the context of the Kyoto Protocol, focuses on the estimated annual flows of carbon from LULUCF, whereas in the context of LCA, the focus is on quantifying the magnitude of the carbon transfers between the biosphere and the atmosphere resulting from land-use activities within the boundaries of a product system. In both accounting systems, there may also be negative emissions, if the land-use activity under assessment leads to sequestration of carbon in land from the atmosphere in relation to the reference system. National reporting focuses on net flows occurring over one year, as they can be physically observed or approximately derived from observations. For example, in IPCC's fifth assessment report, the annual "land use change flux" in the 2000s is estimated at 1.1 GtC/yr, while fossil fuel use and cement production generate 7.8 GtC/yr (Myhre *et al.*, 2013). These figures refer to actual physical transfers of CO_2 to the atmosphere that occurred in the given year or decade average, regardless of the time the event originally took place. As a justification, the existence of a "legacy" of CO_2 flows that physically occur in the years and decades succeeding the execution of a land use change (future emissions from current LUC are reported in the years following the LUC, i.e. every year for the 20 years following LUC) is acknowledged. In contrast, the LCA methodology aims to capture all present and future effects originating from the human activity under assessment. In consequence, all CO_2 flows caused by human economic activity are commonly added up in LCA, irrespective of the time of their occurrence. Nonetheless, it is common in LCA for impacts (such as those associated with land use change) to be allocated over a finite number of years, usually 20. Cowie and co-workers (2012) elaborate on the differences between these approaches.

The scientific knowledge made available by the IPCC in the context of the carbon cycle is a valuable and authoritative source of data to determine carbon balances associated with land use. Moreover, the increasing acceptance and implementation of the carbon accounting methods developed under the Kyoto Protocol in most of the world contribute to data quality improvement. But in the light of the aforementioned differences, care must be taken when using these data for LCA in order to ensure that it is done in an appropriate manner.

4.2.2 The Publicly Available Specification 2050 (PAS 2050)

PAS 2050 is an LCA-based approach to estimate the carbon footprint of products. In the United Kingdom, emissions and sequestration of biogenic carbon (C) is increasingly recognised as something that must be accounted for. For example, a joint endeavour by Defra, the British Standards Institute and the Carbon Trust resulted in the publication of guidelines for the assessment of the life cycle greenhouse gas (GHG) emissions of goods and services: the PAS 2050 (BSI, 2008). The inclusion of land-use changes (LUC) in this standard is an improvement over standard approaches to carbon footprinting that omit them. This is particularly important in the assessment of biofuels and other land-based products. It is interesting to note that the review of PAS 2050 (BSI, 2011) has backed away from the step forward taken in the 2008 document.

Land-use changes are taken into account in PAS 2050, but only the changes that occurred after 1 January 1990 are considered. Carbon emissions from both vegetation and soil are taken into account based on the IPCC guidelines. When determining GHG emissions arising from land-use change, the worst-case scenario for current land use and for land-use change is to be adopted if the former land use or the country of origin is not known: the default value is 37 t CO_2-e ha^{-1} yr^{-1} and represents conversion of Brazilian or Malaysian forest land to annual cropland. This value is based on the IPCC guidelines (2006) and is ascribed equally among the subsequent 20 years of annual cropland following conversion. The choice to amortize land-use change emissions over 20 years is not explained, but we assume that it follows the average 20-year period between steady-states in soil carbon stocks following LUC adopted by the IPCC. The default values for LUC were changed to less extreme values in the revised version.

The PAS2050 only accounts for emissions associated with transition from previous land uses (forestland and grassland) to current land uses (annual cropland and perennial cropland) by recommending four default values for land use change in sixteen different countries. The specified countries do not include certain bio-regions (such as the Mediterranean) where different values could be found. South and North America, Oceania, Central and Northern Europe, South and South-East Asia and Southern Africa are represented; all the other bio-regions are not.

In addition to SOC changes, emissions from waste (excluding biogenic CO_2) are accounted for and allocated to the product that generated them and, in the case of open-loop recycling (e.g. biogas from methane from waste), no consideration is given to whether the methane is from a biogenic source. If from a fossil source, emissions are allocated to the energy produced.

Moreover, the PAS 2050 excludes the biogenic carbon sequestered and emitted by the photosynthesis and combustion of biofuel, despite accounting for carbon storage in other products. However, some perennial energy crops are managed in long rotations and therefore the carbon storage should arguably be accounted for, just as in any other product that stores carbon, and thus benefits from a credit under the PAS 2050 guidelines.

In terms of wood products, the PAS 2050 approach follows the recommendations by Clift and Brandão (2008) to account for carbon storage and delayed emissions and gives credit to the products that store carbon, but this is only for the time the carbon is stored in the product from manufacture and not from earlier carbon sequestration, i.e. tree growth. A more detailed analysis can be found in Clift and Brandão (2008). This approach is based on the Lashof method (see subsequent section), which accounts for carbon storage in biomass by looking at the effect of delaying an emission on radiative forcing, integrated over a 100-year period. The formulae used in PAS 2050 are a linear approximation of the integral. There is no discounting applied but a temporal cut-off is used, since emissions occurring more than 100 years after the sale of the product are not considered. The same concept could be applied to other GHGs, even though this is not done in the standard, as all the GHG emissions are transformed into kg CO_2-e before applying the delay credit. However, the model equations would need to enable reaction as well as removal from the atmosphere.

Despite the limitations identified above, we believe this standard represents a sound basis for an improved carbon-footprinting method, such as those prepared by ISO and the WRI/WBCSD. PAS 2050 is the first standard on carbon footprinting and includes all the following: a life cycle perspective, all GHGs (including some of biogenic origin) and with particular relevance, includes emissions from land-use change and carbon storage (using the 'Tonne-year approaches' summarised in section 4.2.3).

4.2.3 Time dependency of SOC changes for climate-change assessment

LCA has mainly been used as a steady-state tool which excludes any temporal considerations. All emissions of a given pollutant throughout the life cycle of the products under assessment are typically added into a single aggregate emission, regardless of the time when they occurred. All emissions throughout the life cycle are therefore treated equally, and any temporal information is lost. Subsequently, in Life Cycle Impact Assessment (LCIA) the aggregate Life Cycle Inventory (LCI) emissions are characterised in terms of their contribution to a particular impact category, such as climate change. However, in some cases the timing and rates of release may be important. Indeed, the removal of a pollutant (e.g. CO_2 from the atmosphere), or the delay in releasing the emission leading to the impact when compared to a reference situation where the emission takes place instantaneously as a result of a process in a supply chain, warrants an environmental benefit. In this case, a simple mass-balance does not do justice to the impact because it ignores the time the damaging emission spends in the medium (e.g. atmosphere) where it causes the impact in question, and this ought to be reflected in the LCAs of products[11].

Time-horizons are commonly adopted in estimating impacts and these vary between impact categories, which may be arbitrary and in need of harmonisation and consistency. The time-horizons chosen over which impacts are integrated represent subjective time preferences and hence, are not consensual and free from controversy. Analogous to economic assessments, the issue of discounting future impacts in environmental assessments is not a value-free choice. When measuring climate change, for example, LCA practitioners and other researchers commonly adopt one of three time-horizons (20, 100 or 500 years) within which the cumulative radiative forcing effect of the different climate-changing emissions may be compared and after which impacts are ignored. However, it is arguable that the adoption of finite time-horizons is incompatible with a sustainability paradigm where intergenerational equity is a fundamental concept. Nonetheless, given the need for urgent action related to climate-change mitigation, as well as the general consensus that exists in the adoption of finite time horizons for GHG accounting, there is a case for choosing consistency with the current value choices. In addition, an infinite time-horizon would mean that

[11] For example, product A emits 1 tonne of carbon in year 1 and sequesters the same amount in year 2, whereas product B also emits 1 tonne of carbon in year 1 but only sequesters the same amount of carbon in year 11. When comparing these two products from a mass balance perspective, they are both carbon-neutral (ceteris paribus). However, product A is responsible for the presence in the atmosphere of 1 tonne of carbon for one year, whereas product B is responsible for the same quantity of carbon but for a residence period ten times greater. Product B is, thus, more damaging than product A (but not necessarily by 10 times, as the function accounting for residence time is not linear).

short-lived GHGs relative to CO_2 would become insignificant. This has implications to the accounting of SOC, because its residence in soils is temporary.

Atmospheric residence of GHGs, radiative efficiency and GWPs
Figure 13 shows that the different main GHGs have varying residence times in the atmosphere. Carbon dioxide, in particular, is very long-lived and hence, excluding its radiative forcing after a finite number of years will underestimate the importance of CO_2 relative to other GHGs (e.g. Berntsen and Fuglestvedt, 2008; Shine, 2009). When assessing the impacts on climate change, the radiative forcing of all GHGs is included, but in addition to the varying residence times, radiative forcing potencies per molecule or kg also varies (Watson *et al.*, 2000). The cumulative radiative forcing of a GHG is termed Absolute Global Warming Potential (AGWP) and depends on the atmospheric residence time of that GHG and its radiative efficiency. Methane and nitrous oxide are shorter-lived than carbon dioxide, also illustrated in Figure 13, but have much greater radiative efficiency, displayed in numbers in Table 3. A characterisation factor for each gas is therefore used, enabling the total contribution from all GHGs to be expressed as a single value in units termed CO_2-equivalents (CO_2-e).

The CO_2 response function used here comes from the IPCC's Fifth Assessment Report (Myhre *et al.*, 2013), and is based on the revised version of the Bern Carbon cycle model using a background CO_2 concentration value of 387 ppmv. AGWPs are calculated by integrating the radiative forcing (in W m^{-2}) of an emission pulse of CO_2 (e.g. 1 kg) over a specific period, which is usually 20, 100 or 500 years. The radiative forcing of non-CO_2 emissions is measured relative to the integrated radiative forcing of CO_2 over that period (relative GWPs). Table 4 shows the GWP, at three different time periods (20, 100 and 500 years), of three GHGs that are most relevant to land use.

Relative GWP is widely used when assessing products for their contribution to global climate change in LCA and carbon footprinting. The relative GWP of each GHG is a metric commonly used as the characterisation factor for that GHG for the midpoint impact category Climate Change or Global Warming. The most widely-used time period for global warming is 100 years (GWP100). This time-period is used in the

Table 3. Radiative efficiency of the three main GHGs *et al.* Radiative efficiency (W m^{-2} $ppbv^{-1}$).

Carbon Dioxide	1.4×10^{-5}
Methane	3.6×10^{-4}
Nitrous Oxide	3.0×10^{-3}

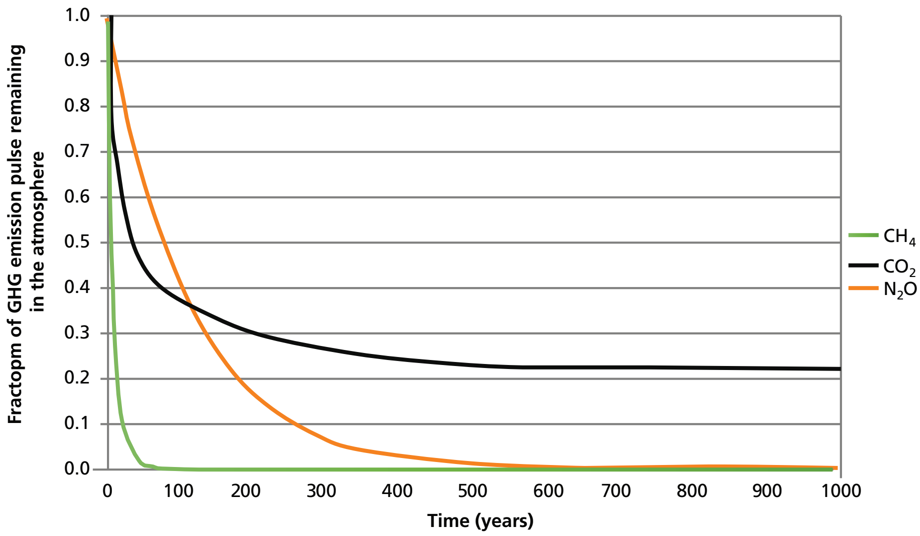
Source: Myhre *et al.*, 2013.

Table 4. Absolute and Relative GWPs.

	Absolute GWPs (W m^{-2} yr kg^{-1})			Relative GWPs (CO_2-e)		
Integration over subsequent time (years)	0-20	0-100	0-500	0-20	0-100	0-500
Carbon dioxide CO_2	2.47×10^{-14}	8.69×10^{-14}	2.86×10^{-13}	1	1	1
Methane (CH_4)	1.78×10^{-12}	2.17×10^{-12}	2.17×10^{-12}	72	25	7.6
Nitrous Oxide (N_2O)	7.14×10^{-12}	2.59×10^{-11}	4.38×10^{-11}	289	298	153

Source: Extrapolated from Forster *et al.*, 2007.

Figure 13
Fraction of a GHG emission pulse remaining in the atmosphere throughout the subsequent 1000 years, calculated according to IPCC's parameterized decay function



Source: equation from Forster *et al.*, 2007.

Kyoto Protocol and is supported by most people who calculate GHG impacts and subject experts (e.g. Fearnside, 2002), including most LCA practitioners, but it is also subject to criticisms by others, due to for example its simplicity and the absence of a discount rate (Forster *et al.*, 2007; Shine, 2009).

Under unlimited or infinite undiscounted time frames, there would be no difference between present and delayed emissions, and the temporary storage of GHGs would not be accounted for. However, given that the 100-year time frame is well established in the research community and in policy-making circles, it makes sense to adopt it. The appropriateness of this time period is discussed at length in Fearnside (2002). The following sub-sections will elaborate on existing protocols and standards, and associated methods and methodological issues. Finally, a proposal is made on how to account for temporary GHG storage in soils and biomass for instance.

Other than residence time, there is no difference in the radiative forcing of biogenic and geogenic (i.e. fossil) CO_2 emissions. The difference arises because whenever there is a transfer of carbon between the biosphere and the atmosphere, it results in an opposing effect due to the balancing CO_2 concentration gradient between the carbon pools in question. For example, burning 1 ha of a tropical forest will release carbon to the atmosphere, the full amount of which will be sequestered subsequently in the same hectare if natural regeneration occurs. If the land-use change is permanent, there is no reason to differentiate the impacts from the biogenic emissions arising from it with those from the release of a similar amount of fossil carbon. In this sense, biogenic carbon emissions (due to changes in biospheric carbon sinks) are reversible, whereas fossil carbon emissions are practically not (due to the excessively long [i.e. slow] time fossil carbon takes to form). Furthermore, carbon in the atmosphere performs a decay function, whereas carbon in the biosphere or anthroposphere can be stored at constant levels up to a certain point.

Although GWPs are widely accepted and used as characterisation factors for various GHG emissions in LCA, they mainly refer to fossil sources and neglect biospheric sources and sinks. The inclusion of biogenic carbon emissions and its temporary additional storage in GWP calculations is both uncommon and inconsistent (Milà i Canals *et al.*, 2007b). Indeed, biogenic carbon emissions and sequestration are usually excluded with the argument that these cancel each other out. This is correct but misses the point that the widely-used adoption of a finite period of time under which radiative forcing is assessed implies a time preference. To be consistent with this approach; the sequestration and temporary storage of carbon can be credited. Two approaches can account for this: the Moura-Costa and Lashof methods (see Fearnside *et al.*, 2000; Moura Costa and Wilson, 2000; Watson *et al.*, 2000).

Accounting for temporary carbon storage: timing issues and reversibility

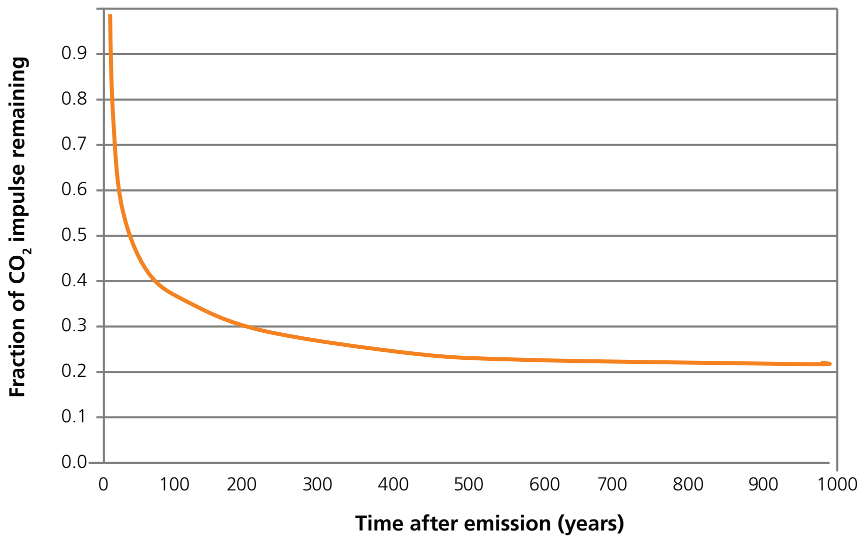
As opposed to the PAS 2050 (refer to the section 4.2.2 about The Publicly Available Specification 2050), the Kyoto Protocol is solely based on carbon stock changes and IPCC's GWPs and gives no consideration to any additional, albeit temporary, storage of carbon in the biosphere. In the current section, methods that have been proposed to account for carbon sequestration and storage are reviewed.

Carbon sequestration and storage, as well as permanence and reversibility, have been a preoccupation to the research community who deals with land use and global warming, not just from a scientific and political perspective (e.g. BSI, 2008), but also from an economic perspective, with issues such as credits and discounting being part of the debate. The arguments are similar for both economic and environmental schools. Specifically, in LCA, general publications on this issue include Müller-Wenk and Brandão (2010) and the PAS 2050 (BSI, 2008) discussed in Section 4.2.2. Cherubini *et al.* (2012) have proposed a method to estimate the climate impact of CO_2 emissions from biomass combustion that uses CO_2 impulse response functions from carbon cycle models to account for carbon storage in plantation forestry. That specific approach has not been discussed in detail within this document.

Figure 14 shows that the airborne fraction of a CO_2 unit pulse decreases fast in the first decades after emission. However, not all the carbon emitted is cycled into other pools. In fact, 56 percent will remain in the atmosphere after 20 years, 36 percent after 100 years and 23 percent after 500 years. The half-life of carbon in the atmosphere is 30 years; i.e. 50 percent of the marginal emission leaves the atmosphere in the 30 years following emission. A further 30 percent will be removed within a few centuries, and the remaining 20 percent will take thousands of years to leave the atmosphere (Denman *et al.*, 2007).

The asymptotic decay curve in Figure 14 explains the resulting increase in the concentration of CO_2 in the atmosphere. If the curve only reflected the biospheric source and sink, it would have a shorter time-span and would reach zero; i.e. the amount representing all historical biogenic carbon emissions can potentially revert to the biosphere. There is no equivalent process that counteracts the burning of fossil carbon in similar time frames, although a large share of the emitted carbon is absorbed by the world's oceans. Photosynthesis, by plants on land and plankton in the oceans, is the only process responsible for transferring carbon from the atmosphere; as it is biological, it is a considerably slower process than the burning of

Figure 14
Decay pattern of a pulse emission of CO_2 to the atmosphere over a 1000-year time frame, calculated according to IPCC's parameterized decay function



Source: Equation from Forster *et al.*, 2007.

geological carbon. This means that carbon is being emitted to the atmosphere at a higher rate than the reverse processes removing carbon from the atmosphere so that atmospheric carbon concentrations increase.

The tonne-year approaches

Two tonne-year approaches - Moura-Costa and Lashof - were proposed to account for the sequestration and temporary storage of carbon. A conceptually different approach has been discussed based on net average global surface temperature change (Shine *et al.*, 2005); this approach is not discussed further here. Both Pedro Moura-Costa and Daniel Lashof were involved in the development of the IPCC special report on LULUCF (Watson *et al.,* 2000). Further development along those lines appears to have been closed in 2003, when the IPCC published the good practice guidelines adopting the mass balance stock change approach (IPCC, 2000). Some years after that, timing issues were again receiving attention with the development of the British standard PAS 2050 for carbon footprinting, where benefits are given to temporary carbon storage and delayed emissions (see BSI, 2008 and Clift and Brandão, 2008). Other standards, such as the GHG Protocol and ISO 14067, also investigated temporal issues. Due to the relevance of the existing carbon footprinting standards, it is important to consistently and rigorously assess the implications of sequestering and temporarily storing carbon.

Tonne-year approaches aim to calculate a credit in kg CO_2-e. to either keep carbon out of the atmosphere for a given number of years (Moura-Costa method) or to delay an emission (Lashof method). There is a subtle difference between the two. This credit can then be subtracted from a GHG inventory. The baseline for both methods is the cumulative radiative forcing, integrated over a given time horizon (usually 100 years), caused by a one-tonne pulse-emission of CO_2.

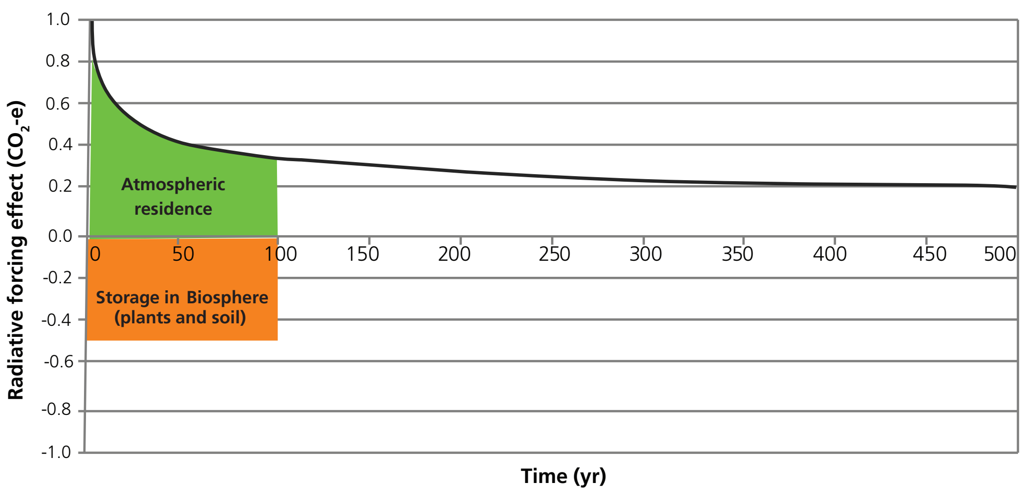
The Moura-Costa method

Moura-Costa and Wilson (2000) developed a method to account for carbon sequestration and for storage by deriving an equivalence factor between t CO_2-e and t CO_2-year. By calculating the integral of the decay function of 1 t CO_2 from emission in year 0 to year 100 using the best estimate for the decay function then available, they demonstrated that 1 t CO_2-e. emitted has an integrated effect of 55 tCO_2-yr (the blue area in Figure 15 is equal to the red area). This means that the integer of the decay curve of 1 tonne of atmospheric CO_2 over 100 years is equivalent to the sequestration and storage of 0.55 tonne of CO_2 for 100 years. However, according to the revised version of the Bern Carbon cycle model, the integer of the CO_2 decay curve from year 0 to year 100 amounts to 53 CO_2-yr. The equivalence factor between sequestering 1 t of CO_2 and storing it for one year (i.e. -1tCO_2-year) and the emission of 1 t of fossil CO_2 is therefore -0.02 (-1/53).

The Moura-Costa approach shown in Figure 15, uses the value of 53 tonne-years of CO_2 to calculate an equivalence factor between radiative forcing and carbon sequestration and temporary storage. In this approach, sequestering 0.53 tonne of biogenic CO_2 for 100 years from the atmosphere (or 1 t of CO_2 over 53 years, or 53 t CO_2 over 1 year), and storing it in the biosphere (plant biomass and soil), is equivalent to avoiding the radiative forcing of a pulse-emission of one tonne of CO_2 integrated over 100 years, as illustrated by the blue area in Figure 15. Therefore, biogenic carbon sequestration and temporary storage can compensate for the impact of fossil-carbon emissions to the atmosphere in a manner consistent with the GWP100 logic.

The t CO_2-year can also be applied to the reverse state: temporary lack of storage. This is further elaborated in Mueller-Wenk and Brandão (2010). This result

Figure 15
The Moura-Costa approach calculated for a 100-year time horizon.
The integer of 1t CO_2 decay in the atmosphere over 100 years (blue area) is equal to 53tCO_2·yr. The blue area is the same size as the red area.



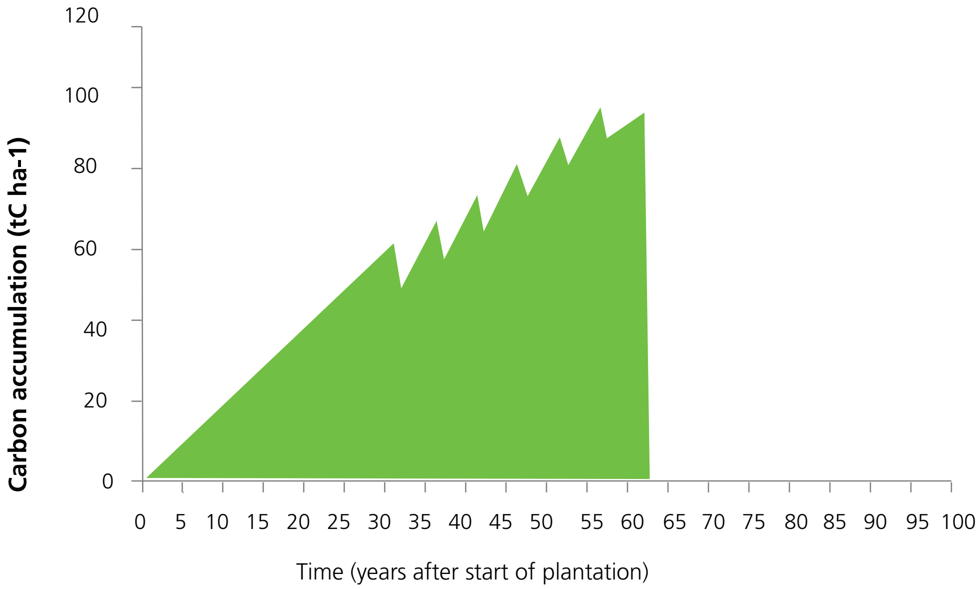
can be expressed in another form which is more relevant for the purpose of the Life Cycle Impact Assessment (LCIA) of land use. The carbon previously stored in the biosphere which is released to the atmosphere, due to land-use change, is not released immediately. Similarly, the increase of the carbon stock in the biosphere following a land-use change (e.g. reforestation) lasts for decades. As a result, the Moura-Costa model needs to be adapted to the determination of GWP impacts from land use. Instead of the rectangular shape in Figure 15, a triangular form is a more realistic representation of the corresponding cumulative carbon flows from the atmosphere as the accumulation of carbon through photosynthesis and SOC build-up is gradual as illustrated in Figure 16. Regardless of the shape for storage, the tonne-year unit is very appropriate to include biogenic carbon flows in GWP calculations.

Other characterisation factors are applied to different time-frames as shown in Table 5. The integer of the decay curve of 1 t CO_2 from year 0 to year 20, 100 and 500 is 15, 53 and 158 t CO_2-year. One tonne of carbon sequestered, stored for one year, and subsequently released is therefore -0.07, -0.02 and -0.01 t CO_2-e over a time period of 20, 100 and 500 years, respectively.

Table 5. Characterisation factors for carbon storage on GWP.

	GWP20	GWP100	GWP500
1 tonne-year carbon dioxide	-(1/15) = = - 0.07 t CO_2-e	-(1/53) = = - 0.02 t CO_2-e	-(1/158) = = - 0.006 t CO_2-e
1 tonne-year carbon	-0.07*44/12= = -0.27 t CO_2-e	-0.02*44/12= = -0.08 t CO_2-e	-0.01*44/12= = -0.02 t CO_2-e

Figure 16
Biomass carbon sequestration in a 63-year Scots pine rotation.



Source: Matthews, 2008b.

The Lashof method

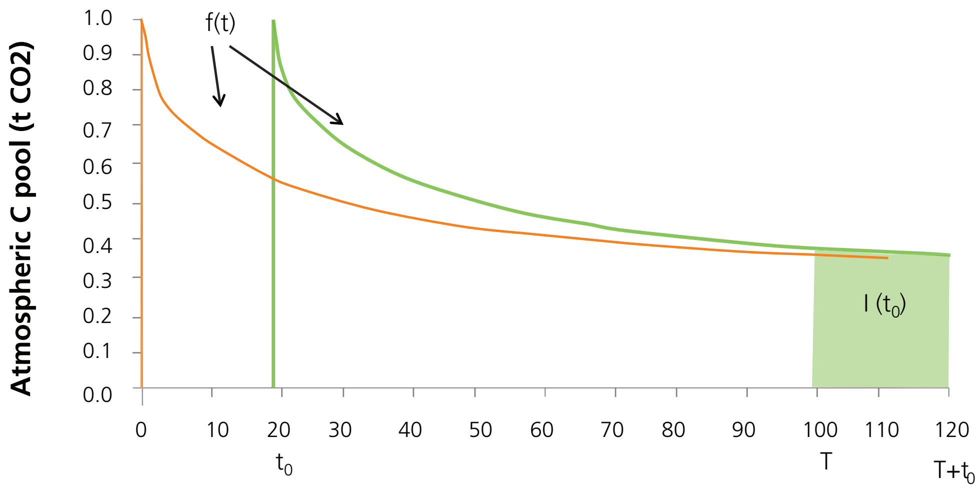
The alternative approach, owing to Lashof, considers that sequestering carbon dioxide and storing its carbon (i.e. not emitting) for a given number of years is equivalent to delaying a CO_2 emission until the end of the storage period. Figure 17 shows the basic approach to account for carbon storage (delayed release) in the Lashof model (Fearnside *et al.*, 2000), later used by Nebel and Cowell (2003), and exemplified with a 20-year storage of carbon. A single emission at time zero leads to an increase in radiative forcing which decays over time, proportional to its concentration in the atmosphere. The decay function is denoted by f(t). The decay curve is displaced up to a certain number of years, equal to the time for which the release is delayed. The portion of the initial 53 tonne-years area, which is now beyond the 100-year time horizon, corresponds to the benefits of the storage. For example, when the release of one tonne of CO_2 is delayed for 20 years, the portion of the area under the decay curve beyond 100 years is 7.5 tonne-years of CO_2. This corresponds to avoiding radiative forcing of 3t CO_2-e.

As previously noted, I (100) = 53 CO_2-years. When the emission of CO_2 is delayed by t0 years, the GWP reduction within the accounting period is given by the shaded-blue area in Figure 17, resulting in the savings of I(t0) in a 100-year perspective:

The full set of equations for evaluating GWP reduction from delayed emissions can be found in Clift and Brandão (2008). The characterisation factors for temporary carbon storage are derived from both the Moura-Costa and Lashof methods (Brandão, 2012).

Figure 17

The Lashof approach calculated for a 100-year time horizon. Storing carbon for a period of t0 years is equivalent to delaying a CO_2 emission to t0, and the benefit is the portion of the decay curve which is now beyond the 100-year time horizon (blue surface).



4.2.4 Critical review and proposed approach

The Moura-Costa and Lashof methods assume that storage of carbon in oceans and storage of carbon in the biosphere are environmentally equivalent, so the problem is solely the residence of CO_2 in the atmosphere. However, a biogenic emission implies the opening of an additional sink, i.e. the ability to sequester carbon later. Whether the carbon is subsequently sequestered or not, and when, is not known. The flows to the atmosphere from geogenic or biogenic sources are similar; the difference is in the reverse flows removing the CO_2 from the atmosphere. Only flows to the biosphere need to be considered, because of the time involved in flows to fossil reservoirs. The biosphere naturally sequesters carbon and it is only an issue of land use that prevents it from doing so. This prevention is, of course, temporary. Neither approach addresses the dynamic nature of the carbon cycle: different concentration gradients between the different carbon pools – oceans, land and atmosphere - will result in differences in their sequestration capacity.

There are consistency issues when adopting either one or the other approach. In the Moura-Costa approach, storing 0.53 tonne of carbon dioxide (in the form of carbon) for 100 years (or 144 kg of carbon - from 1 tonne of CO_2 - for 53 years) can fully compensate a fossil carbon dioxide emission of one tonne when using a 100-year time horizon. This is consistent with the way GWP is used in LCA, in other words that one emission has the same characterisation factor regardless of the timing of its occurrence. This way, sequestering and storing an amount of carbon is accounted consistently, regardless of when that sequestration and storage occurs in the life cycle of a product.

However, some argue that by choosing a fixed time horizon (i.e. independent from the timing of emissions, for example year 2000 to year 2100), one assumes that this time period is critical, and that it is important to look mainly at the impacts occurring during this particular period. To be consistent with this assumption, the full compensation must be reached at the end of the time horizon. The Lashof approach is more consistent in keeping the time horizon in this meaning but, as opposed to the Moura-Costa method, it assesses different time horizons for the same amount of emission, which is inconsistent (for example the radiative forcing of 1 kg CO_2 emitted 20 years into the accounting period is only considered in the subsequent 80 years, whereas the radiative forcing of an identical emission taking place 20 years earlier is considered in the subsequent 100 years).Instead, the Moura-Costa method accounts each year equally, i.e. the impact of storage in year 1 is the same as that in any other year. The Lashof method merely decreases the time horizon by a period equal to the time for which the release is delayed. Thus, it can be seen as adopting different time-frames for emissions happening at different times. This does not have the consistency of the Moura-Costa method, which presents no time preferences other than the 100-year accounting period following every intervention (emission/sequestration), i.e. it does not distinguish between identical emissions (e.g. 1 kg CO_2) occurring at different points in time. As a result, as opposed to the Lashof method, the Moura-Costa method is not aimed at characterising emissions relative to their timing but rather characterise the opposite flow: sequestration (of carbon), also regardless of its timing. In this way, the sequestration and storage of 0.53 t CO_2 (in the form of carbon) for 100 years avoids the radiative forcing equal to 1 t CO_2-e.

One tonne of CO_2-e is equivalent to between 14 and 157 tonne-years of CO_2 on a 20- and 500-year time-frame, respectively. The impacts on climate associated with temporary carbon sequestration and storage therefore highly depend on the time-period adopted for GWP calculations. Against fossil fuel emissions, biogenic carbon sequestration and storage benefit from a short time-horizon (GWP20), whereas biogenic carbon emissions benefit from a longer time horizon (e.g. GWP500). In other words, the emissions of 1 tonne of carbon resident in the atmosphere for 1 year (1t carbon - year) equals 0.07, 0.02 and 0.01 t CO_2-e at a GWP20, GWP100 and GWP500, respectively; meaning that the longer the time period of assessment, the lower the impact of biogenic carbon emissions relative to their fossil counterparts. Conversely, storing 1 tonne of carbon for 1 year saves 0.07, 0.02 and 0.01 t CO_2-e at a GWP20, GWP100 and GWP500, respectively; meaning that the shorter the time period of assessment, the larger the impact of biogenic carbon emissions relative to their geogenic counterparts.

The Moura-Costa method has, however, a large limitation as notedby Korhonen and co-workers (2002) among others. It is argued that adopting a timeframe lower than 100 years makes the tonne-year approach incompatible with GWP100 calculations and inconsistent with their applications, such as the Kyoto Protocol. The limitation of this method is that storage after 53 years results in a saving of 100 percent. Because the time horizon in global warming calculations is 100 years, contributions after year 53 must be covered. Considering 1 tonne of CO_2 sequestered from the biosphere and stored for 106 years means that 106 tonne-years equal -2 t CO_2-e. However, 1 tonne of fossil CO_2 emitted at the same time would only account for 1t CO_2-e. This results from the fact that carbon in the atmosphere decays exponentially, but carbon in the biosphere does not. Nonetheless, it is important to note that t CO_2 and t CO_2-e are two different things: the former refers to the mass of a GHG whereas the latter refers to radiative forcing of the same magnitude as that of a pulse emission of CO_2 over a specific time horizon.

4.3 USE OF SOC MODELS IN LCA

It is clear from section 4.1 and 4.2 that SOC models are very relevant to estimate land use impacts both on soil quality and on climate. For the latter, additional models covering aboveground carbon, such as that in plant biomass, are needed. Goglio and co-workers (2015) have performed a review of agricultural LCA studies that included SOC changes. Petersen and co-workers (2013) propose an approach for including SOC changes in LCA.

4.3.1 In assessing land use impacts on soil quality and ecosystem services

Brandão *et al.* (2011) applied literature values to the assessment of biodiesel from oilseed rape, and combined heat and power from Willow SRC, Miscanthus and forestry residues. Brandão and Milà i Canals (2013) have used the IPCC model to derive characterisation factors for land use impacts on biotic production potential. These have been used widely in subsequent LCA studies of crop and livestock production. Mueller-Wenk and Brandão (2011) have used the GBU database to generate characterisation factors for the impact of land use on climate mitigation potential.

4.3.2 In assessing climate change impacts

SOC models in LCA have been used mainly to estimate the climate change impacts of land-based systems, particularly bioenergy but also food and forestry products. In addition to estimating impacts on soil quality, Brandão *et al.* (2011) quantified

SOC changes in the carbon footprint of energy crops. For the assessment of forestry products, the Q and Yasso models have been popular (see e.g. Gustavsson *et al.*, 2015 and Stendahl *et al.*, 2016). De Rosa *et al.* (2015) and Schmidt and Brandão (2013) have used the RothC model to estimate time-dependent carbon fluxes in forestry systems.

Particularly in the LCA of **livestock products**, the inclusion of SOC models has focused on direct land use change (dLUC) emissions associated to converting land to cropland (for feed) and to grassland. Three key dLUC methods are found here: Leip *et al.* (2010), Vellinga *et al.* (2013) and van Zeist *et al.* (2016). These approaches are reviewed here, but their divergent results (if any) and consistency with IPCC approaches are not analysed in detail here.

Leip *et al.* (2010) evaluated the contribution of the livestock sector to EU greenhouse gas emissions, including those from land use change into feed in Europe and abroad. This applies to feed imported but not to the livestock products imported into the EU, as the scope of the report is delimited by the EU as a production unit. Acknowledgement is made in the report of the uncertainties related to lack of data. Due to the scope and uncertainties in estimating LUC, a simplified approach was adopted, in which an estimation of cropland expansion induced by European livestock production is enabled. This approach quantifies changes in total cropland area and in the area of individual crops over a 10-year period (1999-2008). The additional area of a given crop is divided by the additional production of that crop, so that land requirements can be calculated per kg crop. In addition, three scenarios are used to reflect the array of possibilities for LUC: I) cropland expands onto grasslands and savannas; II) cropland expands onto a probable mix of land uses considering four possible previous land used: grassland, shrubland, forest with less than 30 percent canopy cover, and forest with more than 30 percent canopy cover; and III) cropland expands onto land with the highest carbon stocks, to represent a maximum-emission situation.

Total LUC emissions per ha are then calculated based on the IPCC (2006) guidelines, using a Tier 1 approach, and include carbon stock changes in biomass, dead organic matter and soils, as well as methane and nitrous oxide emissions from biomass burning. The approach followed is the same as the one followed by Carre *et al.* (2010), which was developed in the context of biofuels, and calculates emissions from changes in carbon stocks which, in turn, depend on the climate zone, geographical region and land use, on a 5-min pixel level (with reference to GIS databases, such as GLC2000, GlobCover and M3).There is no differentiation between dLUC and iLUC in this method as total LUC emissions are distributed over all expanding crops in the country, proportionately to the increase in area. Emissions are subsequently calculated per kg feed.

In addition to emissions from LUC, the study also estimates CO_2 emissions due to land use assuming that carbon sequestration is a slow process that has not yet reached equilibrium. The reference land use for “intensive grassland” is “natural grassland”, hence it is possible that there is a negative CO_2 emission as well managed grasslands sequester more carbon relative to natural grassland. Cropland is assessed as a no change in C stocks, but the foregone carbon sequestration that would have occurred under natural vegetation. The model has been derived based on field measurement data compiled by Sousanna *et al.* (2007, 2010).

The Direct Land Use Change Assessment Tool version 2016.1 (described in van Zeist *et al.*, 2016), estimates emissions per ha in different countries and per crop, with reference to FAOSTAT crop expansion data and the Global Forest Resource Assessment 2015. The tool provides three data functionalities, depending on user's access to data: one in which country and land use are known, one in which country and land use are unknown, and one where country is known but land use is unknown. Emission calculations are based on IPCC tier 1. Their tool provides more than 9 000 crop-country combinations on excel. Earlier versions of it were used in the AgriFootprint tools, as well as in the Publicly Available Specification (PAS) 2050. However, the tool is not free of charge and thus was not analysed further.

In Wageningen, Vellinga *et al.* (2013) developed the FeedPrint tool. Although the methodology is described in a detailed manner, the land use change section is relatively short. It includes approaches for both direct and indirect land use change. The authors argued that carbon stocks may not reach equilibrium after 20 years and it is claimed that 200 years after conversion, carbon may be still accumulating in grasslands and decreasing in arable land (40 and 30 kgC/ha/year, respectively). The approach therefore does not follow the IPCC (2006) guidelines. The reference land use is current cropland, and N_2O emissions are also accounted for.

5. Contentious issues in modelling approaches

5.1 THERE ARE NO 'UNIVERSAL' MODELS

Most models are parameterized under particular management, soil or climatic regions. Ideally, SOC models should account for all major SOC-controlling factors, such as soil mineralogy, climate conditions, litter quality, biota activity and management. These factors have extremely complex interactions, and separate analysis of controls could limit predictions of their effects on SOC (Falloon and Smith, 2009). Even the full multidimensional development of a single element of a model can rarely, if ever, be predicted precisely, and the actual consequence is that it is impossible to create "universal" models (Sinclair and Seligman, 1996). There is for example relatively less available data of the performance of SOC models under tropical and arid conditions. Fallon and Smith (2009) have suggested that current SOC models may be limited in their applicability to these systems, and that it could be attributed to differences in soil fauna, the much faster turnover of slow and passive SOM, different temperature and moisture relationships with microbial activity, and differences in mineralogy (Shang and Tiessen, 1998; Tiessen *et al.*, 1998) and solution chemistry (Parton *et al.*, 1989) in tropical soils. The inability to account for cation availability or aluminium (Al) toxicity may also limit SOC model predictions in tropical soils (Parton *et al.*, 1989; Shang and Tiessen, 1998).

Most well-known models may be limited by failing to account for pH effects on soil carbon turnover (Jenkinson, 1988; 1996; Falloon and Smith, 2009). This may be important in grassland and cropland soil with constant mineral fertilizer applications (Kelly *et al.*, 1997), or soils with low pH linked to considerable cation extraction or leaching. Soil organic matter models generally predict faster carbon turnover than the ones observed in very acid soils (Motavalli *et al.*, 1995). Few models can predict SOC changes in allophanic soils or soils developed on recent volcanic ash (Jenkinson *et al.*, 1991; Motavalli *et al.*, 1995; Jenkinson, 1996; Smith *et al.*, 1997; Falloon *et al.*, 1998; Falloon and Smith, 2000; Falloon and Smith., 2009). Nevertheless, there have been efforts to calibrate well known SOC models under these soil conditions (Parshotam and Hewitt, 1995; Saggar *et al.*, 1996; Shirato *et al.*, 2004). Results should be used with caution in situations where there are few good long-term measurements of decomposition rates, like tundra and taiga soils for example, waterlogged or very dry soils (Jenkinson, 1996; Falloon and Smith, 2009). At some level of analysis, all models include empirical functions (Whistler *et al.*, 1986), so they are expected to perform best when operating in situations similar to those for which theywere originally parameterized, which tend to be cropland and grasslands from the temperate zone (Jenkinson, 1996; Petri *et al.*, 2010).

Furthermore, not all models have a comprehensive inclusion of biomass, soil litter and soil carbon stocks. The changes in SOC levels due to management (e.g. tillage, irrigation, manure inputs) is not accounted for by all, and some use simplified factors to represent management parameters.

5.2 DATA AVAILABILITY, COMPARABILITY AND QUALITY

Model evaluation shows how well a model can be expected to perform in a given situation (Falloon and Smith, 2009). Although a model's simulation of future events cannot be verified, it is possible to test its ability to simulate long-term SOC changes using existing datasets (Smith *et al.*, 1997). Models can be evaluated at several different levels against measured laboratory and field data (Falloon and Smith, 2009): at the individual process level, at the level of a sub-set of processes (e.g. net mineralization), or the model's overall outputs (e.g. changes in total SOM over time). However, as stated by Campbell and Paustian (2015) there may be several potential pitfalls for the integration of data to calibrate, drive and evaluate a SOC model. Ideally, calibration and driving data match the scale of the model simulation. However, data limitations may prompt the use of data of coarser resolution for example or mixing data of varying quality from different sources. Data availability for model evaluation may also affect assessment of model accuracy, as well as its ability to support hypothesis testing. The suite of datasets may then become sources of uncertainty in SOC model predictions (Keenan et al 2011, Palosuo et al 2012).

Datasets are also often difficult to identify or compare between SOC models, particularly in large-scale ecosystem or global analyses. Although there is a wealth of measured data from carefully monitored long-term agronomic experiments to evaluate SOC models, there are comparatively few similar datasets from natural ecosystems, and relatively few long-term experiments related to land use change rather than land-management changes (Falloon and Smith, 2009). Furthermore, soil carbon measurements from available experiments are rarely available in replicate and hence attributing uncertainty to these measurements, and ultimately confidence in SOC model predictions is limited (Falloon and Smith, 2003). Meta-analyses and comparisons have often suffered from datasets based on diverging definitions (e.g. concerning definitions of sample depth or the components of soil respiration) and methodologies (e.g. in particular SOM to SOC conversion factors or sampling frequency), (Bahn, 2009). The difficulty in accurately measuring SOC represents another source of problems and challenges for the integration of these data with SOC models (Falloon and Smith, 2009). Obtaining representative undisturbed soil cores, obtaining samples for different layer depths accurately, using adequate replicates, conversion of SOC concentration to mass through accurate bulk density measurements, the high random spatial variation in SOC and changing methodology, are only some aspects to be considered.

5.3 MATCHING MEASURABLE SOC FRACTIONS WITH CONCEPTUAL SOC POOLS OF THE MODELS

Another major limitation of current compartment models of SOC turnover is that most of the conceptual pools they contain do not correspond to experimentally verifiable fractions (Christensen, 1996; Stockmann *et al.*, 2013). The identification of pools with different attributes in terms of stabilization mechanism (physical and chemical), bioavailability and thus turnover time is based on qualitative concepts rather than measurable entities (Christensen, 1996). Thus, compartments are usually theoretical without measurable counterparts, making it difficult to initialize the models and validate model-calculated results (Falloon and Smith, 2009). For example, some models split the microbial biomass into different pools, but so far there is no direct experimental verification of SOC contents of these pools. There can also be discordance between conceptual residence time or stabilization mechanisms and methodologies that can selectively fractionate these particular C pools (Von Lützow *et al.*, 2007; Chabbi and Rumpel, 2009; Stockmann *et al.*, 2013). Models are then usually calibrated against total carbon measurements, without verifying the dynamics of the carbon allocated to the different pools.

Different methods have been proposed to relate SOC fractions to modelled pools. Skjemstad *et al.* (2004) found good agreement between measurable SOC pools like particulate organic carbon, a charcoal-carbon pool and a humic pool and the RothC modelled pools, like the resistant plant material, inert organic matter and humic pools. Zimmermann *et al.* (2007) combined physical and chemical methods (including particulate organic carbon, dissolved organic carbon, carbon associated to clay and silt, or stabilized in aggregates, and oxidation-resistant carbon) to obtain SOC fractions, that were successfully related to SOC pools of the same model. However, as stated by Stockmann *et al.* (2013), this is not always the case, and it may be worthwhile to modify SOC pools used in some models so that they are based on measurable C fractions.

5.4 LANDSCAPE-SCALE MODELLING

Most studies have considered SOC stocks and stock changes at the plot scale, to allow making inferences about SOC stocks and changes in relatively homogeneous conditions (Milne *et al.*, 2007). And at the other end of the spectrum, different authors have attempted to estimate SOC stocks at the global level (Batjes, 1996; Ostle *et al.*, 2009). There is still need for a better understanding of spatial heterogeneity in SOC in the landscape (Falloon and Smith, 2009), and for a better prediction of potential changes in SOC dynamics on the landscape scale (Stockmann *et al.*, 2013). For example, differences in drainage that may be linked to landscape position are often not accounted for in SOC models (Falloon and Smith, 2009). In this sense, three gaps in knowledge have been identified (Stockmann *et al.*, 2013): (1) the development of optimal, but still simple, 3-dimensional representations of landscapes (vertically and horizontally), (2) the implementation of functional interactions and SOC transfers (i.e. the redistribution of SOC to different parts in the landscape due to erosion, transport and deposition) and (3) the availability of adequate datasets for model validations (especially the representation of fluxes between different landscape elements).

For instance, Porporato *et al.* (2003) incorporated soil C and N cycles in a hydrological model to study the influence of soil moisture dynamics on soil C and N dynamics at the landscape scale. It has also been emphasized that developments of SOM models could benefit from cross-scale comparisons and coupling to GIS software to move from site-specific simulations to landscape simulations (McGill, 1996). As mentioned in the previous sections, there have been different examples of successful coupling between soil turnover and GIS software, like CANDY (Franko, 1996), CENTURY (Schimel *et al.*, 1994) and RothC (Post *et al.*, 1982; Jenkinson *et al.*, 1991), and the Global Environment Facility Soil Organic Carbon (GEFSOC) Modelling System (Easter *et al.*, 2007; Milne *et al.*, 2007; Kamoni *et al.*, 2007). However, most of these approaches have been oriented to simulate SOC changes at national and regional scales.

5.5 MODELLING SOC DYNAMICS BEYOND THE SURFACE LAYER

In general, plant production and patterns of biomass allocation strongly influence relative distributions of C with soil depth (Jobbágy and Jackson, 2000). The deeper in the soil profile, the older stored SOC is likely to be (Fontaine *et al.*, 2007). Surface soils (0 to 20 or 30 cm) generally contain a large fraction of total SOC, which is often more rapidly cycling, and more responsive to management changes than SOC in deeper soil layers (Batjes 1996, Paul et al 1997, Jobbagy and Jackson, 2000). SOC in deep layers was thought to be part mainly of relatively inert humic material and mineral-bound Organic Carbon, so many SOC models only used to simulate surface layers dynamics (Campbell and Paustian, 2015). However, more recent analyses show SOC in deeper layers to consist predominantly of highly processed microbial products (Erich *et al.*, 2012) that are responsive to land management change and on shorter timescales than previously understood (Trumbore *et al.,* 1995; Baker *et al.*, 2007; Rumpel and Kögel-Knabner, 2011; Koarashi *et al.*, 2012; Follett*et al.*, 2013; Poeplau and Don, 2013; Schmer *et al.*, 2014). Further progress was made by including process-based information from stable C and N isotopes (13C and 15N), indicating that carbon transport to deep layers may represent an important process in annual grassland ecosystems (Baisden *et al.,* 2002; Rumpel and Kögel-Knabner, 2011). Carbon dynamics in layers below 20-30 cm are still identified as an important knowledge gap (Batjes, 1996; Jobbagy and Jackson, 2000; Stockmann *et al.*, 2013).

Recently, new models and adaptations of known models have been developed to account for SOC dynamics in deep layers with different approaches (Campbell and Paustian, 2015). For example, the DAYCENT model was modified to simulate deeper soil C dynamics by slowing SOC pool turnover and increasing allocation to passive soil C, without separating soil layers (Wieder *et al.*, 2014). Other models like C-TOOL directly simulate whole-soil SOC dynamics (Taghizadeh-Toosi *et al.*, 2014). Jenkinson and Coleman (2008) modified RothC to RothPC-1 to predict the turnover of organic C in subsoils up to 1 m of depth using multiple layers and introduced two additional parameters, one that transports organic C down the soil profile by an advective process, and one that reduces decomposition processes of SOC with depth. However, there is a strong necessity for additional data to confirm or refute hypotheses suggested by the different modelling approaches of SOC in deep layers (Campbell and Paustian, 2015).

5.6 MODELLING SOIL STRUCTURE AND SOC INTERACTIONS

The understanding of the link between how C is sequestered in soil and its consequences for soil functions, and how changes in soil functions affect productivity and hence carbon sequestration is limited (Stockman *et al.*, 2013). The importance of microbial activity and roots in soil aggregation are generally accepted, and there have been advances in the understanding of the relationship between aggregate formation/stabilization/disruption and SOC cycling (Six *et al.*, 2000; 2006). Lipiec *et al.* (2003) reviewed how different Soil-Crop-Water models and submodels simulate the effect of topsoil structure. However, few SOC models simulate aggregation processes and its relation to carbon cycling, or account for the effect of soil structure, which may be important in the stabilization of plant residues, microbial biomass and humic substances (Falloon and Smith., 2009).

Malamoud *et al.* (2009) developed the Struc-C model, which specifically incorporates soil structure (aggregate) hierarchies and physical protection of SOC via aggregates. In the Struc-C model, clay content plays an important role in complexing C and only this complexed C enters the aggregate pool. Turnover of aggregates has predefined rate constants associated with disruption and aggregation that are modified by the time since the last input of fresh C. Disruption of aggregates is associated with a loss of a fraction of C as CO_2 that depends on clay content. Porporato *et al.* (2003) and Batlle-Aguilar *et al.* (2011) presented a process oriented multicompartment model that simulates C and N dynamics in soils, including soil parameters related to soil structure, such as saturated hydraulic conductivity, pore size distribution index, porosity and pore tortuosity. Coupling carbon pools of RothC model with aggregate and structure turnover modules, Stamati *et al.* (2013) developed CAST model, and were able to simulate aggregate and carbon dynamics in cropland soils of the United States and Europe. However, these approaches need further evaluation.

5.7 MODELLING SOIL BIOLOGICAL ACTIVITY

The need to incorporate soil fauna and microbiological activities in relation to decomposition and soil structure into soil models has been widely emphasized (Gregory and Ingram, 1996; Christensen, 1996). However, the degree to which models should represent microbiological and fauna activity is still a matter of debate (Campbell and Paustian, 2015). Recent research on SOM chemical characteristics and interactions with microbial processes, and SOM persistence have generated new hypotheses and SOC modelling approaches (McGuire and Treseder, 2010; Cotrufo *et al.*, 2013; Wieder *et al.*, 2013; Wieder *et al.*, 2014). Explicit microbial control of decomposition processes is also increasingly viewed as critical to simulate SOC dynamics and adaptive responses by soil biota. Lawrence *et al.* (2009) showed that the inclusion of exoenzyme and microbial controls in kinetic representation of decomposition rates improved the ability of some models to simulate changes in soil C stocks under different conditions. However, modelling approaches reflecting these new hypotheses are largely theoretical and difficult to test in complex soil environments (Campbell and Paustian, 2015). It also remains difficult to determine these new approaches applicability, given the paucity of data to validate them (Treseder *et al.*, 2012).

As mentioned before, several organism-oriented and food-web models, where C and N fluxes are simulated through functional groups based on their specific death rates and consumption rates, were developed over the last decades (Hunt *et al.*, 1991; McGill *et al.*, 1981; de Ruiter *et al.*, 1993; de Ruiter and Van Faassen, 1994; de Ruiter *et al.*, 1995; Brussaard, 1998; Smith *et al.*, 1998; Susilo *et al.*, 2004). However, at the present time, validation of organism-oriented models with field data is both cost intensive and unlikely due to highly challenging estimations of intensive parameters such as feeding preferences, N content, life cycles, assimilation efficiencies, production: assimilation ratio, decomposition rates and population sizes (Smith *et al.*, 1998; Stockmann *et al.*, 2013). Moreover, model uncertainties are likely to be very large, reducing their overall effectiveness. Brussaard (1998) and Stockmann *et al.* (2013), pointed out some of the limitations of these approaches. For instance: the quality of organic matter consumed at each trophic interaction is not well known; a number of important functional groups are usually not included in the existing models; the possible spatial habitat restriction of certain functional groups is not incorporated and many biological interactions in the soil are actually non-trophic in nature. Incorporating recent knowledge of the microbiological processes and explicit meso- and macrofauna functions into known SOC models, while maintaining their relative simplicity, and the possibility of validating these functions with measurable field data, is still a challenge for SOC modelling.

5.7.1 Amortization in LCA

Amortizing emissions from land use change over 20 years of subsequent cropping is common practice in LCA. However, the choice is arbitrary and any other would influence results dramatically. Alternative approaches to amortization in LCA can be found in Schmidt *et al.* (2015) and Kloverpis *et al.* (2013), which represent a consistent approach to the notion of delayed emission previously described in section 4.2.3.

5.7.2 Climate impacts of biogenic emissions: timing and effects of storage

Most methods do not distinguish CO_2 flows relative to their timing. Again, this methodological choice, as well as the choice of the particular methods (which are several), would be a large source of uncertainty in LCA studies.

5.7.3 Reference land use

Reference land use is also a key parameter for models like the IPCC, responsible for large discrepancies in results. Assuming carbon stocks associated to natural vegetation will entail a much larger value than those assuming current cropland, grassland or natural regeneration as a reference. See Koponen and co-workers (2017); Soimakallio and co-workers (2015) and Koellner *et al.* (2013).

5.7.4 Indirect land use change (iLUC), and other indirect effects

iLUC is excluded from the scope of this report, and from several methods evaluated. Some methods, however, include iLUC (e.g. Vellinga *et al.*, 2013 and Schmidt *et al.*, 2015).

6. Recommendations for the LEAP Technical Advisory Group on soil carbon stock changes

6.1 PROPOSED BOUNDARIES

This section deals with definitions, approaches to consider carbon stock changes after a land use transformation, methodological considerations, existing sources of data for soil carbon storage and models, overview of the main research groups and international task forces working on soil carbon storage and related issues.

6.2 TARGET PRODUCTIVE SYSTEMS

We consider that the LEAP approach should include the estimation of SOC stocks and changes of the different types of land intended to produce forage supplies for livestock consumption, (native or domesticated plant species and its residues; directly grazed or harvested as conserved fodder or supplements). These productive resources should therefore include: rangeland (including grasslands, savannas, shrublands, woodlands, wetlands, and tundras); pastureland and cropland forages (following a classification similar to that of Hannaway and Fribourg, 2011).

Rangelands can be defined as types of land on which the climax or potential plant cover is composed principally of native species (grasses, grass-like plants, forbs, or shrubs), suitable for grazing and browsing (EPA, 2016). Rangelands are distinguished from pasturelands because they grow primarily native vegetation, rather than domesticated plants. Generally, rangelands are also managed with extensive practices rather than more intensive agricultural practices of seeding, fertilizer and herbicide applications. However, there are different rangeland production systems in which a particular desirable plant species is promoted by herbicide control of other species or fertilizing. Some rangeland livestock systems may include (Suttie *et al.*, 2005; Allen *et al.*, 2011; FAO, 2016):

- Grasslands: lands covered with native grasses and other herbaceous species, where woody plants may be present, but do not cover more than 10 percent of the ground. In their natural state, grasslands are dominated by light to dark brown chernozemic soils in relatively flat to gently rolling areas, and dry warm summers. Generally, grasslands occur where there is sufficient moisture for grass growth, but where environmental conditions, (climatic, topographic, edaphic, and anthropogenic) prevent tree growth. South American Pampas, Eurasian Steppes, North American Prairies and Plains are examples of these ecosystems.
- Savannas: lands with herbaceous understory, typically graminoids, and with tree or shrub cover between 10-30 percent, generally with a height that exceeds 2 meters. The trees or shrubs are sufficiently widely spaced so the canopy does not close. Generally found in tropical and sub-tropical regions and characterized by a climate with alternating wet and dry seasons. It is often a transitional vegetation type between grassland and forestland.

African savannas, Australian savannas, Argentine Caldenal, and Brazilian Savanna Cerrados can be classified within these ecosystems.

- Shrublands: lands on which the vegetation is dominated by low-growing woody plants with a height less than 2 meters, often also including grasses, herbs, and geophytes. The total percent shrub cover may exceed 30 percent (closed shrubland) or between 10-30 percent (open shrublands). North American Chaparrals, Mediterranean shrublands, Patagonian Monte Shrublands are examples of these type of rangelands.
- Woodlands: low-density forests that form open habitats with plenty of sunlight and limited shade, hence supporting an understory of shrubs and herbaceous plants like grasses. Generally, the woody species coverage exceeds 30 percent, with a height over 2 m. Cerrados woodlands in Brazil, Angolan woodlands, Australian Eucalyptus woodlands are some examples of these ecosystems.
- Wetlands: land areas saturated with water and covered by hydric soils (Vepraskas and Sprecher, 1997), either permanently or seasonally. Generally treeless, and usually dominated by marsh grasses, rushes, sedges, other grass-like plants and forbs. The main wetland types include swamps, marshes, bogs and fens as well as river deltas and riverine floodplains from all over the world.
- Tundras: land areas in arctic and alpine regions devoid of large trees, varying from bare ground to various types of vegetation consisting of grasses, sedges, forbs, dwarf shrubs and trees, mosses and lichens.

Rangeland productive systems are generally grazed, but there are different native grasses and other herbaceous vegetation intended for the preparation of conserved forage, on sites as different as meadows, almost sheer clearings on hillsides, subtropical forest land closed for regeneration, alpine grassland, steppes, prairies, or a host of other uncultivated lands (Suttie and Reynolds, 2005). Vast areas of forest land closed for regeneration or protection in India, where grazing is forbidden but grass-cutting allowed; the steep clearings of sub-Himalayan Mountains; meadows in Turkey; the steppes of Mongolia (where cooperative stock-rearing has recently been replaced by private); the Sahel; and the Ethiopian highlands, are some examples of these systems.

Pastures: systems where forage is established or sown with domesticated introduced or indigenous species, usually a mix of grasses and legumes. It may receive periodic cultural treatment such as resowing, renovation, irrigation, fertilization, pest or weed control, and other intensive agricultural practices, which are generally not applied in rangelands. Pastures may be biannual or pluriannual, and permanent (if composed of perennial or self-seeding annual forage species which may persist indefinitely) or temporary (if forage species are kept for a short period of time, generally integrated in a crop rotation). Silvo-pastoral systems, in which grass or legume species are aerial or land sown, may be considered as pastures. Pasturelands include either forage directly grazed or intended as conserved forage (hay, haylage, silage or stockpiled forage). Pure or multi-specific pastures are an important part of livestock systems of North America, Southern South America and, notably, New Zealand.

Forage and fodder crops: a crop of cultivated plants, other than separated dry grain, produced to be grazed or harvested for use as feed for animals (Allen *et al.*, 2011). Forage crops tend to be monospecific rather than multipecific as pastures, and annual or bi-annual. Fodder growing is traditional in some smallholder areas, but unlike sown pasture, fodder can be used on any size of farm, not only large ones, whether for use green or conserved (Dost, 2004; Suttie and Reynolds, 2005). Maize, sorghum, rye, oats, millet, triticale, green harvested or directly grazed, are some examples of forage crops (FAO, 2016b). Grain crops in agricultural or integrated systems, in our opinion should be considered as part of agricultural systems or croplands, as it is often impossible to determine their final use (industry, animal feed, etc.).

Crop Residues: lands where agricultural crop residues are intended for livestock consumption should be also considered in the analysis of SOC stocks and changes. Residues like straw (from fine grains such as wheat, oat, rice etc.) and stover (from coarse grains such as maize, sorghum, millets etc.) obtained after harvesting the crops, may be an important feed resource in some integrated livestock production systems.

We consider that all these forage resources should be included in a SOC carbon stocks and changes assessment, as it may help to analyse the effect of management practices on SOC levels in different livestock systems and identify those with greater potential as carbon sinks.

6.3 SOC REFERENCE STATE

There is a need to define a reference SOC level in two aspects. First, it is necessary to define an initial SOC level prior to the implementation of management practices or land use changes, so as to assess their effect on SOC stocks and SOC dynamics. Ideally, this should be measured on site, before the implementation of the practices under analysis. An alternative when this not possible, is to use measured SOC levels on a neighbouring system, within the same or similar soil texture, and landscape position, which has been managed similarly to the initial state of the target system for 20 years or more. The period of 20 years has been highlighted by the IPCC Guidelines (IPCC, 2004) as a period in which SOC levels may attain equilibrium under specific land use and management practices.

The second aspect to consider is the magnitude of SOC stocks and changes of different livestock systems relative to the soil carbon sequestration potential, for a certain type of soil and climate. Some ecosystems permit the possibility to compare the SOC level under productive soils with those of surrounding areas under "pristine" or "virgin" conditions. Multiple studies and analysis comparing SOC changes under productive systems with those of the same soils under native vegetation, like unexploited grasslands and forests (Bauer *et al.*, 1981; Mann, 1986; Saviozzi *et al.*, 2001; Guo *et al.*, 2002; Ogle *et al.*, 2005; Toledo *et al.*, 2013; Cheong and Umrit, 2015) have been executed. These types of comparisons with reference conditions have been plausible in continents with a more "recent" colonization and livestock husbandry like Oceania and America. However, this kind of "undisturbed" conditions are rare, and many authors have questioned that many "virgin" soils might not be as pristine as originally thought and have undergone substantial modifications (Heckenberger *et al.*, 2003; Willis *et al.*, 2004; Barlow *et al.*, 2012).

It has been proposed that soils have a certain capacity to sequester C, and this level could be used as a reference, especially where it is not possible to find suitable "pristine" conditions. Field and laboratory research suggest there is an upper limit, or "saturation level", in the amount of SOM that can be held in soil, determined by its physical characteristics (like silt and clay content, type of clay; Paustian *et al.*, 1997, Six *et al.*, 2002, Stewart *et al.*, 2007, Gulde *et al.*, 2008). The theoretical value of C saturation (Csat) may be calculated according to the equation proposed by Hassink (1997):

Equation 4

$$C_{sat}\,(\%) = 4.09 + 0.37\,(Clay + fine\ silt)$$

where C_{sat} is the C saturation (gC / kg) expressed as the C content of the Clay fraction (0–2 μm particles) + fine silt fraction (2–20 μm particles), on a whole-soil basis, (% or g / 100 g for this original equation). Using this approach, Angers *et al.* (2011) estimated SOC saturation levels and carbon deficits for different agricultural topsoils in France. However, this specific value of C saturation does not necessarily represent the maximum attainable carbon under specific soil-climate conditions, so care should be taken when using this value as a reference state.

Several researchers have proposed that the capacity of the soil to sequester C is based on more than just the chemical association with silt and clay, being attributable to aggregate protection and biochemical recalcitrance as well. Baldock and Skjemstad (2000) proposed that each mineral matrix has a unique capacity to stabilize organic C depending not only on the presence of mineral surfaces capable of adsorbing organic materials (a protective capacity), but also the chemical nature of the soil mineral fraction, the presence of cations, and the architecture of the soil matrix. Carter (2002) proposed a conceptual model that includes a variable capacity related to C input, aggregate stability, and macro-organic carbon in addition to the silt and clay protective capacity. He related the storage capacity of soil to specific soil fractions including the association of SOC with silt + clay particles (<20 μm), microaggregates (20–250 μm), macroaggregates (>250 μm), and sand-sized macro-OC. Six *et al.* (2002) proposed a saturation model that includes not only a silt + clay protected pool, but a microaggregate-protected pool, a biochemically protected pool, and an unprotected pool. A fourth, unprotected C pool is limited by the steady-state balance of C inputs and decomposition, dictated primarily by climate. So, according to these authors, whole soil C saturation occurs due to the cumulative behaviour of these four soil C pools. Determining the maximum capacity for a given soil to store SOC, considering all these factors, is still a key challenge (Campbell and Paustian, 2015).

However, it is important to consider that the way of soil C loss is usually fast, while the way of soil C recovering is often slower and incomplete. This is because of the changes in soil structural organization taking place when a given soil undergoes soil C losses (Dexter, 1988), showing another instance of the history dependence of a physical system or hysteresis principle (Setna, 2011).

Another possibility to determine a reference SOC state is by using simulation models. It is standard procedure to run both RothC and Century through an equilibrium period (7000–10,000 years) to represent SOC levels prior to human disturbance, based on vegetation, soil characteristics and climatic conditions (Parton *et al.*, 1987; Jenkinson *et al.*, 1992; Coleman and Jenkinson, 1996; Kamoni *et al.*, 2007). For example, using the CENTURY model, Alvarez (2001) estimated SOC levels under natural grasslands at the climax stage (reference state), and SOC losses from agriculture and cattle grazing in the Rolling Pampa Region of Argentina. Farage *et al.* (2007) used a similar approach with RothC and CENTURY models to estimate equilibrium SOC levels and SOC changes in savannas converted to dryland farming

Table 6: Reference Soil organic C stocks for soils under native vegetation (tonnes C ha^{-1} in 0-30 cm)

Climate Region	HAC Soils[1]	LAC Soils[2]	Sandy Soils[3]	Spodic Soils[4]	Volcanic Soils[5]	Wetland Soils[6]
Boreal	68	NA	10	117	20	146
Cold Temperate, dry	50	33	34	NA	20	87
Cold temperate, moist	95	85	71	115	130	87
Warm temperate, dry	38	24	19	NA	70	88
Warm temperate, moist	88	63	34	NA	80	88
Tropical, dry	38	35	31	NA	50	86
Tropical, moist	65	47	39	NA	70	86
Tropical, wet	44	60	66	NA	130	86
Tropical, montane	88	63	34	NA	80	86

Source: extracted from IPCC, 2006.

[1] HAC - High Activity Clay Soils: lightly to moderately weathered soils, dominated by 2:1 silicate clay minerals (in the World Reference Base for Soil Resources (WRB) classification these include Leptosols, Vertisols, Kastanozems, Chernozems, Phaeozems, Luvisols, Alisols, Albeluvisols, Solonetz, Calcisols, Gypsisols, Umbrisols, Cambisols, Regosols; in USDA classification includes Mollisols, Vertisols, high-base status Alfisols, Aridisols, Inceptisols.

[2] LAC - Low Activity Clay (LAC) soils: highly weathered soils, dominated by 1:1 clay minerals and amorphous iron and

[3] Includes all soils (regardless of taxonomic classification) having > 70% sand and < 8% clay, based on standard textural analyses (in WRB classification includes Arenosols; in USDA classification includes psamments).

[4] Soils exhibiting strong podzolization (in WRB classification includes Podzols; in USDA classification Spodosols)

[5] Soils derived from volcanic ash with allophanic mineralogy (in WRB classification Andosols; in USDA classification Andisols)

[6] Soils with restricted drainage leading to periodic flooding and anaerobic conditions (in WRB classification Gleysols; in USDA classification Aquic suborders).

systems of Africa and Latin America. The GEFSOC modelling System (Easter *et al.*, 2007), enables the estimation of SOC equilibrium levels with different types of native vegetation (forests, grasslands, savannah, and shrub/grasslands).
Finally, reference SOC levels may be estimated using IPCC (2006) default values for different climates and soils under native vegetation (Table 6). There are also multiple publicly available databases where reference Topsoil or 1m SOC stocks (under native or estimated current use) may be estimated for different world regions (Hiederer and Köchy, 2011; EEA, 2012; USDA, 2013; Scharlemann *et al.*, 2014; West, 2014; de Brogniez *et al.*, 2015; ISRIC, 2016.

6.4 APPROACH TO ESTIMATE CARBON STOCKS AND CHANGES WITH BIOPHYSICAL SOC MODELS AFTER AND DURING LAND USE CHANGE

As explained in section "5. Contentious issues in modelling approaches", not all available C models seem to be capable of estimating SOC stocks and changes in livestock systems. This is mainly due to existing constraints in relation to: (1) Data availability, comparability and quality; and (2) Matching measurable SOC fractions with conceptual of the models. However, constraints related to (3) Landscape-scale modelling, and (4) Modelling SOC dynamics beyond the surface layer may also weaken output results of soil C models. In addition, it is particularly true that (1) there are no universal models suitable to every situation.

Taking this into account, we propose a general modelling approach for the LEAP TAG Scoping analysis. Firstly, we propose to focus exclusively on stocks and changes of soil carbon, rather than on the whole system carbon estimation, i.e. the C contained on other sinks/sources, such as below and above ground plant biomass C, animal biomass C, litter C, dead organic matter C, etc. For example, IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) account for stocks and changes in carbon as a sum of the C stocks and changes of some of these mentioned pools. However, measuring and checking model estimated C stocks in the different pools would be costly, time consuming and highly variable. Soil C contained in these pools could also show a high interannual variation in relation to climatic conditions and management practices. Carbon stocks and dynamics in these pools could be modelled to estimate soil carbon changes, but to account for and to focus on a whole system, C stock would be beyond the scope of this approach.

Secondly, although both organic and inorganic forms of C are found in soils, land use and management typically have a larger impact on organic C stocks. Consequently, the approach should focus on Soil Organic Carbon (SOC).

Thirdly, three methodological approach levels, according to data quality and availability, similar to the "tier" (1-3) structure proposed by the IPCC (2004; 2006) are proposed for this assessment. Although the level structure is not hierarchical, moving to a higher level should improve the accuracy of the estimation and reduce uncertainties, as the complexity and data resources required for modelling SOC changes also increases. The approaches are not mutually exclusive, and a mix of approaches could be applied for different calculation needs or national/regional circumstances. We propose the following three levels with different methodological model approaches, ranging from the use of default data and simple equations to the use of more complex, and specific, locally validated models:

- Level 1: Minimum Data Requirements – Empirical IPCC Model
- Level 2: Intermediate Data Requirements – Roth-C Model
- Level 3: Maximum Data Requirements – Specific/local Models and GIS integration

6.4.1 Level 1. Minimum Data - Empirical IPCC Model:

SOC stocks and changes in this level are estimated using the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) computed over a defined time period. This approach may be used for systems with a limited availability of historic climatic data, soil databases, and/or productive registers (management practices and its effects on net primary production, or estimations of biomass returns and exports, etc.).

For each time period, SOC stocks are estimated for the first and last year, based on multiplying a reference C stock found under native vegetation (for a specific climate and soil type) by stock change factors (land use, management, organic matter inputs, and land area). Annual rates of carbon stock change are estimated as the difference in stocks at two points in time divided by the time dependence of the stock change factors. Annual change in SOC stocks (ΔC, Tonnes C $year^{-1}$) is therefore estimated as:

Equation 5

$$\Delta C = (SOC_n - SOC_1)/(T)$$

Where:

- SOC_n is the organic carbon stock in the last year of the time period (Tonnes C);
- SOC_1 is soil organic carbon stock at the beginning of the period (Tonnes C); and

- T is the number of years over a single time period (yr). SOC initial and final levels are estimated as:

Equation 6

$$SOC = SOC\,Ref_{c,s,i} \;\; x \;\; FLU_{c,s,i} \;\; x \;\; FMG_{c,s,i} \;\; x \;\; FI_{c,s,i} \;\; x \;\; A_{c,s,I}$$

Where:

- SOC Ref c,s is the reference SOC stock under native vegetation (Tonnes C ha-1 in 0-30cm depth), related to specific climatic conditions (c) and soil type (s), and may be measured or estimated with the different approaches mentioned in section 2;
- FLU c,s,i is a dimensionless land use factor that reflects changes associated with land use, and for example may be fixed to 1 for grasslands and from 0.48 to 1.10 for croplands (default FLU factors are provided by IPCC, 2006);
- FMG is a dimensionless management factor that reflects changes associated to management practices within a land use, and for example may range from 0.7 in degradated grasslands to 1.17 in improved grasslands systems (default FLU factors are provided by IPCC, 2006);
- FI is a dimensionless organic matter input factor that reflects the effect of different levels of C inputs to the soil, and for example may vary from 0.92 in low residue return systems to 1.44 in systems that practice regular addition of animal manure (default FI factors are provided by IPCC, 2006); and
- A is the land area with common soil and climate conditions and is under the same management history in the evaluated period.

6.4.2 Level 2. Intermediate – RothC Model:

As mentioned in previous sections, RothC is a process oriented, multi-compartment model, widely used to simulate SOC dynamics under different land uses. Carbon stocks and changes associated with land use change as well as SOC dynamics during land use may be adequately simulated and estimated with this model, under different environmental and management conditions. We consider this model to be simpler than other SOC models, with fewer data requirements, and it should be relatively easy to obtain climatic, soil and productive data inputs to run the model. Current and historic registers of monthly rainfall, monthly pan-evaporation and average monthly mean air temperature could be obtained from national public or private institutions, or via the internet from sources that are recognised as being authoritative on a global level. NASA's satellite and modelled derived solar and meteorological data (NASA, 2016), NOAA's National Centers for Environmental Information data (NOAA, 2016), or the FAO CLIMWAT Database (FAO, 2015), are some examples of free available climatic data that may be obtained computing site coordinates. Soil clay content and soil cover are the only soil parameters needed to run the model, and are also easily measured or estimated inputs, and available at different national or international databases (ISRIC, 2016), with varying scales. A monthly input of plant residues (t C ha^{-1}) is needed for the model to run. This input may be estimated from NPP registers for grasslands and pastures under different land use available at national or international databases, published and publicly downloadable (e.g. Kucharick *et al.*, 2000; Haberl *et al.*, 2007; NEO, 2016), or estimated from production registers (based on forage biomass estimations, harvest indexes, above/below-ground biomass ratios, livestock harvest and conversion efficiencies, etc.), as estimated by Liu *et al.* (2011) or Poeplau (2016). As stated by the model authors (Coleman and Jenkinson, 1996), an annual biomass and C production may be estimated and split in different months if there are no registers of monthly production, without appreciably affecting the results in long run simulations.

This way of entering measurable data may represent an advantage as other models tend to estimate this input from the computed climatic, soil, vegetation and management conditions. However, when this input is not known, the model may be run in "inverse" mode, generating this input from known soil, site and weather data. RothC parametrizations and functions were originally developed for the 0-30 cm layer, thus enabling better integration with data from the IPCC empirical method (also focused in changes in this depth), but it has been adapted for estimations up to 1 m (Jenkinson and Coleman, 2008).

SOC estimations by the model should be periodically checked with measured field SOC data, at least with total organic carbon determinations every 4 to 5 years. A clear advantage of RothC is the model's pool outputs may be contrasted against measurable C pools (Skjemstad *et al.*, 2004; Zimmermann *et al.*, 2007). The evaluation of any model like RothC, using local existing long-term data is essential as it will usually be impossible to check whether a particular model projection is correct (Powlson, 1996). It is desirable to previously test the model against as much existing local SOC data as possible, covering the different range of conditions (climatic, soil, and management) that may be encountered for the target livestock production system.

6.4.3 Level 3: Maximum– Specific/local Models and GIS integration

At level 3, more complex and locally calibrated and validated models like CENTURY or DNDC could be used. Another possibility is the use of models tailored to address local conditions, or to use specific adaptations of known models like CENTURY or ROTHC: e.g. to allophanic soils (Shirato *et al.*, 2004), saline soils (Setia *et al.*, 2011), organic soils (Smith *et al.*, 2007), and subsoils (Jenkinson and Coleman, 2008). SOC modelling at this level should use high resolution data (temporal and spatial scales), and ideally be integrated into a GIS system with terrain and soil data, to estimate SOC stocks and changes at paddock and landscape levels. As in the case of previous levels, models should undergo quality checks, audits, and validations.

Remote sensing analysis could do an important contribution at level 3. The soil organic carbon stock results from the balance of C inputs from primary productivity and the return of carbon to the atmosphere through mineralization of organic matter (Jenny 1941). Several studies have shown that the annual integral of Normalized Difference Vegetation Index (I-NDVI), derived from satellite imagery, is a good estimator of above-ground Net Primary Production (ANPP; Tucker *et al.,* 1983; Prince 1991). Therefore, the temporal analysis of NDVI obtainedfrom the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor (spatial resolution 250 m) for example, can help to model and to monitorchanges in SOC content at a landscape scale.

If the approach above does not fulfil the goal and scope of the LCA study, it is recommended that IPCC data be used as far as possible, along with the extrapolations made by Carré *et al.* (2010) enabling ease of application at country and crop level. Regarding methodological choices, a 20-year amortization period for LUC emissions is recommended. In case timing issues are a part of the scope of the assessment, the approach developed by Mueller-Wenk and Brandão (2010) is recommended. The reference state shall be the regeneration rate, so foregone carbon sequestration can be included.

7. Conclusions

Land use in livestock production systems, such as grasslands and rangelands, offers a significant potential to sequester and store carbon from the atmosphere and thereby compensate for Greenhouse Gas (GHG) emissions. However, soils are extremely complex systems, spatially heterogeneous at different scales, and include biogeochemical processes with temporal dynamics ranging from hourly responses to time scales characteristic in soils. Estimating SOC in livestock systems have additional complexities compared to other land uses. Moreover, to estimate the impacts of livestock production systems at a broader scale, not only from a soil perspective, a combination of tools that provide robust estimations of SOC dynamics and that can be combined with Life Cycle Assessment (LCA) methods are required. However, no consensus exists on the appropriate methodologies to assess SOC stocks and changes under livestock production systems, and its potential environmental impact.

In this document some of the most used SOC models differing in their structure, mechanisms, purpose, scale and complexity, are reviewed. Some of the most contentious issues in the use of SOC models are: a) the lack of universally validated models, b) the uneven data availability, comparability and quality between countries and regions, c) the difficulty to reconcile measurable SOC fractions with those determined by the models (i.e. lack of validation), d) the uncertainty of modelling SOC changes beyond the surface layers, and e) including the effects of soil structure or soil biota in SOC dynamics. We propose a three-level approach, according to the availability of original data to run the models and the purpose of the study: 1. IPCC empiric model, 2. RothC-Model, 3. CENTURY/DNDC models. We also emphasize the need to define a reference SOC state by different proposed methods to evaluate SOC changes.

SOC models have also been used in LCA mainly to estimate the climate change impacts on land-based systems, to estimate time-dependent carbon fluxes in productive systems, and to estimate the effects of direct land use change (dLUC) and management changes on GHG emissions. However, LCA combining LCA with SOC models raises additional issues necessary to consider: a) not all carbon models have a comprehensive inclusion of biomass, soil litter and soil carbon stocks that LCA methods may require; b) the need to define a reference situation; c) the period of time considered to amortize GHG emissions; d) the consideration of climate impacts on biogenic emissions, related to their timing; and e) the decision to include or not indirect land use changes (iLUC).

When combining SOC models with LCA, we recommend that IPCC data should be used as far as possible, with the extrapolations made by Carré *et al.* (2010) enabling ease of application at a country and crop level. Regarding methodological choices, we recommend a 20-year amortization period for LUC emissions. In case timing issues are part of the scope of the assessment, the approach developed by Mueller-Wenk and Brandão (2010) is recommended. Finally, the reference state shall be the regeneration rate, so that foregone carbon sequestration can be included.

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Appendices

MAIN RESEARCH GROUPS WORKING ON SOC DYNAMICS

National Resource Ecology Laboratory – Colorado State University – UNITED STATES OF AMERICA. Representative Members (2016): Keith Paustian; Karolien Denef; Eleanor Milne; Mark Easter.
Contact available at: http://www.nrel.colostate.edu/paustian-group.html

Carbon sequestration in soils: 4 per 1000 Programme – INRA/IRD/CIRAD – FRANCE. Representative Members (2016): Jean-François Soussana; D. Arrouays, J. Balesdent, J.C. Germon, P.A. Jayet
Contact available at: http: www.inra.fr

Sustainable Soil & Grassland Systems Department - Rothamsted Research Station – UNITED KINGDOM. Representative Members (2016): Steve McGrath; Goetz Richter; Philip Brookes; Andy Whitmore.
Contact available at: http://www.rothamsted.ac.uk/sustainable-soils-and-grassland-systems

The Institute of Biological and Environmental Sciences. University of Aberdeen. UNITED KINGDOM. Representative Members (2016): Pete Smith.
Contact available at: https://www.abdn.ac.uk

National Soil Carbon Program – Filling the Research Gap on Soil Carbon Program – University of Queensland/University of Sidney/CSIRO/Department of Agriculture and Water Resources – AUSTRALIA. Representative Members (2015): Jeff Baldock; Jonathan Sanderman; Lynne Macdonald; Uta Stockmann; Mark A. Adams.
Contact available at: http://www.agriculture.gov.au/ag-farm-food/climatechange/carbonfarmingfutures/ftrg

Laboratório de Biogeoquímica Ambiental- USP (University of Sao Paulo) – Brazil. Representative Members (2015): Carlos Cerri; Brigitte Josefine Feigl

Global Research Alliance on Agricultural Greenhouse Gases – International Livestock research Group. Representative Members (2016): Harry Clark; Martin Scholten
Contact available at: http://globalresearchalliance.org/research/livestock/

Global Research Alliance on Agricultural Greenhouse Gases - MAGGnet (Managing Agricultural Greenhouse Gases Network) – International Research Network. Representative Members (2016): Franzluebbers, Alan, Liebig, M.A., J., Alvarez, C., Chiesa, T.D., Lewczuk, N., Pineiro, G.

http://www.fao.org/partnerships/leap

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