CHAPTER 2

GENERIC METHODOLOGIES APPLICABLE TO MULTIPLE LAND-USE CATEGORIES

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Contents

Equations

Figures

Tables

Boxes

2 GENERIC METHODOLOGIES APPLICABLE TO MULTIPLE LAND USE CATEGORIES

2.1 INTRODUCTION

No refinement

2.2 INVENTORY FRAMEWORK

This section outlines a systematic approach for estimating carbon stock changes (and associated emissions and removals of carbon dioxide (CO_2) from biomass, dead organic matter, and soils, as well as for estimating non-CO_2 greenhouse gas emissions from fire. General equations representing the level of land-use categories and strata are followed by a short description of processes with more detailed equations for carbon stock changes in specific pools by land-use category. Principles for estimating non-CO_2 emissions and common equations are then given. Specific, operational equations to estimate emissions and removals by processes within a pool and by category, which directly correspond to worksheet calculations, are provided in Sections 2.3 and 2.4.

2.2.1 Overview of carbon stock change estimation

The emissions and removals of CO_2 for the AFOLU Sector, based on changes in ecosystem C stocks, are estimated for each land-use category (including both land remaining in a land-use category as well as land converted to another land use). Carbon stock changes are summarized by Equation 2.1.

EQUATION 2.1
ANNUAL CARBON STOCK CHANGES FOR THE AFOLU SECTOR ESTIMATED AS THE SUM OF CHANGES IN ALL LAND-USE CATEGORIES

$$\Delta C_{AFOLU} = \Delta C_{FL} + \Delta C_{CL} + \Delta C_{GL} + \Delta C_{WL} + \Delta C_{SL} + \Delta C_{OL}$$

Where:

ΔC_{AFOLU} = Total annual carbon stock change in the AFOLU sector; tonnes C yr^{-1}

Indices denote the following land-use categories:

AFOLU = Agriculture, Forestry and Other Land Use

FL = Forest Land

CL = Cropland

GL = Grassland

WL = Wetlands

SL = Settlements

OL = Other Land

For each land-use category, carbon stock changes are estimated for all *strata* or subdivisions of land area (e.g., climate zone, ecotype, soil type, management regime etc., see Chapter 3) chosen for a land-use category (Equation 2.2). Carbon stock changes within a stratum are estimated by considering carbon cycle processes between the five carbon pools, as defined in Table 1.1 in Chapter 1. The generalized flowchart of the carbon cycle (Figure 2.1) shows all five pools and associated fluxes including inputs to and outputs from the system, as well as all possible transfers between the pools. Overall, carbon stock changes within a stratum are estimated by adding up changes in all pools as in Equation 2.3. Further, carbon stock changes in soil may be disaggregated as to changes in C stocks in mineral soils and emissions from organic soils. Harvested wood products (HWP) are also included as an additional pool.

EQUATION 2.2
ANNUAL CARBON STOCK CHANGES FOR A LAND-USE CATEGORY AS A SUM OF CHANGES IN EACH STRATUM WITHIN THE CATEGORY

$$\Delta C_{LU} = \sum_i \Delta C_{LU_I}$$

Where:

ΔC_{LU} = carbon stock changes for a land-use (LU) category as defined in Equation 2.1.

i = denotes a specific stratum or subdivision within the land-use category (by any combination of species, climatic zone, ecotype, management regime etc., see Chapter 3), i = 1 to n.

EQUATION 2.3
ANNUAL CARBON STOCK CHANGES FOR A STRATUM OF A LAND-USE CATEGORY AS A SUM OF CHANGES IN ALL POOLS

$$\Delta C_{LU_i} = \Delta C_{AB} + \Delta C_{BB} + \Delta C_{DW} + \Delta C_{LI} + \Delta C_{SO} + \Delta C_{HWP}$$

Where:

ΔC_{LU_i} = carbon stock changes for a stratum of a land-use category

Subscripts denote the following carbon pools:

AB = above-ground biomass

BB = below-ground biomass

DW = deadwood

LI = litter

SO = soils

HWP = harvested wood products

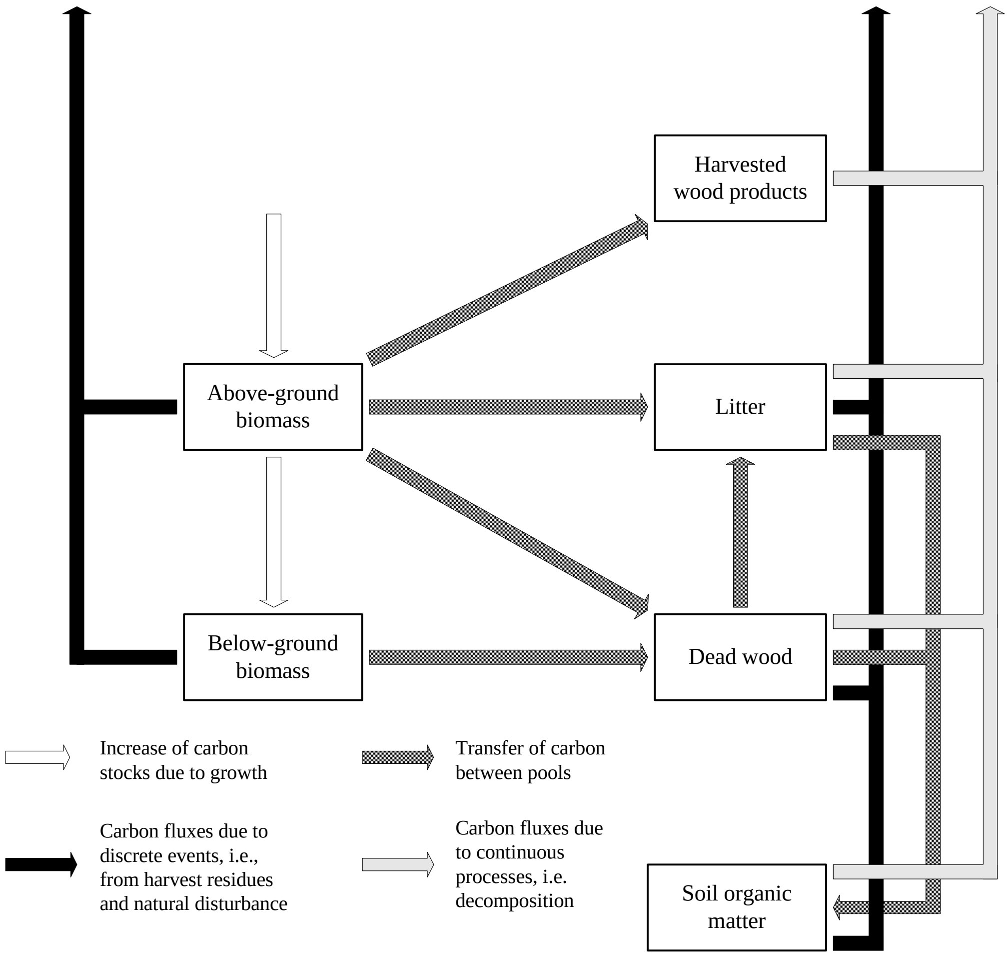
Estimating changes in carbon pools and fluxes depends on data and model availability, as well as resources and capacity to collect and analyse additional information (See Chapter 1, Section 1.3.3 on key category analysis). Table 1.1 in Chapter 1 outlines which pools are relevant for each land-use category for Tier 1 methods, including cross references to reporting tables. Depending on country circumstances and which tiers are chosen, stock changes may not be estimated for all pools shown in Equation 2.3. Because of limitations to deriving default data sets to support estimation of some stock changes, Tier 1 methods include several simplifying assumptions:

- change in below-ground biomass C stocks are assumed to be zero under Tier 1 (under Tier 2, country-specific data on ratios of below-ground to above-ground biomass can be used to estimate below-ground stock changes);
- under Tier 1, dead wood and litter pools are often lumped together as 'dead organic matter' (see discussion below); and
- dead organic matter stocks are assumed to be zero for non-forest land-use categories under Tier 1. For Forest Land converted to another land use, default values for estimating dead organic matter carbon stocks are provided in Tier 1.

The carbon cycle includes changes in carbon stocks due to both continuous processes (i.e., growth, decay) and discrete events (i.e., disturbances like harvest, fire, insect outbreaks, land-use change and other events). Continuous processes can affect carbon stocks in all areas in each year, while discrete events (i.e., disturbances) cause emissions and redistribute ecosystem carbon in specific areas (i.e., where the disturbance occurs) and in the year of the event.

Disturbances may also have long-lasting effects, such as decay of wind-blown or burnt trees. For practicality, Tier 1 methods assume that all post-disturbance emissions (less removal of harvested wood products) are estimated as part of the disturbance event, i.e., in the year of the disturbance. For example, rather than estimating the decay of dead organic matter left after a disturbance over a period of several years, all post-disturbance emissions are estimated in the year of the event.

Figure 2.1(unchanged) Generalized carbon cycle of terrestrial AFOLU ecosystems showing the flows of carbon into and out of the system as well as between the five C pools within the system.



Under Tier 1, it is assumed that the average transfer rate into dead organic matter (dead wood and litter) is equal to the average transfer rate out of dead organic matter, so that the net stock change is zero. This assumption means that dead organic matter (dead wood and litter) carbon stocks need not be quantified under Tier 1 for land areas that remain in a land-use category[2]. The rationale for this approach is that dead organic matter stocks, particularly dead wood, are highly variable and site-specific, depending on forest type and age, disturbance history and management. In addition, data on coarse woody debris decomposition rates are scarce and thus it was deemed that globally applicable default factors and uncertainty estimates cannot be developed. Countries experiencing significant changes in forest types or disturbance or management regimes in their forests are encouraged to develop domestic data to estimate the impact from these changes using Tier 2 or 3 methodologies and to report the resulting carbon stock changes and non-CO_2 emissions and removals.

All estimates of changes in carbon stocks, i.e., growth, internal transfers and emissions, are in units of carbon to make all calculations consistent. Data on biomass stocks, increments, harvests, etc. can initially be in units of dry matter that need to be converted to tonnes of carbon for all subsequent calculations. There are two fundamentally different and equally valid approaches to estimating stock changes: 1) the process-based approach, which estimates the net balance of additions to and removals from a carbon stock; and 2) the stock-based approach, which estimates the difference in carbon stocks at two points in time.

Annual carbon stock changes in any pool can be estimated using the process-based approach in Equation 2.4 which sets out the *Gain-Loss Method* that can be applied to all carbon gains or losses. Gains can be attributed to growth (increase of biomass) and to transfer of carbon from another pool (e.g., transfer of carbon from the live biomass carbon pool to the dead organic matter pool due to harvest or natural disturbances). Gains are always marked with a positive (+) sign. Losses can be attributed to transfers of carbon from one pool to another (e.g., the carbon in the

[2] Emissions from litter C stocks are accounted for under Tier 1 for forest conversion to other land-use.

slash during a harvesting operation is a loss from the above-ground biomass pool), or emissions due to decay, harvest, burning, etc. Losses are always marked with a negative (-) sign.

EQUATION 2.4
ANNUAL CARBON STOCK CHANGE IN A GIVEN POOL AS A FUNCTION OF GAINS AND LOSSES (GAIN-LOSS METHOD)

$$\Delta C = \Delta C_G - \Delta C_L$$

Where:

ΔC = annual carbon stock change in the pool, tonnes C yr^{-1}

ΔC_G = annual gain of carbon, tonnes C yr^{-1}

ΔC_L = annual loss of carbon, tonnes C yr^{-1}

Note that CO_2 removals are transfers from the atmosphere to a pool, whereas CO_2 emissions are transfers from a pool to the atmosphere. Not all transfers involve emissions or removals, since any transfer from one pool to another is a loss from the donor pool but is a gain of equal amount to the receiving pool. For example, a transfer from the above-ground biomass pool to the dead wood pool is a loss from the above-ground biomass pool and a gain of equal size for the dead wood pool, which does not necessarily result in immediate CO_2 emission to the atmosphere (depending on the Tier used).

The method used in Equation 2.4 is called the *Gain-Loss Method*, because it includes all processes that bring about changes in a pool. An alternative stock-based approach is termed the *Stock-Difference Method*, which can be used where carbon stocks in relevant pools are measured at two points in time to assess carbon stock changes, as represented in Equation 2.5.

EQUATION 2.5
CARBON STOCK CHANGE IN A GIVEN POOL AS AN ANNUAL AVERAGE DIFFERENCE BETWEEN ESTIMATES AT TWO POINTS IN TIME (STOCK-DIFFERENCE METHOD)

$$\Delta C = \frac{(C_{t_2} - C_{t_1})}{(t_2 - t_1)}$$

Where:

ΔC = annual carbon stock change in the pool, tonnes C yr^{-1}

C_{t_1} = carbon stock in the pool at time t_1, tonnes C

C_{t_2} = carbon stock in the pool at time t_2, tonnes C

If the C stock changes are estimated on a per hectare basis, then the value is multiplied by the total area within each stratum to obtain the total stock change estimate for the pool. In some cases, the activity data may be in the form of country totals (e.g., harvested wood) in which case the stock change estimates for that pool are estimated directly from the activity data after applying appropriate factors to convert to units of C mass. When using the Stock-Difference Method for a specific land-use category, it is important to ensure that the area of land in that category at times t_1 and t_2 is identical, to avoid confounding stock change estimates with area changes.

The process method lends itself to modelling approaches using coefficients derived from empirical research data. These will smooth out inter-annual variability to a greater extent than the stock change method which relies on the difference of stock estimates at two points in time. Both methods are valid so long as they are capable of representing actual disturbances as well as continuously varying trends and can be verified by comparison with actual measurements.

2.2.2 Overview of non-CO_2 emission estimation

Non-CO_2 emissions are derived from a variety of sources, including emissions from soils, livestock and manure, and from combustion of biomass, dead wood and litter. In contrast to the way CO_2 emissions are estimated from biomass stock changes, the estimate of non-CO_2 greenhouse gases usually involves an emission rate from a source directly to the atmosphere. The rate (Equation 2.6) is generally determined by an emission factor for a specific gas (e.g., CH_4, N_2O) and source category and an area (e.g., for soil or area burnt), population (e.g., for livestock) or mass (e.g., for biomass or manure) that defines the emission source.

EQUATION 2.6
NON-CO_2 EMISSIONS TO THE ATMOSPHERE

$$Emission = A \bullet EF$$

Where:

Emission = non-CO_2 emissions, tonnes of the non-CO_2 gas

A = activity data relating to the emission source (can be area, animal numbers or mass unit, depending on the source type)

EF = emission factor for a specific gas and source category, tonnes per unit of A

Many of the emissions of non-CO_2 greenhouse gases are either associated with a specific land use (e.g., CH_4 emissions from rice) or are typically estimated from national-level aggregate data (e.g., CH_4 emissions from livestock and N_2O emissions from managed soils). Where an emission source is associated with a single land use, the methodology for that emission is described in the chapter for that specific land-use category (e.g., methane from rice in Chapter 5 on Cropland). Emissions that are generally based on aggregated data are dealt with in separate chapters (e.g., Chapter 10 on livestock-related emissions, and Chapter 11 on N_2O emissions from managed soils and CO_2 emissions from liming and urea applications). This chapter describes only methods to estimate non-CO_2 (and CO_2) emissions from biomass combustion, which can occur in several different land-use categories.

BOX 2.0A (NEW)
CONSISTENCY BETWEEN AFOLU PROJECTS OR ACTIVITIES AND IPCC INVENTORY GUIDELINES

The information presented in this Box is for information purposes only

IPCC guidelines have been designed for national GHG inventories (NGHGI). They are, however, often applied, in conjunction with other guidance, to estimate GHG emissions and removals for different situations than those in a NGHGI. These different situations include scales (i.e. to any sub-aggregation of land), time resolution (i.e., on a non-annual basis), length of time series (i.e., for a limited period) and/or for selected carbon pools. Using IPCC guidelines for estimating emissions and removals from sub-aggregations - i.e. projects and activities – can help countries maintain consistency with the NGHGI. However, projects and activities can introduce additional complexities including, but not limited to, system boundaries, double-counting, leakage, and attribution. Moreover, projects and activities may use different definitions, sources of data, data and methods compared to those used for the NGHGI, including different Approaches for land representation and methodological Tiers, impacting the consistency between the two. These need to be considered when applying the IPCC Guidelines outside of a NGHGI (IPCC, 2015), particularly when there is a need for consistency and comparability.

Thus, when using IPCC guidelines for projects and activities the following steps should be considered:

i) Define the spatial boundaries of the territory impacted by the activity;

ii) Identify the land-use categories and subcategories of the NGHGI impacted by the activity.

iii) Identify pools and gases impacted by the activity;

iv) Identify the time frame (temporal boundaries) of the activity and ensure full reporting of any legacy emissions and removals associated with it[3];

v) Develop estimates by applying methods consistent with IPCC guidance, so ensuring consistency among the results of activities and the trends of times series of relevant NGHGI categories.

[3] To deal with the limited time frame of reducing deforestation and forest degradation mitigation activities, reporting methods provided by the GFOI apply the stock difference approach to estimate the net difference between two long-term average C

BOX 2.0A (NEW) (CONTINUED)
CONSISTENCY BETWEEN AFOLU PROJECTS OR ACTIVITIES AND IPCC INVENTORY GUIDELINES

For example, 1) Reducing Emissions from deforestation and forest degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries (REDD-plus) activities could be identified in the NGHGI as IPCC categories, subcategories, or sums of categories or sub-categories (GFOI, 2016), and relevant IPCC methods applied consistently; 2) The Australian Government has developed a framework as part of the Emissions Reduction Fund[4] for ensuring consistency in emissions estimation between AFOLU project-level mitigation activities and Australia's NGHGI. This framework includes integrity standards[5] to ensure emissions estimation methods are consistent with IPCC guidelines, and consequently estimated GHG reductions are consistent with trends of times series of relevant NGHGI categories.

Emissions and removals estimates for activities are likely to apply Approach 2 or 3 and Tier 2 or 3 methods because of the need to prepare GHG estimates that are more disaggregated per activity, e.g. organic farming vs traditional farming or coppice vs high-stand, and per population, e.g. by livestock sub-populations, crop types and forest types. Moreover, stratification of NGHGI categories/subcategories into subdivisions helps avoid double counting of emissions and removals from a single category that is impacted by more than an activity.

Stratification also supports transparency among activity report and NGHGI estimates when the activity does not correspond to an entire NGHGI category. In many cases, activities and projects require tracking of land where they occur through time, e.g. no tillage. In such cases, Approach 3 for land representation is required since it is the only approach that provides the spatially explicit information (either wall-to-wall or from sampling) across time needed to track activities and drivers, and to support estimation of GHG emissions or removals with higher accuracy. Where activities are known to lead to permanent changes or the activity includes management practices that determine temporary changes in the land cover, Approach 2 methods may provide sufficient information to prepare accurate estimates.

Where activity and project data have been collected and analysed consistently with *good practice*, they can be used in the NGHGI either for deriving activity data and/or emission factors, or any other ancillary data used for preparing GHG estimates for the land subject to the activity, or for calibrating the model used in the NGHGI for the same land and/or verifying the outputs of such model. Where data have inconsistencies with those collected for the NGHGI, iterations and cross-checks between NGHGI experts and experts involved in the monitoring of the activity should be done until improvements applied to the activity and/or the NGHGI estimates enable consistency. When using data collected from activities and projects for improving or evaluating information and estimates reported in the NGHGI, it is important to:

i) Define and report the reference conditions (e.g. climate, soil, management system) for which the data from the activity or project are valid and how it could be used in the NGHGI compilation;

ii) Determine if the activity or emissions factor data in the project are representative of the national average and, if not, apply methods that ensure the NGHGI is not biased by them, e.g. limiting the use of the data to the land subject to the activity or project only and modifying the data used in the NGHGI to prevent bias

iii) Define and report the level of variability (heterogeneity) of the data;

iv) Ensure the data is available and consistently applied for the entire time series.

stocks at a single point in time (i.e. by assuming instantaneous oxidation). This is to allow a complete reporting of total net C stock changes associated with the activities, including lagged emissions and removals.

[4] http://www.environment.gov.au/climate-change/government/emissions-reduction-fund/publications

[5] http://www.environment.gov.au/climate-change/emissions-reduction-fund/publications/erf-methods-development

2.2.3 Conversion of C stock changes to CO_2 emissions

For reporting purposes, changes in C stock categories (that involve transfers to the atmosphere) can be converted to units of CO_2 emissions by multiplying the C stock change by -44/12. In cases where a significant amount of the carbon stock change is through emissions of CO and CH_4, then these non-CO_2 carbon emissions should be subtracted from the estimated CO_2 emissions or removals using methods provided for the estimation of these gases. In making these estimates, inventory compilers should assess each category to ensure that this carbon is not already covered by the assumptions and approximations made in estimating CO_2 emissions.

It should also be noted that not every stock change corresponds to an emission. The conversion to CO_2 from C, is based on the ratio of molecular weights (44/12). The change of sign (-) is due to the convention that increases in C stocks, i.e. positive (+) stock changes, represent a removal (or 'negative' emission) from the atmosphere, while decreases in C stocks, i.e. negative (-) stock changes, represent a positive emission to the atmosphere

2.3 GENERIC METHODS FOR CO_2 EMISSIONS AND REMOVALS

No refinement.

2.3.1 Change in biomass carbon stocks (above-ground biomass and below-ground biomass)

No refinement.

2.3.1.1 LAND REMAINING IN A LAND-USE CATEGORY

No refinement.

2.3.1.2 LAND CONVERTED TO A NEW LAND-USE CATEGORY

No refinement.

2.3.1.3 ADDITIONAL GENERIC GUIDANCE FOR TIER 2 METHODS

A. USING ALLOMETRIC MODELS FOR BIOMASS ESTIMATION

This section provides new guidance to inventory compilers on the use of allometric models (see Box 2.0b for definitions) for quantifying volume, biomass and carbon stocks in land uses containing vegetation. Allometric models can be used with country specific data to estimate carbon stocks at the Tier 2 level. Allometric models may also form part of more sophisticated Tier 3 approaches including measurement-based inventories and model-based inventories.

Allometric models quantify the relationships between certain size variables of organisms. Allometric models[6] can be used to estimate volume, biomass or carbon stocks of individuals, vegetation or forest stands. Allometric models have been developed for a wide range of species, habitats, regions and environmental conditions (e.g. documented in the GlobAllomeTree database (http://www.globallometree.org/; Schepaschenko et al, 2017). Allometric models used for forest tree species are commonly estimated from individual trees through destructive sampling from a population using a sampling design that provides accurate and representative data. As destructive sampling is usually costly and labour intensive or ecologically sensitive, it makes sense to utilize existing allometric models when valid under the respective conditions as outlined below (in the section on the use of allometric models).

[6] The term "allometric equation" is also used when referencing to the mathematical descriptions of allometric models and relationships. When the parameters are estimated from sample data and/or uncertainty is involved, "model" is the correct term. Although allometric models are used to predict the values of a variable, for practical reasons in the context of these guidelines the term estimates is also used.

BOX 2.0B (NEW)
ALLOMETRIC DEFINITIONS

Allometry: The term allometry refers to the proportional relationship between the relative dimensional relationships or growth rates of two size variables and therefore allometric relations allow that one variable can be used to predict the corresponding value of another variable. For example, tree diameter at breast height (DBH) can be used to estimate tree volume or total tree biomass. Allometry can also describe the change of one part of an organism in relation to the change of its body size, either in the same organism (while growing over time), in populations (e.g., tree stands), or between species (e.g. different tree species). These changes follow rules, so the change in proportion between two variables of an organism can be described mathematically.

Allometric model: An allometric model is a formula that quantitatively describes an allometric relationship. The basic form is an equation: y=f(x) where y and x are the dependent and independent variables. Often the equation is in the form of y = a*x^b + c, where a, b and c are parameters (please note: "c" is not identical to the statistical error term "ε"). If "x" is equal to zero (e.g., if height is below breast height when using DBH to estimate tree biomass), then "y" is equal to the parameter "c", noting that biologically "y" is always a positive number. Parameter "a" is the value of *y* if *x* is 1 and describes the initial ratio between x and y . The parameter "b" is also called an "allometric parameter" or "allometric constant" and gives the proportionality between the relative increases of "x" and "y" (Fabrika und Pretzsch 2013; Picard et al. 2012). The general form of an allometric model, without intercept (i.e. when "c" = 0), is also often represented in its logarithmic transformation as a linear relationship, log(y) = log(a) + b*log(x) or ln(y) = ln(a) + b*ln(x). Other mathematical functions have also been adopted to describe allometric relationships.

This basic model can be augmented by additional terms that include e.g. tree height as a second predictor variable (e.g. Ketterings et al. 2001). Models are usually provided with a residual error term (e.g., y = f(x) + ε), set in the model fitting against the sample data; to consider the residual error, calculated for each model, can be used to assess the uncertainty related to use of the selected model in the estimation process.

The use of allometric models

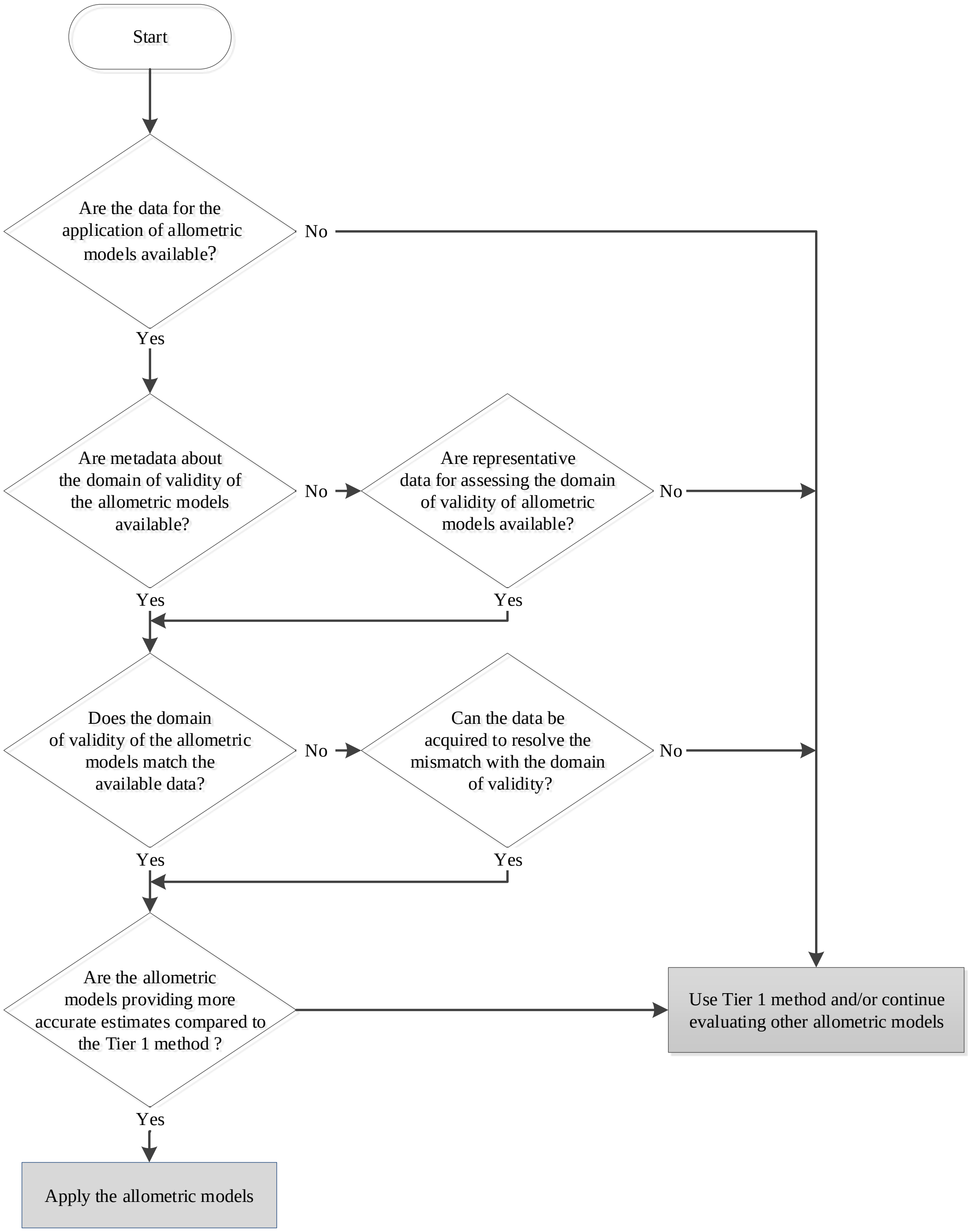
The choice of appropriate allometric models should be based on several criteria including the availability of country-specific data, the meta-data about the allometric models, the coincidence of data with the models' domain of validity according to the meta-data, and the appropriateness of the allometric model by comparing the estimates to ones obtained with the Tier 1 method (Figure 2.2a). The accuracy of the models may be lower than e.g. available default factors or Biomass Emission Factors (BEFs), so it is *good practice* to choose the method with the higher accuracy. When applying an allometric model for predicting the biomass of a given species or at a given site, data on required variables must be available as e.g. from national forest inventories (Tomppo et al. 2010, Vidal et al. 2016). For woody plant species, these variables commonly include DBH and height, and to lesser extent crown variables such as crown length or crown width. For shrubs or smaller trees and understorey vegetation, diameters nearer to the ground or shoot length may be used, among other variables. Carbon fractions and basic wood density may also be required for some models. Individual tree estimates can then be aggregated up to provide volume, biomass or carbon stock estimates at higher spatial scales (e.g. by plot, region or nation-wide). Tree-level estimates may refer to the whole tree, or individual components like above-ground and below-ground parts, stem, branches and/or foliage. Allometric models may be used within a specified forest stratum, to estimate above-ground and below-ground biomass estimation from direct measurements e.g. forest inventory plots. Allometric models may also be used for non-woody plant biomass estimates. Data collection programmes are often designed to collect the data specifically for this purpose.

Allometries are influenced by an individual's growing conditions and size classes, so in each case the allometric models developed will have a limited domain of validity. When selecting an appropriate allometric model, check the associated metadata supplied. Conditions such as:

- Ecoregion, geographic range, environmental factors (e.g., ecosystem, climatic or soil types),
- Representativeness of the model in consideration of individual size range and sampled population,
- Plant components estimated (e.g., above-ground, below-ground, stem, branches, foliage),
- Species functional traits (e.g., wood density and tree architecture),
- Land or crop management practices, current and historic,

should be assessed for their suitability (Henry et al. 2011; Rock 2007; Vieilledent et al. 2012) as well as sample size and accuracy assessment. The use of existing allometric models beyond the range they were developed for may result in a lack of accuracy (e.g. Mugasha et al 2016; Nam et al, 2016), depending on the degree to which external variables control the partitioning of biomass among components and the geometric relationships of the species. The applicability of a model can also be tested using a representative data set (e.g. Paul et al, 2016; Perez-Cruzado et al, 2015; Youkhana et al 2017). The accuracy of the allometric model should be assessed by evaluating the related statistical indicators.

Figure 2.2a Generic decision tree for the identification of appropriate allometric models to estimate volume, biomass or carbon stocks



Generalized and site or species-specific allometric models have been developed for use in different circumstances. While species-specific models will give more accurate estimates for the respective tree species (all other aspects being the same as the ones for which the model was developed) (Henry et al. 2011), generalized models may be better suited in regions with a very large diversity of tree species, where models are lacking for a large proportion of species. The use of species-specific models however is encouraged for the species for which specific models and appropriate input data are available. For natural forests, which may contain many different species, application of species-specific allometric models may be impractical; in this case, a model specific for the ecosystem type can be used (Krisnawati et al, 2012). When species-specific or ecosystem-specific models are not available, regionally relevant allometric models can be applied (Chave et al., 2004). Generic models developed based on a large number of sample trees across landscapes tend to be more reliable than locally developed models if these are based on only a small number of individuals (Chave et al 2005; Chave et al 2014; Paul et al, 2016).

Stand level models and their equations

When individual or species specific allometric models for biomass or carbon stocks are not appropriate, stand level allometric models, which may include canopy height, basal area and community age as predictor variables, may be applicable to estimate biomass parameters. Stand-level allometric models using canopy height estimate carbon stocks per unit area based on the assumption that canopy height is directly proportional to biomass (Mascaro et al, 2011; Saatchi et al, 2011). Information on canopy height can be predicted from ground-based inventory or by remote sensing such as airborne Light Detection and Ranging (LiDAR), polarimetric interferometry SAR or airborne imagery. Auxiliary information such as digital elevation models are necessary to predict canopy height from airborne and satellite-borne imagery because only canopy surface elevation can be predicted from them. The accuracy of carbon stock estimation from canopy height depends on the number of field measurement plots used to estimate the relationship between canopy height and carbon stocks. Basal area is an important parameter to understand stand characteristics and it is used in the model to estimate stand volume or stand biomass. Basal area is estimated easily in the field using simple equipment. When basal area is used in the stand-level model to estimate biomass or carbon stocks, mean tree height is also needed in the model (Lang et al, 2016; Mensah et al, 2016). The stand-level allometric model estimated from community age estimates carbon stocks per unit area by assuming that community biomass increases monotonically as the forest ages, and then drawing a saturation curve for community age (Inoue et al, 2010). It is applicable where land use is rotated at fixed intervals, so that a mosaic of communities of different ages exists.

Tier 3 methods

The hierarchical tier structure implies that use of higher tiers (Tier 2 or Tier 3) usually results in an increased accuracy of the method and/or emissions factor and other parameters used in the estimation of the emissions and removals. Tier 3 approaches for biomass carbon stock change estimation allow for a variety of methods, including measurement-based forest inventories. Measurement-based Tier 3 inventories require detailed national forest inventories containing data on growing stock, and, ideally, repeated measurements from which periodic increments can be estimated. In some circumstances these data are used directly in empirical models while in other cases they are supplemented with allometric models (for example, Chambers *et al.* (2001) and Baker *et al.* (2004) for the Amazon; Seiler et al. (2014) for tropical forest of Bolivia, Jenkins et al. (2004) and Kurz and Apps (2006) for North America; and Zianis *et al*. (2005) for Europe, Paul et al. (2016) for Australia, Luo et al. (2014) for China, Youkhana et al 2017 for tropical grasses), calibrated to national circumstances that allow for direct estimation of biomass increment or growth. Model-based Tier 3 inventories build on model-specific input data and may contain allometric models as empirical model components. Additional information related to the use of higher Tier methods can be found in Section 2.5.

Uncertainty

Sources of uncertainty when using allometric models include:

1. Model-related uncertainty, i.e. the uncertainty related to the model used, stemming from the estimation of the parameters of this model and residual variability around model;
2. Sampling variability and measurement errors in input data (see volume 1, chapter 3, section 3.1.6 for additional information);
3. The uncertainty of transferring the model to trees not used for estimation of the parameters (lack of representativeness) (see volume 1, chapter 3, section 3.1.6 for additional information).

Magnitudes of the effects of the first and second sources should be reported with the model, the latter can be reduced by careful selection of models.

Recalculations

Recalculations of C stocks may be necessary, if new and/or better data or methodology becomes available. When BEF's are replaced with parameters that are estimated using allometries, recalculations across the time series will be required. The replacement of generalised models with species-specific models also may require recalculations. It should be noted that allometry can change over time (Lopez-Serrano et al. 2005), for example, if the thinning regime in a plantation forest is changed. This may influence the ratio of crown biomass / DBH and, over time, the trees in this plantation may show different allometric relationships at two distant points in time. An updated allometric model would therefore be required in order to reflect the impact of the changes. In this case, to ensure time series consistency, apply the guidance provided in Volume 1 Chapter 5 and in Volume 4, Chapter 4 in relation to the Forest Land category

New technologies

Remotely sensed data from airborne or terrestrial platforms can be useful sources of information for deriving variables relevant for constructing and validating allometric models. They can improve measurements of height, volume and crown dimensions of individual trees that are difficult to collect with traditional ground-based approaches, particularly in dense and complex canopies. They can underpin a new generation of allometric models which have tree height and crown size as explanatory variables (Jucker et al, 2017). Of particular potential is terrestrial laser scanning, offering a means to collect data on tree volume in a non-destructive manner (see Box 2.0c).

BOX 2.0C (NEW)
NEW TECHNOLOGY: TERRESTRIAL LASER SCANNING

Terrestrial laser scanning is a ground-based active remote sensing technique which can be used to derive 3D vegetation structure, and compute key variables such as tree height, stem diameter, crown dimensions and tree volume for above-ground biomass predictions and to develop and validate allometric models (Calders et al., 2015). These under-canopy terrestrial laser systems emit millions of laser pulses that reflect off solid objects such as trunks, branches and leaves and form 3D point clouds. Individual trees can be segmented from plot-scale point cloud data and individual tree point clouds can then be used to reconstruct the woody elements of a tree.

Terrestrial laser scanning provides non-destructive and highly detailed measurements independent of the size and shape of a tree that are otherwise only available from destructive methods (Disney et al., 2018). Aboveground biomass calculated from the point cloud data is independent of allometry and with quantifiable accuracy. Many trees can be sampled and measured in an efficient manner and can provide most of the fundamental data needed to develop new or test the usefulness of existing allometric models for NGHGIs. Terrestrial laser scanning has proven useful for large and complex tropical trees (Gonzalez de Tanago et al., 2018). Terrestrial laser scanners cannot measure belowground or look inside trees, i.e. they do not provide information on wood density or whether a tree is hollow.

B. USING ABOVEGROUND BIOMASS DENSITY MAP CONSTRUCTED FROM REMOTELY SENSED DATA FOR BIOMASS ESTIMATION

Biomass density maps are wall-to-wall, polygon- or pixel-based predictions of above-ground biomass for woody plants and trees.

Consideration when developing biomass density maps

Biomass density maps are constructed by combining remotely sensed data (see Box 2.0d) and field observations. They have been developed at national scales (e.g., Avitabile et al., 2012) as well as for continental to global scales (e.g., Baccini et al., 2012; Saatchi et al., 2011, Avitabile et al., 2016). The characteristics and usefulness of biomass density maps for NGHGIs depend on multiple factors:

1. The definitions for forest and aboveground woody biomass used to produce the map and how this definition relates to the one used in the NGHGI.
2. The type of remotely sensed data sources in terms of spatial resolution, temporal coverage and the degree to which the signal responds to aboveground biomass (sensitivity). The response depends on the type and biomass ranges of the woody plants. Different remote sensing technologies have varying abilities for predicting biomass for different types of woody plants (i.e. boreal versus tropics) and combining remotely sensed data from multiple sources can increase sensitivity and the resulting accuracy of biomass density predictions.
3. The method used to construct the map. Such methods can range from simple interpolation of field estimates of biomass density using spatial covariates to more complex modelling of above-ground woody biomass using field estimates and observed remotely sensed signals.
4. The availability and reliability of biomass estimates obtained from field data needed to produce and validate the biomass density map. Combining co-located remotely sensed data and field observations can be challenging because of the size and shape of the primary elements (i.e. field plot size and shape versus geometric resolution of remotely sensed data), the timing of their acquisition, accuracy of geolocations, and

differences in the variables and parameters that are measured and estimated in the field and predicted from the remotely sensed data.

5. The degree to which map uncertainty is characterized and the manner in which it is used to assess bias and precision for large area estimates in support of NGHGIs (see Volume IV, Chapter 3).

BOX 2.0D (NEW)
REMOTE SENSING TECHNOLOGIES

Optical, Synthetic Aperture Radar (SAR) and Light Detection and Ranging (Lidar) sensors are available currently as remote sensing data sources for producing biomass density maps. Data from optical satellite sensors are classified into three types on the basis of their spatial resolution; coarse resolution data with a pixel size greater than about 250 m (e.g., MODIS), medium resolution data with a pixel size of 10-80 m (e.g., Landsat and Sentinel 1 and 2), and fine resolution data with a pixel size smaller than 10 m (e.g., Rapideye or SPOT and ALOS-2).

SAR and LiDAR are active sensors available as air borne and space borne instruments whose derived metrics are used to predict height, volume or biomass of woody plants and trees. SAR emits microwave pulses obliquely and measures attributes of the pulses that are reflected back from the Earth's surface towards the sensor. In forest land, emitted pulses reflect from the ground, or canopy or trunk of woody plants and trees. Using the strength of the signal of the reflected pulses, volume or biomass of woody plants and trees can be predicted as demonstrated for satellite data from ALOS-PALSAR and Sentinel 1 (Santoro and Cartus, 2018). LiDAR emits laser pulses and measures the traveling time from the sensor to the target which can be converted to distance. When the LiDAR emitter is aimed at woody plants and trees, these laser pulses can be reflected by the woody components, the leaves within the canopy, or the ground surface. Using the difference of a laser pulse reflected from canopy and ground surface, the height, volume or biomass of woody plants and trees can be predicted (Næsset 1997a,b, Lim et al 2003). Starting in 2019, a series of targeted space-based missions will improve the capabilities for forest biomass predictions from LiDAR (e.g. GEDI, ICESAT-2) and SAR (e.g. BIOMASS, NISAR), that might be found useful for national purposes (Herold et al. 2019).

Besides mapping biomass density, there are evolving approaches that monitor changes in biomass density through time directly from remotely sensed data (Baccini et al., 2017). Such approaches require consistent measurements and estimates, and such consistency can be challenging when different satellite data sources and different ways of processing and analysing the data are used. In principle, the direct prediction of wall-to-wall biomass change has the advantage of including all detectable change events, including those occurring in forest remaining forest (i.e., forest degradation and regrowth) which are not considered when a single biomass map is combined with activity data characterizing land use change. However, the sensitivity of the remotely sensed data to subtle biomass changes needs to be carefully evaluated. The mapped biomass change might also not distinguish between anthropogenic or natural causes and not fully characterize all components of the carbon emissions. For example, some carbon loss may have accumulated as dead organic matter (e.g., dead wood or litter), and additional data are usually required to estimate the fate of that initial biomass (e.g., burned, left on site, and removed from the site).

Because above-ground woody biomass is the variable predicted from remotely sensed data, additional information such as country-specific data for root-to-shoot ratios are needed to estimate carbon stocks in other pools.

Guidance on the use of biomass density maps for national GHG inventories

Biomass density maps can be used to enhance the stratification of ground carbon inventories, to improve the estimation of carbon emissions by increasing data density in under-sampled or inaccessible areas, and as an independent data source for verification purposes (provided that the field data were not used to predict the biomass density maps used for stratification).

Use of biomass maps for the estimation of carbon emissions at Tier 2 and Tier 3 levels can be achieved in several ways:

1. Combination with activity data where a biomass density map provides the base to estimate emission factors. Such analyses require consistency among the activity data and biomass maps concerning definitions, geolocation, and spatial and temporal data characteristics. The use of regionally aggregated emission factor analysis (i.e., using average estimates for different forest types, or change trajectories) helps to reduce inherent pixel-level uncertainties in biomass map data for national-scale estimations. Countries have used such an approach to increase data density in areas under-sampled by ground inventories (see Box 2.0e).

2. Estimate biomass change directly from multi-temporal biomass density maps. Such an approach would provide an assessment of carbon stock changes in above-ground biomass from land use change and, in

particular, it would also include changes within forests remaining forests such as degradation and regrowth, management and harvest, and natural disturbances. Such analysis requires consistent and well-calibrated biomass density maps using ground and remotely sensed data to accurately estimate biomass changes; a quality requirement that has so far not been achieved for the NGHGIs at this stage. Improvements in both the field estimates of biomass change and remote sensing technologies and analysis in the coming years can lead to such approaches becoming more efficient and accurate for NGHGI purposes.

3. Biomass density maps can be integrated with remote sensing-assisted, time-series of land change and/or with Tier 3 models to localize emissions estimates. This way the biomass map data can be linked to land and carbon evolution over time that better reflect the complexity of forest-related carbon fluxes. Critical for this type of application is the consistency among the various data sources and models concerning definitions (forest, biomass pools), and, spatial and temporal data characteristics. Map unit uncertainties in biomass maps propagate to larger area estimates and can lead to substantial uncertainties in national emissions estimation if not properly considered.

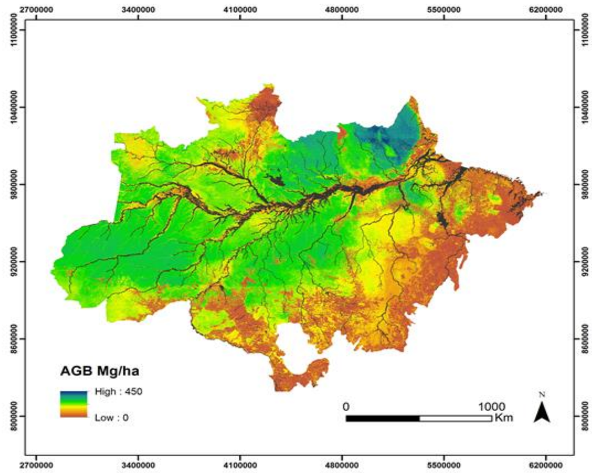
The application of such approaches requires maps well-calibrated for national circumstances. Many available large-area biomass maps, such as global biomass maps, might not be consistent with national definitions of forest and/or biomass pools, and often exhibit large systematic errors in the estimation of carbon stock and changes for national and local assessments (Avitabile et al., 2016). Since countries may have national products, including biomass maps, large-area biomass maps can be useful for the purpose of independent comparison and verification. Depending on how a map is produced and how it is used to enhance NGHGIs, additional metadata on the applied models and procedures used to produce the map, such as for example the covariance matrix of model parameters of a model that was used to generate the map (see Volume 1, Chapter 6, section 6.1.4.2), may be required for characterization and reporting of uncertainty in a fully compliant way, particularly for application to country-specific circumstances.

BOX 2.0E (NEW)
USING A BIOMASS MAP FOR GHG ESTIMATION: AN EXAMPLE FROM THE BRAZILIAN AMAZON

Brazil is applying a methodology for estimating forest biomass combining data from airborne LiDAR, satellite remote sensing and forest inventories. The aim for using the biomass map for the NGHGI is to provide coverage over the whole Amazon where the availability and quality of ground data varies. Deforestation and associated land use change in the Amazon are heterogeneous and patchy. Related estimates of carbon emissions carry some level of uncertainty unless this spatial variability in both types of change and biomass variability is captured.

The methodology to estimate the biomass was based on 1,000 LiDAR transects randomly distributed across 3.5 million km^2 of the Amazon forests. Aboveground biomass is estimated at three different levels. At field plot level (first level), the data are used to validate the biomass estimated by LiDAR (second level) by adopting and using the models and data provided by Chave et al 2014 and Longo et al 2016. A total of 407 field plots were used for this validation. At the third level the biomass was estimated by extrapolating the biomass to the Brazilian Amazon Biome by the use of MODIS vegetation index, Shuttle Radar Topography Mission data, precipitation data from the Tropical Rainfall Measuring Mission and Synthetic Aperture Radar data of the Phased Array type L-band Synthetic Aperture Radar, soil and vegetation maps. A nonparametric regression method (Random Forest) is used for correlating the above ground biomass within the LiDAR transects to a list of variables, and then used for the extrapolation of the biomass to the region. The coefficient of determination and the root mean squared error between the third level extrapolated biomass data and the LiDAR data were R2=0.7485 and RMSE=27.18 MgCha^{-1}, respectively. In this process, the SRTM elevation data were the most important variable for the biomass extrapolation process, followed by the TRMM precipitation data and Enhanced Vegetation Index data. The estimated biomass map uncertainty is calculated by propagating the uncertainties through the different levels of biomass estimation, i.e., field plots, LiDAR and satellite (Longo et al 2016). This process allows us to obtain total uncertainty estimates for each pixel in the final biomass map.

BOX 2.0E (NEW) (CONTINUED)
USING A BIOMASS MAP FOR GHG ESTIMATION: AN EXAMPLE FROM THE BRAZILIAN AMAZON



Biomass map of the Amazon biome in Brazil (Ometto et al. 2018)

2.3.2 Change in carbon stocks in dead organic matter

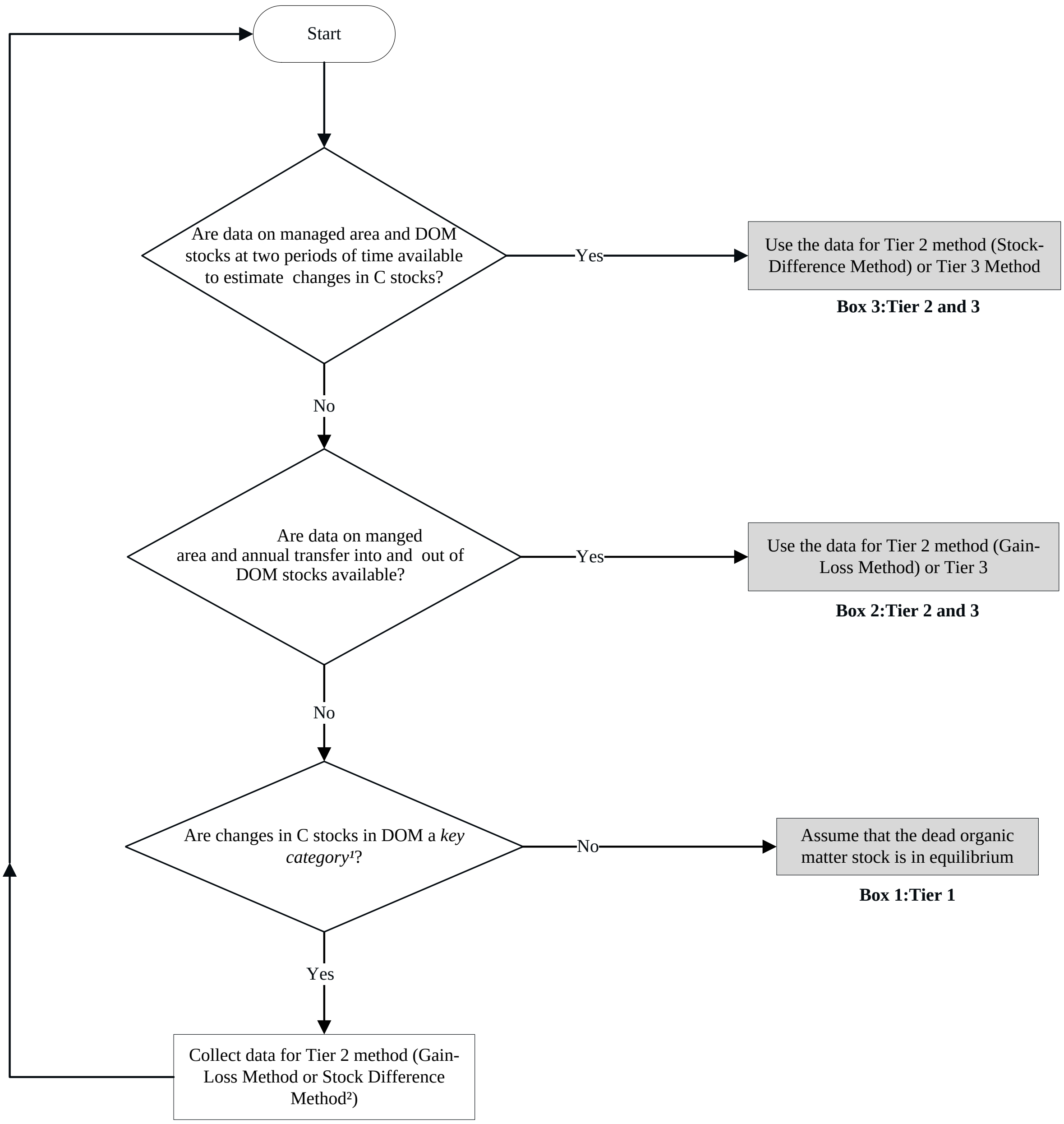
No refinement in Introduction.

2.3.2.1 LAND REMAINING IN A LAND-USE CATEGORY

The Tier 1 assumption for both dead wood and litter pools (see table 1.1 for definitions) for all land-use categories is that their stocks are not changing over time if the land remains within the same land-use category. Thus, the carbon in biomass killed during a disturbance or management event (less removal of harvested wood products) is assumed to be released entirely to the atmosphere in the year of the event. This is equivalent to the assumption that the carbon in non-merchantable and non-commercial components that are transferred to dead organic matter is equal to the amount of carbon released from dead organic matter to the atmosphere through decomposition and oxidation. Countries can use higher tier methods to estimate the carbon dynamics of dead organic matter. This section describes estimation methods if Tier 2 (or 3) methods are used.

Countries that use Tier 1 methods to estimate dead organic matter (DOM) pools in land remaining in the same land-use category, report zero changes in carbon stocks or carbon emissions from those pools. Following this rule, CO_2 emissions resulting from the combustion of dead organic matter during fire are not reported, nor are the increases in dead organic matter carbon stocks in the years following fire. However, emissions of non-CO_2 gases from burning of DOM pools are reported. Tier 2 methods for estimation of carbon stock changes in DOM pools calculate the changes in dead wood and litter carbon pools (Equation 2.17). Two methods can be used: either track inputs and outputs (the *Gain-Loss Method*, Equation 2.18) or estimate the difference in DOM pools at two points in time (*Stock-Difference Method*, Equation 2.19). These estimates require either detailed inventories that include repeated measurements of dead wood and litter pools, or models that simulate dead wood and litter dynamics. It is *good practice* to ensure that such models are tested against field measurements and are documented. Figure 2.3 provides the decision tree for identification of the appropriate tier to estimate changes in carbon stocks in dead organic matter.

Figure 2.3 Generic decision tree for identification of appropriate tier to estimate changes in carbon stocks in dead organic matter for a land-use category



Note:
1: See Volume 1 Chapter 4 "Methodological Choice and Identification of key Categories" (noting Section 4.1.2 on limited resources), for discussion of *key categories* and use of decision trees
2: The two methods are defined in Equations 2.18 and 2.19, respectively.

Equation 2.17 summarizes the calculation to estimate the annual changes in carbon stock in DOM pools:

EQUATION 2.17
ANNUAL CHANGE IN CARBON STOCKS IN DEAD ORGANIC MATTER

$$\Delta C_{DOM} = \Delta C_{DW} + \Delta C_{LT}$$

Where:

ΔC_{DOM} = annual change in carbon stocks in dead organic matter (includes dead wood and litter), tonnes C yr^{-1}

ΔC_{DW} = change in carbon stocks in dead wood, tonnes C yr^{-1}

ΔC_{LT} = change in carbon stocks in litter, tonnes C yr^{-1}

The changes in carbon stocks in the dead wood and litter pools for an area remaining in a land-use category between inventories can be estimated using two methods, described in Equation 2.18 and Equation 2.19. The same equation is used for dead wood and litter pools, but their values are calculated separately.

EQUATION 2.18
ANNUAL CHANGE IN CARBON STOCKS IN DEAD WOOD OR LITTER (GAIN-LOSS METHOD)

$$\Delta C_{DOM} = A \bullet \{(DOM_{in} - DOM_{out}) \bullet CF\}$$

Where:

ΔC_{DOM} = annual change in carbon stocks in the dead wood/litter pool, tonnes C yr^{-1}

A = area of managed land, ha

DOM_{in} = average annual transfer of biomass into the dead wood/litter pool due to annual processes and disturbances, tonnes d.m. ha^{-1} yr^{-1} (see next Section for further details).

DOM_{out} = average annual decay and disturbance carbon loss out of dead wood or litter pool, tonnes d.m. ha^{-1} yr^{-1}

CF = carbon fraction of dry matter, tonne C (tonne d.m.)$^{-1}$

The net balance of DOM pools specified in Equation 2.18, requires the estimation of both the inputs and outputs from annual processes (litterfall and decomposition) and the inputs and losses associated with disturbances. In practice, therefore, Tier 2 and Tier 3 approaches require estimates of the transfer and decay rates as well as activity data on harvesting and disturbances and their impacts on DOM pool dynamics. Note that the biomass inputs into DOM pools used in Equation 2.18 are a subset of the biomass losses estimated in Equation 2.7. The biomass losses in Equation 2.7 contain additional biomass that is removed from the site through harvest or lost to the atmosphere, in the case of fire.

The method chosen depends on available data and will likely be coordinated with the method chosen for biomass carbon stocks. Transfers into and out of a dead wood or litter pool for Equation 2.18 may be difficult to estimate. The stock difference method described in Equation 2.19 can be used by countries with forest inventory data that include DOM pool information, other survey data sampled according to the principles set out in Annex 3A.3 (Sampling) in Chapter 3, and/or models that simulate dead wood and litter dynamics.

When the gain – loss method is chosen, inventory measurements may provide estimates for DOM stocks. Alternatively, relevant information on transfers out of the litter and dead wood pools through decomposition can be found in the literature. Care must be taken not to confound decomposition flow "rates" and decomposition "rate-constants" (e.g., k's) when DOM_{out} is estimated. DOM_{out} using the second approach is the product of the rate-constant describing the proportion lost per year and the stock of DOM (e.g., DOM_{out} = k *DOM). One should be aware that decomposition rate-constants describe total losses and not just those via respiration. The fate of leached and fragmented carbon is not well understood; much of the material is likely respired but whether this is slower or faster than the source material is highly variable. Negative exponential decay models are commonly used to determine the decomposition rate-constants that characterize the volume, mass, or density loss in dead wood and litter over time (Cook et al. 2016, Harmon et al. 2000, Russell et al. 2014). While models to predict volume, biomass, or density loss are relatively simple, the decomposition rate-constants may vary substantially. The decomposition of dead wood and litter mass is driven by many factors including: woodiness (i.e., wood and bark versus foliage); position (i.e., standing versus downed dead wood); species of the material decomposing; state of decomposition (i.e., fresh versus highly decomposed) and decomposers present (e.g., the presence of termites and/or soil biota); climate under the canopy (for example condition by openness of the canopy) (Lavelle et al., 1993; Hattenschwiler et al., 2005, Harmon et al. 2011, García-Palacios et al., 2013, Russell et al., 2014, Filser et al. 2016, Chertov et al. 2017, Hu et al., 2017, Kornarnov et al. 2017), among others. Having specific information on these attributes will help to assign a specific decomposition constant to a particular DOM stock (Rock et al. 2008).

EQUATION 2.19
ANNUAL CHANGE IN CARBON STOCKS IN DEAD WOOD OR LITTER (STOCK-DIFFERENCE METHOD)

$$\Delta C_{DOM} = \left[A \bullet \frac{(DOM_{t_2} - DOM_{t_1})}{T} \right] \bullet CF$$

Where:

ΔC_{DOM} = annual change in carbon stocks in dead wood or litter, tonnes C yr^{-1}

A = area of managed land, ha

DOM_{t_1} = dead wood/litter stock at time t_1 for managed land, tonnes d.m. ha^{-1}

DOM_{t_2} = dead wood/litter stock at time t_2 for managed land, tonnes d.m. ha^{-1}

$T = (t_2 - t_1)$ = time period between time of the second stock estimate and the first stock estimate, yr

CF = carbon fraction of dry matter (default for litter = 0.37 (Smith & Heath 2002), default for dead wood (temperate species) = 0.5 tonne C (tonne d.m.)$^{-1}$

Note that whenever the stock change method is used (e.g., in Equation 2.19), the area used in the carbon stock calculations at times t_1 and t_2 must be identical. If the area is not identical then changes in area will confound the estimates of carbon stocks and stock changes. It is *good practice* to use the area at the end of the inventory period (t_2) to define the area of land remaining in the land-use category. The stock changes on all areas that change land-use category between t_1 and t_2 are estimated in the new land-use category, as described in the sections on land converted to a new land category.

INPUT OF BIOMASS TO DEAD ORGANIC MATTER

Whenever a tree is felled, non-merchantable and non-commercial components (such as tops, branches, leaves, roots, and non-commercial trees) are left on the ground and transferred to dead organic matter pools. In addition, annual mortality can add substantial amounts of dead wood to that pool. For Tier 1 methods, the assumption is that the carbon contained in all biomass components that are transferred to dead organic matter pools will be released in the year of the transfer, whether from annual processes (litterfall and tree mortality), land management activities, fuelwood gathering, or disturbances. For estimation procedures based on higher Tiers, it is necessary to estimate the amount of biomass carbon that is transferred to dead organic matter. The quantity of biomass transferred to DOM is estimated using Equation 2.20.

EQUATION 2.20
ANNUAL CARBON IN BIOMASS TRANSFERRED TO DEAD ORGANIC MATTER

$$DOM_{in} = \{L_{mortality} + L_{slash} + (L_{disturbance} \bullet f_{BLol})\}$$

Where:

DOM_{in} = total carbon in biomass transferred to dead organic matter, tonnes C yr^{-1}

$L_{mortality}$ = annual biomass carbon transfer to DOM due to mortality, tonnes C yr^{-1} (See Equation 2.21)

L_{slash} = annual biomass carbon transfer to DOM as slash, tonnes C yr^{-1} (See Equations 2.22)

$L_{disturbance}$ = annual biomass carbon loss resulting from disturbances, tonnes C yr^{-1} (See Equation 2.14)

f_{BLol} = fraction of biomass left to decay on the ground (transferred to dead organic matter) from loss due to disturbance. As shown in Table 2.1, the disturbance losses from the biomass pool are partitioned into the fractions that are added to dead wood (cell B in Table 2.1) and to litter (cell C), are released to the atmosphere in the case of fire (cell F) and, if salvage follows the disturbance, transferred to HWP (cell E).

Note: If root biomass increments are counted in Equation 2.10, then root biomass losses must also be counted in Equations 2.20, and 2.22.

Examples of the terms on the right-hand side of Equation 2.20 are obtained as follows:

Transfers to dead organic matter from mortality, $L_{mortality}$

Mortality is caused by competition during stand development, age, diseases, and other processes that are not included as disturbances. Mortality cannot be neglected when using higher Tier estimation methods. In extensively managed stands without periodic partial cuts, mortality from competition during the stem exclusion phase, may represent 30-50 percent of total productivity of a stand during its lifetime. In regularly tended stands, additions to the dead organic matter pool from mortality may be negligible because partial cuts extract forest biomass that would otherwise be lost to mortality and transferred to dead organic matter pools. Available data for increment will normally report net annual increment, which is defined as net of losses from mortality. Since in this text, net annual growth is used as a basis to estimate biomass gains, mortality must not be subtracted again as a loss from biomass pools. Mortality must, however, be counted as an addition to the dead wood pool for Tier 2 and Tier 3 methods.

The equation for estimating mortality is provided in Equation 2.21:

EQUATION 2.21
ANNUAL BIOMASS CARBON LOSS DUE TO MORTALITY

$$L_{mortality} = \sum (A \bullet G_W \bullet CF \bullet m)$$

Where:

$L_{mortality}$ = annual biomass carbon transfer to DOM due to mortality, tonnes C yr^{-1}

A = area of land remaining in the same land use, ha

G_W = above-ground biomass growth, tonnes d.m. ha^{-1} yr^{-1} (see Equation 2.10)

CF = carbon fraction of dry matter, tonne C (tonne d.m.)$^{-1}$

m = mortality rate expressed as a fraction of above-ground biomass growth

When data on mortality rates are expressed as proportion of growing stock volume, then the term Gw in Equation 2.21 should be replaced with growing stock volume to estimate annual transfer to DOM pools from mortality.

Mortality rates differ between stages of stand development and are highest during the stem exclusion phase of stand development. They also differ with stocking level, forest type, management intensity and disturbance history. Thus, providing default values for an entire climatic zone is not justified because the variation within a zone will be much larger than the variation between zones.

Annual carbon transfer to slash, L_{slash}

This involves estimating the quantity of slash left after wood removal or fuelwood removal and transfer of biomass from total annual carbon loss due to wood harvest (Equation 2.12). The estimate for logging slash is given in Equation 2.22 and which is derived from Equation 2.12 as explained below:

EQUATION 2.22
ANNUAL CARBON TRANSFER TO SLASH

$$L_{slash} = \left[\left\{ H \bullet BCEF_R \bullet (1+R) \right\} - \left\{ H \bullet D \right\} \right] \bullet CF$$

Where:

L_{slash} = annual biomass carbon transfer to DOM as slash, tonnes C yr^{-1}, including dead roots, tonnes C yr^{-1}

H = annual wood harvest (wood or fuelwood removal), m^3 yr^{-1}

$BCEF_R$ = biomass conversion and expansion factors applicable to wood removals, which transform merchantable volume of wood removal into above-ground biomass removals, tonnes biomass removal (m^3 of removals)$^{-1}$. If $BCEF_R$ values are not available and if BEF and Density values are separately estimated then the following conversion can be used:

$$BCEF_R = BEF_R \bullet D$$

- D is basic wood density, tonnes d.m. m^{-3}
- Biomass Expansion Factors (BEF_R) expand merchantable wood removals to total aboveground biomass volume to account for non-merchantable components of the tree, stand and forest. BEF_R is dimensionless.

R = ratio of below-ground biomass to above-ground biomass, in tonne d.m. below-ground biomass (tonne d.m. above-ground biomass)$^{-1}$. R must be set to zero if root biomass increment is not included in Equation 2.10 (Tier 1)

CF = carbon fraction of dry matter, tonne C (tonne d.m.)$^{-1}$

Fuelwood gathering that involves the removal of live tree parts does not generate any additional input of biomass to dead organic matter pools and is not further addressed here.

Inventories using higher Tier methods can also estimate the amount of logging slash remaining after harvest by defining the proportion of above-ground biomass that is left after harvest (enter these proportions in cells B and C of Table 2.2 for harvest disturbance) and by using the approach defined in Equation 2.14. In this approach, activity data for the area harvested would also be required.

2.3.2.2 LAND CONVERSION TO A NEW LAND-USE CATEGORY

The reporting convention is that all carbon stock changes and non-CO_2 greenhouse gas emissions associated with a land-use change be reported in the new land-use category. For example, in the case of conversion of Forest Land to Cropland, both the carbon stock changes associated with the clearing of the forest as well as any subsequent carbon stock changes that result from the conversion are reported under the Cropland category.

The Tier 1 assumption is that DOM pools in non-forest land categories after the conversion are zero, i.e., they contain no carbon. The Tier 1 assumption for land converted from forest to another land-use category is that all DOM carbon losses occur in the year of land-use conversion. Conversely, conversion to Forest Land results in build-up of litter and dead wood carbon pools starting from zero carbon in those pools. DOM carbon gains on land converted to forest occur linearly, starting from zero, over a transition period (default assumption is 20 years). This default period may be appropriate for litter carbon stocks, but in temperate and boreal regions it is probably too short for dead wood carbon stocks. Countries that use higher Tier methods can accommodate longer transition periods by subdividing the remaining category to accommodate strata that are in the later stages of transition.

The estimation of carbon stock changes during transition periods following land-use conversion requires that annual cohorts of the area subject to land-use change be tracked for the duration of the transition period. For example, DOM stocks are assumed to increase for 20 years after conversion to Forest Land. After 20 years, the area converted enters the category *Forest Land Remaining Forest Land*, and no further DOM changes are assumed, if a Tier 1 approach is applied. Under Tier 2 and 3, the period of conversion can be varied depending on vegetation and other factors that determine the time required for litter and dead wood pools to reach steady state.

Higher Tier estimation methods can use non-zero estimates of litter and dead wood pools in the appropriate land-use categories or subcategories. For example, settlements and agro-forestry systems can contain some litter and dead wood pools, but because management, site conditions, and many other factors influence the pool sizes, no global default values can be provided here. Higher Tier methods may also estimate the details of dead organic matter inputs and outputs associated with the land-use change.

The conceptual approach to estimating changes in carbon stocks in dead wood and litter pools is to estimate the difference in C stocks in the old and new land-use categories and to apply this change in the year of the conversion (carbon losses), or to distribute it uniformly over the length of the transition period (carbon gains) Equation 2.23:

EQUATION 2.23
ANNUAL CHANGE IN CARBON STOCKS IN DEAD WOOD AND LITTER DUE TO LAND CONVERSION

$$\Delta C_{DOM} = \frac{(C_n - C_o) \bullet A_{on}}{T_{on}}$$

Where:

ΔC_{DOM} = annual change in carbon stocks in dead wood or litter, tonnes C yr^{-1}

C_o = dead wood/litter stock, under the old land-use category, tonnes C ha^{-1}

C_n = dead wood/litter stock, under the new land-use category, tonnes C ha^{-1}

A_{on} = area undergoing conversion from old to new land-use category, ha

T_{on} = time period of the transition from old to new land-use category, yr. The Tier 1 default is 20 years for carbon stock increases and 1 year for carbon losses.

Inventories using a Tier 1 method assume that all carbon contained in biomass killed during a land-use conversion event (less harvested products that are removed) is emitted directly to the atmosphere and none is added to dead wood and litter pools. Tier 1 methods also assume that dead wood and litter pool carbon losses occur entirely in the year of the transition.

Countries using higher Tier methods can modify C_o in Equation 2.23 by first accounting for the immediate effects of the land-use conversion in the year of the event. In this case, they would add to C_o the carbon from biomass killed and transferred to the dead wood and litter pools and remove from C_o any carbon released from dead wood and litter pools, e.g., during slash burning. In that case C_o in Equation 2.23 would represent the dead wood or litter carbon stocks immediately after the land-use conversion. C_o will transit to C_n over the transition period, using linear or more complex dynamics. A disturbance matrix (Table 2.1) can be defined to account for the pool transitions and releases during the land-use conversion, including the additions and removals to C_o.

Countries using a Tier 1 approach can apply the Tier 1 default carbon stock estimates for litter, and if available dead wood pools, provided in Table 2.2, but should recognize that these are broad-scale estimates with considerable uncertainty when applied at the country level. Table 2.2 is incomplete because of the paucity of published data. A review of the literature has identified several problems. The IPCC definitions of dead organic matter carbon stocks include litter and dead wood. The litter pool contains all litter plus fine woody debris up to a diameter limit of 10 cm (see Chapter 1, Table 1.1). Published litter data generally do not include the fine woody debris component, so the litter values in Table 2.2 are incomplete.

There are numerous published studies of coarse woody debris (Harmon and Hua, 1991; Karjalainen and Kuuluvainen, 2002) and a few review papers (e.g., Harmon *et al.*, 1986), and but to date only two studies are found to provide regional dead wood carbon pool estimates that are based on sample plot data. Krankina *et al.* (2002) included several regions in Russia and reported coarse woody debris (> 10 cm diameter) estimates of 2 to 7 Mg C ha^{-1}. Cooms *et al.* (2002) reported regional carbon pools based on a statistical sample design for a small region in New Zealand. Regional compilations for Canada (Shaw *et al.*, 2005) provide estimates of litter carbon pools based on a compilation of statistically non-representative sample plots, but do not include estimates of dead wood pools. Review papers such as Harmon *et al.* (1986) compile a number of estimates from the literature. For example, their Table 5 lists a range of coarse woody debris values for temperate deciduous forests of 11 – 38 Mg dry matter ha^{-1} and for temperate coniferous forests of 10 – 511 Mg dry matter ha^{-1}. It is, however, statistically invalid to calculate a mean from these compilations as they are not representative samples of the dead wood pools in a region.

While it is the intent of these IPCC Guidelines to provide default values for all variables used in Tier 1 methodologies, it is currently not feasible to provide estimates of regional defaults values for litter (including fine woody debris < 10 cm diameter) and dead wood (> 10 cm diameter) carbon stocks. Litter pool estimates (excluding fine woody debris) are provided in Table 2.2. Tier 1 methodology only requires the estimates in Table 2.2 for lands converted from Forest Land to any other land-use category (carbon losses) and for lands converted to Forest Land (carbon gains). Tier 1 methods assume that litter and dead wood pools are zero in all non-forest categories and therefore transitions between non-forest categories involve no carbon stock changes in these two pools.

TABLE 2.2 (UPDATED)
TIRE 1 DEFAULT VALUES FOR LITTER AND DEAD WOOD CARBON STOCKS

Climate [1]	Forest type						
	Broadleaf deciduous		Needleleaf evergreen		All vegetation types		References[2]
	Litter carbon stocks (tonnes C ha^{-1})						
	Mean	Min/Max	Mean	Min/Max	Mean	Min/Max	
Boreal coniferous forest	19.1	4.0-38.7	40.3	4.0-117.4	31.4	4.0-117.4	93, 98, 99, 100, 101
Boreal tundra woodland	29.3	23.7-33.7	67.4	23.7-85.1	49.5	23.7-85.1	100, 101
Polar	n.a	n.a	n.a	n.a	n.a	n.a	n.a.
Subtropical desert	n.a	n.a	n.a	n.a	n.a	n.a	n.a.
Subtropical humid forest	5.6	4.4-8.1	6.8	4.7-11.6	8.7	1.2-24.0	6, 7, 44, 93, 98, 99, 103
Subtropical mountain system	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Subtropical steppe	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Temperate continental forest	23.9	4.6-64.4	66.3	6.0-279.1	47.8	4.6-279.1	93, 98, 99, 100, 101
Temperate desert	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Temperate mountain system	3.4	n.a.	3.9	n.a.	3.7	3.4-3.9	98
Temperate oceanic forest	n.a.	n.a.	n.a.	n.a.	2.9	n.a.	15
Temperate steppe	36.9	7.6-98.8	26.4	7.1-43.0	28.7	3.8-98.8	97, 98, 100, 101
Tropical dry forest	n.a.	n.a.	n.a.	n.a.	2.4	2.1-2.7	11
Tropical moist forest	4.3	2.0-9.0	14.8	n.a.	5.9	1.9-14.8	21, 93, 98
Tropical mountain system	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Tropical rainforest	2.5	n.a.	4.7	n.a.	4.8	2.1-16.4	11, 26, 35, 89, 93, 99
Climate	Dead wood carbon stocks (tonnes C ha^{-1})						
	Min/Max	Min/Max	Min/Max	Min/Max	Min/Max	Min/Max	Min/Max
Boreal coniferous forest	16.4	2.3-50.7	22.2	4.1-76.5	19.7	2.3-76.5	46, 54, 55, 56, 59, 62, 63, 70, 81, 87, 88, 93
Boreal tundra woodland	5.7	n.a.	1.3	0.5-2.4	3.1	0.5-6.1	5, 70
Polar	n.a	n.a	26.2	n.a.	26.2	n.a.	70
Subtropical desert	n.a	n.a	64.4	14.4-134.5	64.4	14.4-134.5	40
Subtropical humid forest	4.1	2.5-7.5	10.9	3.5-32.8	13.2	0.2-43.8	6,7,44, 46, 68, 93
Subtropical mountain system	n.a.	n.a.	11.8	7.2-16.3	11.8	7.2-16.3	77

TABLE 2.2 (UPDATED) (CONTINUED)
TIRE 1 DEFAULT VALUES FOR LITTER AND DEAD WOOD CARBON STOCKS

Climate [1]	Forest type						
	Broadleaf deciduous		Needleleaf evergreen		All vegetation types		References[2]
	Dead wood carbon stocks (tonnes C ha^{-1})						
	Mean	Min/Max	Mean	Min/Max	Mean	Min/Max	
Subtropical steppe	n.a.	n.a.	6.8	6.0-7.7	6.8	6.0-7.7	27
Temperate continental forest	23.6	1.6-150.0	22.1	2.1-59.5	23.0	1.6-150.0	1, 2, 23, 28, 36, 37, 46, 54, 55, 64, 70, 80, 83, 87, 92, 93, 95,110
Temperate desert	n.a.	n.a.	10.5	n.a.	10.5	n.a.	22
Temperate mountain system	21.2	2.8-80.6	48.1	1.7-181.8	37.6	1.7-181.8	3, 9, 10, 12, 13, 17, 25, 29, 30, 31, 33, 34, 39, 41, 50, 57, 58, 60, 67, 68, 69, 71, 75, 76, 78, 82, 84, 90, 91, 105, 109
Temperate oceanic forest	40.5	2.8-95.0	24.3	n.a.	36.8	2.8-95.0	15, 16, 24, 32, 52, 61, 85, 86
Temperate steppe	26.2	9.7-50.0	8.0	n.a	21.7	8.0 -50.0	4, 70, 83, 98
Tropical dry forest	16.0	14.7-17.3	n.a.	n.a.	9.0	1.3-17.3	11, 20
Tropical moist forest	8.4	1.2-21.2	3.4	n.a.	8.0	1.2-21.2	19, 20, 21, 38, 4893, 96, 107
Tropical mountain system	3.3	n.a.	n.a.	n.a.	3.3	n.a.	20
Tropical rainforest	17.7	0.9-218.9	1.9	n.a.	14.8	0.6-218.9	11, 14, 18, 26, 35, 42, 43, 45, 46, 47, 49, 51, 53, 65, 66, 72, 73, 74, 79, 89, 93, 94, 104, 105, 107, 108

[1] FAO. 2012. Forest Resources Assessment Working Paper 179.

[2] References: 1Canada NFI, 2006; 2Alban and Perala, 1992; 3Arthur and Fahey, 1992; 4Barney and Fahey, 1992; 5Barney and Van Cleve, 1973; 6Beets et al. 2011; 7Beets et al. 2014; 8Beets, 1980; 9Bingham and Sawyer Jr., 1988; 10Blackwell et al., 1992; 11FRA2015, Brazil; 12Brown and See, 1981; 13Busing, 1998; 14Chambers et al., 2000; 15FRA2015, Chile; 16Christensen, 1977; 17Clark et al., 1998; 18Cochrane et al., 1999; 19Collins, 1981; 20Delaney et al., 1998; 21FRA2015, Ecuador; 22Fahey, 1983; 23Falinski, 1978; 24Frangi et al., 1997; 25Franklin et al., 1984; 26FRA2015, French Guyana; 27Fule and Covington, 1994; 28Goodburn and Lorimer, 1998; 29Gore and Patterson, III, 1986; 30Gosz, 1980; 31Grahom and Cromack, 1982; 32Green and Peterken, 1998; 33Grier, 1978; 34Grier et al., 1981; 35FRA2015, Guyana; 36Hale et al., 1999; 37Harmon and Chen, 1991; 38Harmon et al., 1995; 39Harmon et al., 1986; 40Harmon et al., 1987; 41Harmon, 1980; 42Higucki and Biot, 1995; 43Hofer et al., 1996; 44Holdaway et al., 2017; 45Hughes et al., 2000; 46Japanese NFI, 2018; 47John, 1973; 48Jordan, 1989; 49Kauffman and Uhl, 1990; 50Keenan et al., 1993; 51Kira, 1978; 52Kirby et al., 1998; 53Klinge, 1973; 54Krankina et al., 1999; 55Krankina, Unpublished; 56Lamas and Fries, 1994; 57Lambert et al., 1980; 58Lang, 1985; 59Lee et al., 1997; 60Lesica et al., 1990; 61Levett et al., 1985; 62Linder and Ostlund, 1992; 63Linder et al. 1997; 64MacMillan, 1981; 65Martinelli et al., 1988; 66Martius, 1997; 67McCarthy and Bailey, 1994; 68McMinn and Hardt, 1996; 69Muller and Liu, 1991; 70Canada NFI, 2018b; 71Nicholas and White, 1984; 72Proctor et al. 1983; 73Revilla, 1987; 74Robertson and Daniel, 1989; 75Robertson and Bowser, 1999; 76Roskoski, 1980; 77Sackett, 1980; 78Sackett, 1979; 79Saldarriaga et al., 1988; 80Shifley et al., 1997; 81Sippola, 1998; 82Sollins, 1982; 83Spetich et al., 1999; 84Spies et al., 1988; 85Stewart and Burrows, 1994; 86Stokland, ; 87Storozhenko, 1997; 88Sturtevant et al., 1997; 89FRA2015, Suriname; 90Taylor and Fonda, 1990; 91Tritton 1980; 92Tyrrell and Crow, 1994; 93Ugawa et al., 2012; 94Uhl et al., 1988; 95van Hees and Clerkx, 1999; 96Zhou et al.,; 97FRA2015, Argentina; 98Domke et al., 2016; 99Japan NFI, 2018; 100Canada NFI, 2018; 101Canada NFI, 2018a; 102Shaw et al. 2005; 103Beets et al., 2012; 104Klinge et al., 1975; 105Kaufman et al., 1988; 106Nicholas and White, 1985; 107Revilla, 1986; 108Revilla, 1988; 109Sollins et al., 1980; 110Lang and Forman, 1978

n.a. denotes 'not available'

2.3.3 Change in carbon stocks in soils

Although both organic and inorganic forms of C are found in soils, land use and management typically has a larger impact on organic C stocks. Consequently, the methods provided in these guidelines focus mostly on soil organic C. Overall, the influence of land use and management on soil organic C is dramatically different in a mineral versus an organic soil type. Organic (e.g., peat and muck) soils have a minimum of 12 percent organic C by mass (see Chapter 3 Annex 3A.5, for the specific criteria on organic soil classification), and develop under poorly drained conditions of wetlands (Brady & Weil 1999). All other soils are classified as mineral soil types, and typically have relatively low amounts of organic matter, occurring under moderate to well drained conditions, and predominate in most ecosystems except wetlands. Discussion about land-use and management influences on these contrasting soil types is provided in the next two sections.

MINERAL SOILS

Mineral soils contain an organic carbon pool that is influenced by land-use and management activities. Land use can have a large effect on the size of this pool through activities such as conversion of native Grassland and Forest Land to Cropland, where 20-40 percent of the original soil C stocks can be lost (Mann 1986; Davidson & Ackerman 1993; Ogle *et al.* 2005). Within a land-use type, a variety of management practices can also have a significant impact on soil organic C storage, particularly in Cropland and Grassland (e.g., Paustian *et al.* 1997; Conant *et al.* 2001; Ogle *et al.* 2004 and 2005). In principle, soil organic C stocks can change with management or disturbance if the net balance between C inputs and C losses from soil is altered. Management activities influence organic C inputs through changes in plant production (such as fertilisation or irrigation to enhance crop growth), direct additions of C in organic amendments, and the amount of carbon left after biomass removal activities, such as crop harvest, timber harvest, fire, or grazing. Decomposition largely controls C outputs and can be influenced by changes in moisture and temperature regimes as well as the level of soil disturbance resulting from the management activity. Other factors also influence decomposition, such as climate and edaphic characteristics. Specific effects of different land-use conversions and management regimes are discussed in the land-use specific chapters (Chapters 4 to 9).

Land-use change and management activity can also influence soil organic C storage by changing erosion rates and subsequent loss of C from a site; some eroded C decomposes in transport and CO_2 is returned to the atmosphere, while the remainder is deposited in another location. The net effect of changing soil erosion through land management is highly uncertain, however, because an unknown portion of eroded C is stored in buried sediments of wetlands, lakes, river deltas and coastal zones (Smith *et al.* 2001).

ORGANIC SOILS

No refinement. See Chapter 2, Sections 2.2 and 2.3 of the *2013 Wetlands Supplement.*

2.3.3.1 SOIL ORGANIC C ESTIMATION METHODS (LAND REMAINING IN A LAND-USE CATEGORY AND LAND CONVERSION TO A NEW LAND USE)

Soil C inventories include estimates of soil organic C stock changes for mineral soils and CO_2 emissions from organic soils due to enhanced microbial decomposition caused by drainage and associated management activity. In addition, inventories can address C stock changes for soil inorganic C pools (e.g., calcareous grassland that become acidified over time) if sufficient information is available to use a Tier 3 approach. The equation for estimating the total change in soil C stocks is given in Equation 2.24:

EQUATION 2.24 (UPDATED)
ANNUAL CHANGE IN CARBON STOCKS IN SOILS

$$\Delta C_{Soils} = \Delta C_{Mineral} - L_{Organic} + \Delta C_{Inorganic}$$

Where:

ΔC_{Soils} = annual change in carbon stocks in soils, tonnes C yr^{-1}

$\Delta C_{Mineral}$ = annual change in organic carbon stocks in mineral soils, tonnes C yr^{-1}

$L_{Organic}$ = annual loss of carbon from drained organic soils, tonnes C yr^{-1}

$\Delta C_{Inorganic}$ = annual change in inorganic carbon stocks from soils, tonnes C yr^{-1} (assumed to be 0 unless using a Tier 3 approach)

For Tier 1 methods, soil organic C stocks for mineral soils are computed to a default depth of 30 cm because default reference soil organic C stocks (SOC_{REF} – see Equation 2.25 and Table 2.3) and stock change factors (e.g. F_{LU}, F_{MG} and F_I see Equation 2.25) are based on a 30 cm depth. In addition, the reference condition is defined as that present in native lands (i.e. non-degraded, unimproved lands under native vegetation) for the default reference soil organic C stocks (SOC_{REF}). For Tier 2, a different reference condition and depth can be used as described in the section on Tier 2 methods. Residue/litter C stocks are not included in Tier 1 because they are addressed by estimating dead organic matter stocks (see section 2.3.2). Inventories can also estimate the change in mineral soil organic C stock due to biochar amendments to soils (Tier 2 and Tier 3 only). Stock changes in organic soils are based on emission factors that represent the annual loss of organic C throughout the profile due to drainage and associated management activity.

No Tier 1 or 2 methods are provided for estimating the change in soil inorganic C stocks ($\Delta C_{Inorganic}$) due to limited scientific data for derivation of stock change factors; thus, the net flux for inorganic C stocks is assumed to be zero. Tier 3 methods could be developed to estimate changes in the stock of inorganic carbon in mineral or organic soils.

It is possible that compilers will use different tiers to prepare estimates for mineral soils, organic soils, biochar amendments and soil inorganic C, depending on the availability of resources. Thus, stock changes are discussed separately for organic carbon in mineral and organic soils and for inorganic C pools (Tier 3 only). Generalised decision trees in Figures 2.4 and 2.5 can be used to assist inventory compilers in determining the appropriate tier for estimating stock changes for mineral and organic soil C, respectively.

Figure 2.4 Generic decision tree for identification of appropriate tier to estimate changes in carbon stocks in mineral soils by land-use category.

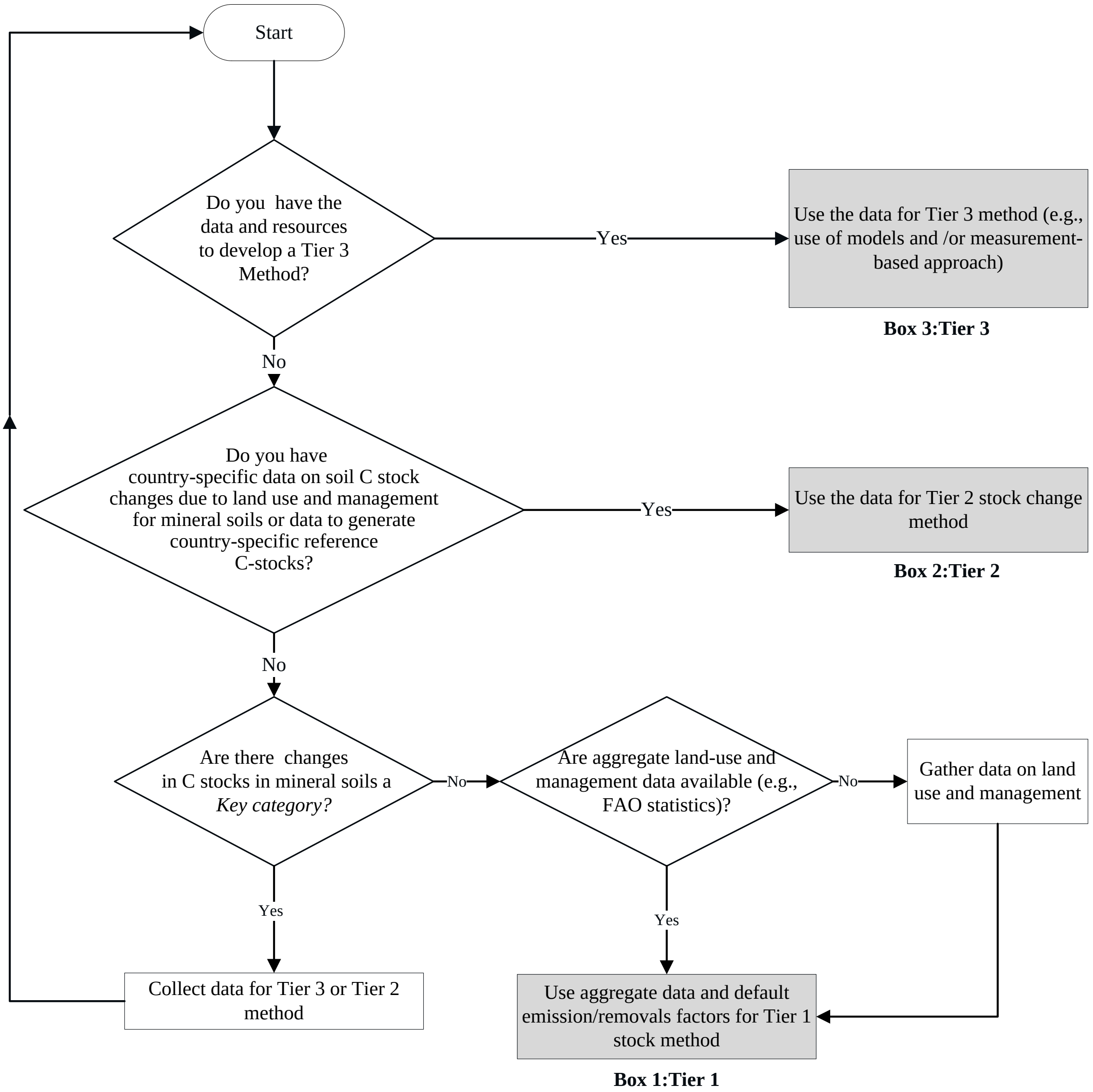
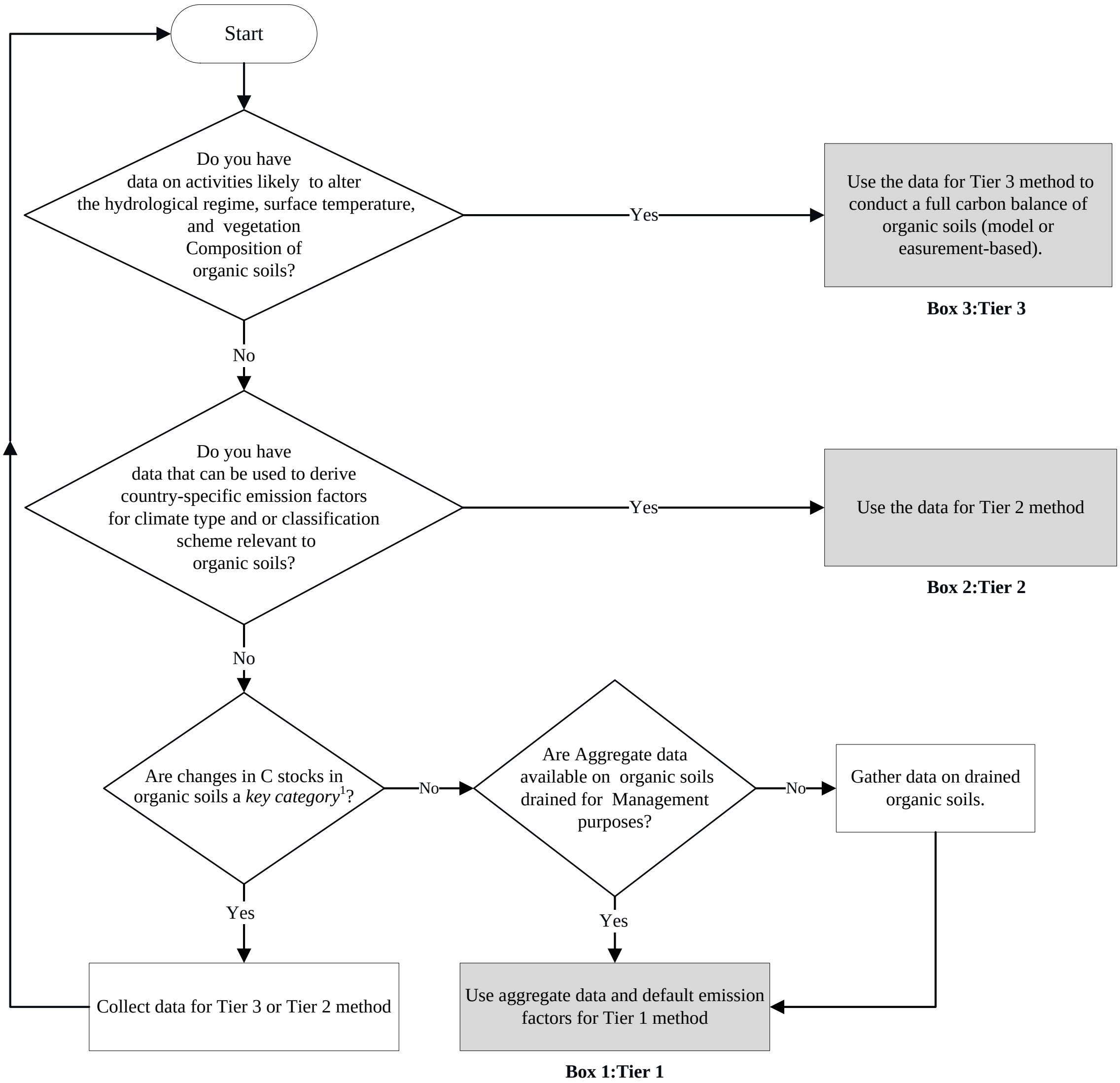


Figure 2.5 Generic decision tree for identification of appropriate tier to estimate changes in carbon stocks in organic soils by land-use category



Tier 1 – Default Method

Mineral soils

For mineral soils, the stock change factor method is based on changes in soil C stocks ($\Delta C_{Mineral}$) over a finite period of time of 20 years (Equation 2.25). The change in organic C stock in mineral soil ($SOC_{Mineral}$) is computed by calculating the organic C stock remaining after a management change relative to the organic C stock in a reference condition and summing this change over all climate zones, soil types and management practices included in the inventory. The soil organic C stock present under the reference condition for the Tier 1 method is defined as that in non-degraded, unimproved lands under native vegetation (Table 2.3). The following assumptions are made:

(i) Over time, soil organic C stock reaches a spatially-averaged, stable value specific to the soil, climate, land-use and management practices; and

(ii) Soil organic C stock change during the transition to a new equilibrium SOC occurs in a linear fashion over a period of 20 years.

Assumption (i), that under a given set of climate and management conditions soils tend towards an equilibrium organic C stock, is widely accepted. Although, soil organic C stock changes in response to management changes may often be best described by a curvilinear function, assumption (ii) greatly simplifies the Tier 1 methodology and provides a good approximation over a multi-year inventory period, where changes in management and land-use conversions are occurring throughout the inventory period.

Using the default method, changes in mineral soil organic C stocks are computed over an inventory time period. Inventory time periods will likely be established based on the years in which activity data are collected, such as 1990, 1995, 2000, 2005 and 2010, which would correspond to inventory time periods of 1990-1995, 1995-2000, 2000-2005, 2005-2010. For each inventory time period, the soil organic C stocks are estimated for the first (SOC_{0-T}) and last year (SOC_0) based on multiplying the reference C stocks by stock change factors. 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.

EQUATION 2.25
ANNUAL CHANGE IN ORGANIC CARBON STOCKS IN MINERAL SOILS

$$\Delta C_{Mineral} = \frac{(SOC_0 - SOC_{(0-T)})}{D}$$

$$SOC_{Mineral} = \sum_{c,s,i} \left(SOC_{REF_{c,s,i}} \bullet F_{LU_{c,s,i}} \bullet F_{MG_{c,s,i}} \bullet F_{I_{c,s,i}} \bullet A_{c,s,i} \right)$$

(Note: T is used in place of D in the $\Delta C_{Mineral}$ equation if T is ≥ 20 years, see note below associated with the parameter D)

Where:

$\Delta C_{Mineral}$ = annual change in organic C stocks in mineral soils, tonnes C yr^{-1}

SOC_0 = mineral soil organic C stock ($SOC_{Mineral}$) in the last year of an inventory time period, tonnes C

$SOC_{(0-T)}$ = mineral soil organic C stock ($SOC_{Mineral}$) at the beginning of the inventory time period, tonnes C

T = number of years over a single inventory time period, yr

D = Time dependence of mineral soil organic C stock change factors which is the default time period for transition between equilibrium SOC values, yr. Commonly 20 years, but depends on assumptions made in computing the factors F_{LU}, F_{MG} and F_I. If T exceeds D, use the value for T to obtain an annual rate of change over the inventory time period (0-T years).

c = represents the climate zones included in the inventory

s = represents the soil types included in the inventory

i = represents the set of management systems included in the inventory.

$SOC_{Mineral}$ = total mineral soil organic C stock at a defined time, tonnes C

$SOC_{REF_{c,s,i}}$ = the soil organic C stock for mineral soils in the reference condition, tonnes C ha^{-1} (Table 2.3)

$F_{LU_{c,s,i}}$ = stock change factor for mineral soil organic C land-use systems or sub-systems for a particular land-use, dimensionless

[Note: F_{ND} is substituted for F_{LU} in forest soil organic C stock calculations to estimate the influence of natural disturbance regimes (see Chapter 4, Section 4.2.3 for more discussion)].

$F_{MG_{c,s,i}}$ = stock change factor for mineral soil organic C for management regime, dimensionless

$F_{I_{c,s,i}}$ = stock change factor for mineral soil organic C for the input of organic amendments, dimensionless

$A_{c,s,i}$ = land area of the stratum being estimated, ha

[Note: All land in the stratum should have common biophysical conditions (i.e., climate and soil type) and management history over the inventory time period to be treated together for analytical purposes.]

Inventory calculations are based on land areas that are stratified by climate regions (see Chapter 3 Annex 3A.5, for default classification of climate), and default soils types as shown in Table 2.3 (see Chapter 3, Annex 3A.5, for default classification of soils). The stock change factors are very broadly defined and include: 1) a land-use factor (F_{LU}) that reflects C stock changes associated with type of land use, 2) a management factor (F_{MG}) representing the principal management practice specific to the land-use sector (e.g., different tillage practices in cropland), and 3) an input factor (F_I) representing different levels of C input to soil. As mentioned above, F_{ND} is substituted for F_{LU} in Forest Land to account for the influence of natural disturbance regimes (see Chapter 4, Section 4.2.3 for more discussion). The stock change factors are provided in the soil C sections of the land-use chapters. Each of these factors represents the change over a specified number of years (D), which can vary across sectors, but is typically invariant within sectors (e.g., 20 years for the cropland systems). In some inventories, the time period for inventory (T years) may exceed D, and under those cases, an annual rate of change in C stock may be obtained by dividing the product of $[(SOC_0 – SOC_{(0 – T)}) \bullet A]$ by T, instead of D. See the soil C sections in the land-use chapters for detailed step-by-step guidance on the application of this method.
When applying the stock change factor method using Equation 2.25, the type of land-use and management activity data has a direct influence on the formulation of the equation (See Box 2.1). Formulation A is based on activity data collected with Approach 1, while Formulation B is based on activity data collected with Approaches 2 or 3 (Box 2.1). See Chapter 3 for additional discussion on the approaches for activity data collection.

Special consideration is needed if using Approach 1 activity data (see Chapter 3) as the basis for estimating land-use and management effects on soil C stocks, using Equation 2.25. Approach 1 data do not track individual land transitions, and so SOC stock changes are computed for inventory time periods equivalent to D years, or as close as possible to D, which is 20 years in the Tier 1 method. For example, Cropland may be converted from full tillage to no-till management between 1990 and 1995, and Formulation A (see Box 2.1) would estimate a gain in soil C for that inventory time period. However, assuming that the same parcel of land remains in no-till between 1995 and 2000, no additional gain in C would be computed (i.e., the stock for 1995 would be based on no-till management and it would not differ from the stock in 2000 (SOC_0), which is also based on no-till management). If using the default approach, there would be an error in this estimation because the change in soil C stocks occurs over 20 years (i.e., D = 20 years). Therefore, $SOC_{(0 – T)}$ is estimated for the most distant time that is used in the inventory calculations up to D years before the last year in the inventory time periods (SOC_0). For example, assuming D is 20 years and the inventory is based on activity data from 1990, 1995, 2000, 2005 and 2010, $SOC_{(0 – T)}$ will be computed for 1990 to estimate the change in soil organic C for each of the other years, (i.e., 1995, 2000, 2005 and 2010). The year for estimating $SOC_{(0 – T)}$ in this example will not change until activity data are gathered at 2011 or later (e.g., computing the C stock change for 2011 would be based on the most distant year up to, but not exceeding D, which in this example would be 1995).

If transition matrices are available (i.e., Approach 2 or 3 activity data), the changes can be estimated between each successive year. From the example above, some no-till land may be returned to full tillage management between 1995 and 2000. In this case, the gain in C storage between 1990 and 1995 for the land base returned to full tillage would need to be discounted between 1995 and 2000. Further, no additional change in the C stocks would be necessary for land returned to full tillage after 2000 (assuming tillage management remained the same). Only land remaining in no-till would continue to gain C up to 2010 (i.e., assuming D is 20 years). Hence, inventories using transition matrices from Approach 2 and 3 activity data will need to be more careful in dealing with the time periods over which gains or losses of SOC are computed. See Box 2.2 for additional details. The application of the soil C estimation approach is much simpler if only using aggregated statistics with Approach 1 activity data. However, it is *good practice* for countries to use transition matrices from Approach 2 and 3 activity data if that information is available because the more detailed statistics will provide an improved estimate of annual changes in soil organic C stocks.

There may be some cases in which activity data are collected over time spans longer than the time dependence of the stock change factors (D), such as every 30 years with a D of 20. For those cases, the annual stock changes can be estimated directly between each successive year of activity data collection (e.g., 1990, 2020 and 2050) without over- or under-estimating the annual change rate, as long as T is substituted for D in Equation 2.25.

TABLE 2.3 (UPDATED)
DEFAULT REFERENCE CONDITION SOIL ORGANIC CARBON STOCKS (SOC_{REF}) FOR MINERAL SOILS (TONNES C HA^{-1} IN 0-30 CM DEPTH) [1, 2]

IPCC Climate Zone [5]	IPCC soil class [6]		
	High activity clay soils (HAC) [7]	**Low activity clay soils (LAC)** [8]	**Sandy soils (SAN)** [9]
Polar Moist/Dry (Px - undiff)[13]	59 ± 41% (24)	NA	27 ± 67% (18)
Boreal Moist/Dry (Bx - undiff)[13]	63 ± 18% (35)	NA	10 ± 90% [4]
Cool temperate dry (C2)	43 ± 8% (177)	33 ± 90% [3]	13 ± 33% (10)
Cool temperate moist (C1)	81 ± 5% (334)	76 ± 51% (6)	51 ± 13% (126)
Warm temperate dry (W2)	24 ± 5% (781)	19 ± 16% (41)	10 ± 5% (338)
Warm temperate moist (W1)	64 ± 5% (489)	55 ± 8% (183)	36 ± 23% (39)
Tropical dry (T4)	21 ± 5% (554)	19 ± 10% (135)	9 ± 9% (164)
Tropical moist (T3)	40 ± 7% (226)	38 ± 5% (326)	27 ± 12% (76)
Tropical wet (T2)	60 ± 8% (137)	52 ± 6% (271)	46 ± 20% (43)
Tropical montane (T1)	51 ± 10% (114)	44 ± 11% (84)	52 ± 34% (11)
	Spodic soils (POD) [10]	**Volcanic soils** (VOL) [11]	**Wetland soils** (WET) [12]
Polar Moist/Dry (Px - undiff)[13]	NO	NA	NA
Boreal Moist/Dry (Bx - undiff)[13]	117 ± 90% [3]	20 ± 90% [4]	116 ± 65% (6)
Cool temperate dry (C2)	NO	20 ± 90% [4]	87 ± 90% [3]
Cool temperate moist (C1)	128 ± 14% (45)	136 ± 14% (28)	128 ± 13% (42)
Warm temperate dry (W2)	NO	84 ± 65% (10)	74 ± 17% (49)
Warm temperate moist (W1)	143 ± 30% (9)	138 ± 12% (42)	135 ± 28% (28)
Tropical dry (T4)	NA	50 ± 90% [4]	22 ± 17% (32)
Tropical moist (T3)	NA	70 ± 90% [4]	68 ± 17% (55)
Tropical wet (T2)	NA	77 ± 27% (14)	49 ± 19% (33)
Tropical montane (T1)	NA	96 ± 31% (10)	82 ± 50% (12)

Note: Data are derived from Batjes (2010) and Batjes (2011) unless otherwise noted through the use of superscripts.

[1] NA denotes that soil categories the soil category may occur in a climate zone, but no data was available. NO denotes that the soil type does not normally occur within a climate zone. [2] All values are presented in the format of the mean for the soil by climate combination ± the 95% confidence limit expressed as a percentage of the mean (that is ± 1.96 * standard error /mean *100). Values in parentheses are the number of soils included in the derivation of mean and standard error values for each combination of soil and climate types. [3] Indicates where no data were available from Batjes (2011) but values were derived for the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* and have been used in the table. No values of n were available. A nominal error estimate of ±90% of the mean was assigned as per the *2006 IPCC Guidelines*. [4] Indicates where no data were available either from Batjes (2011) or in the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Mean values present the default values used in the 1996 IPCC Guidelines. No values of n were available. A nominal error estimate of ±90% of the mean was assigned as per the *2006 IPCC Guidelines*. [5] Climate classes are defined according to (IPCC 2006, p. 3.39) using elevation, mean annual temperature, mean annual precipitation, mean annual precipitation to potential evapotranspiration ratio and frost occurrence. [6] Soil classes are inferred from the FAO-1990/WRB-2006 classification in accordance with IPCC (2006, p. 3.40 - 3.41). [7] Soils with high activity clay (HAC) minerals are lightly to moderately weathered soils dominated by 2:1 silicate clay minerals (in the World Reference Base for Soil Resources (WRB) classification: Leptosols, Vertisols, Kastanozems, Chernozems, Phaeozems, Luvisols, Alisols, Albeluvisols, Solonetz, Calcisols, Gypsisols, Umbrisols, Cambisols, Regosols; in USDA classification: Mollisols, Vertisols, high-base status Alfisols, Aridisols, Inceptisols). [8] Soils with low activity clay (LAC) minerals are highly weathered soils, dominated by 1:1 clay minerals and amorphous iron and aluminium oxides (in WRB classification: Acrisols, Lixisols, Nitisols, Ferralsols, Durisols; in USDA classification: Ultisols, Oxisols, acidic Alfisols). [9] Soils (regardless of taxonomic classification) having > 70% sand and < 8% clay (in WRB classification: Arenosols; in USDA classification: Psamments). [10] Soils exhibiting strong podzolization (in WRB classification includes Podzols; in USDA classification Spodosols). [11] Soils derived from volcanic ash with allophanic mineralogy (in WRB classification Andosols; in USDA classification Andisols). [12] Soils with restricted drainage leading to periodic flooding and anaerobic conditions (in WRB classification Gleysols; in USDA classification Aquic suborders). [13] The Boreal dry and Boreal moist zones and the Polar dry and Polar moist zones were not differentiated. Results presented represent the SOC_{30} stocks for the undifferentiated (undiff.) Boreal (Bx) and Polar (Px) classes.

BOX 2.1 (UPDATED)
ALTERNATIVE FORMULATIONS OF EQUATION 2.25 FOR APPROACH 1 ACTIVITY DATA VERSUS APPROACH 2 OR 3 ACTIVITY DATA WITH TRANSITION MATRICES

Two alternative formulations are possible for Equation 2.25 depending on the Approach used to collect activity data, including

Formulation A (Approach 1 for Activity Data Collection)

$$\Delta C_{Mineral} = \frac{\left[\sum_{c,s,i}\left(SOC_{REF_{c,s,i}} \bullet F_{LU_{c,s,i}} \bullet F_{MG_{c,s,i}} \bullet F_{I_{c,s,i}} \bullet A_{c,s,i}\right)\right]_0 - \left[\sum_{c,s,i}\left(SOC_{REF_{c,s,i}} \bullet F_{LU_{c,s,i}} \bullet F_{MG_{c,s,i}} \bullet F_{I_{c,s,i}} \bullet A_{c,s,i}\right)\right]_{(0-T)}}{D}$$

Formulation B (Approaches 2 and 3 for Activity Data Collection)

$$\Delta C_{Mineral} = \frac{\sum_{c,s,p}\left[\left\{\begin{array}{l}\left(SOC_{REF_{c,s,p}} \bullet F_{LU_{c,s,p}} \bullet F_{MG_{c,s,p}} \bullet F_{I_{c,s,p}}\right)_0 - \\ \left(SOC_{REF_{c,s,p}} \bullet F_{LU_{c,s,p}} \bullet F_{MG_{c,s,p}} \bullet F_{I_{c,s,p}}\right)_{(0-T)}\end{array}\right\} \bullet A_{c,s,p}\right]}{D}$$

Where:

p = a parcel of land representing an individual unit of area over which the inventory calculations are performed.

See the description of other terms under the Equation 2.25.

Activity data may only be available using Approach 1 for data collection (Chapter 3). These data provide the total area at two points in time for climate, soil and land-use/management systems, without quantification of the specific transitions in land use and management over the inventory time period (i.e., only the aggregate or net change is known, not the gross changes in activity). With Approach 1 activity data, mineral C stock changes are computed using formulation A of Equation 2.25. In contrast, activity data may be collected based on surveys, remote sensing imagery or other data providing not only the total areas for each land management system, but also the specific transitions in land use and management over time on individual parcels of land. These are considered Approach 2 and 3 activity data in Chapter 3, and soil C stock changes are computed using formulation B of Equation 2.25. Formulation B contains a summation by land parcel (i.e., "*p*" represents land parcels in formulation B rather than the set of management systems "*i*") that allows the inventory compiler to compute the changes in C stocks on a land parcel by land parcel basis.

BOX 2.2 (UPDATED)
COMPARISON BETWEEN USE OF APPROACH 1 AGGREGATE STATISTICS AND APPROACH 2 OR 3 ACTIVITY DATA WITH TRANSITION MATRICES

This box examines the application of Equation 2.25 to calculate $\Delta C_{mineral}$. Assume a country where a fraction of the land is subjected to land-use changes, as shown in the following table, where each line represents one land unit with an area of 1 Mha (F = Forest Land; C = Cropland; G = Grassland). Where a land-use change occurs, it is assumed to occur in the year following the previous inventory year (e.g. for land unit 1, the conversion from F to C occurred at the start of 1991 such that for the five years from the start of 1991 to the end of the 1995 inventory year the land was under land-use C)

BOX 2.2 (UPDATED) (CONTINUED)
COMPARISON BETWEEN USE OF APPROACH 1 AGGREGATE STATISTICS AND APPROACH 2 OR 3 ACTIVITY DATA WITH TRANSITION MATRICES

Land Unit ID	1990	1995	2000	2005	2010	2015	2020
1	F	C	C	C	C	C	C
2	F	C	C	C	G	G	G
3	G	C	C	C	C	G	G
4	G	G	F	F	F	F	F
5	C	C	C	C	G	G	G
6	C	C	G	G	G	C	C

For simplicity, it is assumed that the country has a single soil type, with a SOC_{REF} (0-30 cm soil C stock under native forest vegetation) value of 77 tonnes C ha^{-1}. Values for F_{LU} are 1.00, 1.05 and 0.92 for F, G and C, respectively. F_{MG} and F_I are assumed to be equal to 1. The time dependence of the stock change factors (D) is 20 years. Finally, the soil C stock is assumed to be at equilibrium in 1990 (i.e., no changes in land-use occurred during the 20 years prior to 1990). When using Approach 1 activity data (i.e., aggregate statistical data), annual changes in C stocks are computed for every inventory year following Equation 2.25 above. The following table shows the results of calculations[1]:

	1990	1995	2000	2005	2010	2015	2020
F (Mha)	2	0	1	1	1	1	1
G (Mha)	2	1	1	1	3	3	3
C (Mha)	2	5	4	4	2	2	2
SOC_0 (Mt C)	**457.4**	**435.1**	**441.2**	**441.2**	**461.2**	**461.2**	**461.2**
$SOC_{(0-T)}$ (Mt C)	457.4	457.4	457.4	457.4	457.4	435.1	441.2
$\Delta C_{Mineral}$ (Mt C yr^{-1})	**0.0**	**-1.1**	**-0.8**	**-0.8**	**0.2**	**1.3**	**1.0**

If Approach 2 or 3 data are used in which land-use changes are explicitly known, C stocks can be computed taking into account historical changes for every individual land unit. The total C stocks for the sum of all units is compared with the most immediate previous inventory year, rather than with the inventory of 20 years before to estimate annual changes in C stocks:

	1990	1995	2000	2005	2010	2015	2020
SOC_0 (Mt C) for unit 1	77.0	75.5	73.9	72.4	70.8	70.8	70.8
SOC_0 (Mt C) for unit 2	77.0	75.5	73.9	72.4	74.5	76.6	78.7
SOC_0 (Mt C) for unit 3	80.9	78.3	75.8	73.3	70.8	73.3	75.8
SOC_0 (Mt C) for unit 4	80.9	80.9	79.9	78.9	78.0	77.0	77.0
SOC_0 (Mt C) for unit 5	70.8	70.8	70.8	70.8	73.3	75.8	78.3
SOC_0 (Mt C) for unit 6	70.8	70.8	73.3	75.8	78.3	76.5	74.6
SOC_0 (Mt C)	**457.4**	**451.8**	**447.8**	**443.7**	**445.8**	**450.1**	**455.4**
$SOC_{(0-T)}$ (Mt C)	457.4	457.4	451.8	447.8	443.7	445.8	450.1
$\Delta C_{Mineral}$ (Mt C yr^{-1})	**0.0**	**-1.1**	**-0.8**	**-0.8**	**0.4**	**0.9**	**1.0**

BOX 2.2 (UPDATED) (CONTINUED)
COMPARISON BETWEEN USE OF APPROACH 1 AGGREGATE STATISTICS AND APPROACH 2 OR 3 ACTIVITY DATA WITH TRANSITION MATRICES

Both methods yield different estimates of C stocks, and use of Approach 2 or 3 data with land transition matrices would be more accurate than use of Approach 1 aggregate statistics. However, estimates of annual changes of C stocks would not differ greatly, as shown in this example. The effect of underlying data approaches on the estimates differ more when there are multiple changes in land-use on the same piece of land (as in land units 2, 3 and 6 in the example). It is noteworthy that Approach 1, 2 and 3 activity data produce the same changes in C stocks if the systems reach a new equilibrium, which occurs with no change in land-use and management for a 20-year time period using the Tier 1 method. Consequently, no C stock increases or losses are inadvertently lost when applying the methods for Approach 1, 2 or 3 activity data, but the temporal dynamics do vary somewhat as demonstrated above. A spreadsheet is available with the full set of calculations: Vol4_Ch2_Spreadsheet_Box_2.2_Calculations.xlsx.

Organic soils

No refinement. See Chapter 2, Section 2.2 of the *2013 Wetlands Supplement.*

Soil inorganic C

No refinement.

Tier 2 Methods

Mineral soils

A Tier 2 method is an extension of the Tier 1 method that allows an inventory to incorporate country-specific data. It is *good practice* for countries to use a Tier 2 method, if possible, even if they are only able to better specify certain components of the Tier 1 method. For example, a compiler may only have data to derive country-specific reference C stocks, which would then be used with default stock change factors to estimate changes in soil organic C stocks for mineral soils.

Country-specific data can be used to improve four components when applying the Tier 1 equations for estimating stock changes in mineral soils. The components include a) derivation of region or country-specific stock change factors, b) reference condition C stocks, c) specification of management systems, and/or d) classification of climate and soil categories (e.g., Ogle *et al.*, 2003; VandenBygaart *et al.*, 2004; Tate *et al.*, 2005). Inventory compilers can choose to derive specific values for all of these components, or any subset, which would be combined with default values provided in the Tier 1 method to complete the inventory calculations using Equation 2.25. Also, the Tier 2 method uses the same procedural steps for calculations as provided for Tier 1.

1) *Defining management systems*. Although the same management systems may be used in a Tier 2 inventory as found in the Tier 1 method, the default systems can be disaggregated into a finer categorisation that better represents management impacts on soil organic C stocks in a particular country based on empirical data (i.e., stock change factors vary significantly for the proposed management systems). Such an undertaking, however, is only possible if there is sufficient detail in the underlying data to classify the land area into the finer, more detailed set of management systems.

2) *Climate regions and soil types.* Countries that have detailed soil classifications and climatic data have the option of developing country-specific classifications. Moreover, it is considered *good practice* to specify better climate regions and soil types during the development of a Tier 2 inventory if the new classification improves the specification of reference C stocks and/or stock change factors. In practice, reference C stocks and/or stock change factors should differ significantly among the proposed climate regions and soil types based on an empirical analysis. Note that specifying new climate regions and/or soil types requires the derivation of country-specific reference C stocks and stock change factors. The default reference soil C stocks and stock change factors are only appropriate for inventories using the default climate and soil types.

3) *Reference C stocks.* Deriving country-specific reference condition soil C stocks (SOC_{REF}) is another possibility for improving an inventory using a Tier 2 method (Bernoux *et al.* 2002), which will likely produce more accurate and representative values. Country-specific stocks can be estimated from soil measurements, for example, as part of a country's soil survey. It is important that reliable taxonomic descriptions be used to group soils into categories. Three additional points require consideration when deriving the country-specific values, including possible specification of country-specific soil categories and climate regions (i.e., instead of using the IPCC default classification), choice of reference condition, and choice of depth increment over which the stocks are estimated.

Stocks are computed by multiplying the proportion of organic C (i.e., %C divided by 100) by the depth increment (default is 30 cm), bulk density, and the proportion of coarse-fragment free soil (i.e., < 2mm fragments) in the depth increment (Ogle *et al.* 2003). The coarse fragment-free proportion is on a mass basis (i.e., mass of coarse fragment-free soil/total mass of the soil). If the soil C reference condition differs from that used in Table 2.3 or the soil depth used differs from 30 cm, then appropriate country specific soil C stocks for the reference condition and stock change factors must be derived. For developing a Tier 2 method, it would also be possible to define reference SOC stocks and SOC stock change factors using an equivalent mass approach (see Box 2.2b) rather than an approach based on a fixed depth.

The soil reference condition is the land-use/cover category (or condition within a land-use/cover category) that is used for evaluating the relative effect of land-use change on the amount of soil C storage (e.g., relative difference in soil C storage between a reference condition, such as native lands, and another land use, such as cropland, forming the basis for F_{LU} in Equation 2.25). It is likely that many countries will use the Tier 1 default soil reference condition in a Tier 2 method. However, another land use or condition can be selected to define the reference condition, which is *good practice* if it allows for a more accurate assessment of soil C stock changes. The same reference condition should be used for each climate zone and soil type, regardless of the land use. The soil C stock associated with the reference condition is then multiplied by land use, input and management factors to estimate the stocks at the beginning and last year in an inventory time period (See Equation 2.25).

Another consideration in deriving country-specific reference soil C stocks is the possibility of estimating C stocks to a different depth in the soil. Default soil C stocks given in Table 2.3 are based on the amount of soil organic C in the top 30 cm of a soil profile. A different depth can be selected and used for Tier 2 methods if all appropriate data are available. Consideration should be given to the introduction of bias (positive or negative) that may arise in response to the depth selected. For example, where depth is set to 20 cm and cultivation mixes soils to a depth >20 cm, an apparent difference in SOC stock between cultivated and uncultivated soils may be observed for the 20cm depth that is not representative of the change in SOC stocks to the depth over which mixing occurs in the cultivated soil. It is *good practice* to derive reference condition soil C stocks to the depth at which land use and management impact soil C stocks, but this will require that the data are available or could be acquired to the selected depth. Any change in the depth for reference condition soil C stocks will require derivation of new stock change factors (e.g. F_{LU}, F_{MG} and F_I see Equation 2.25) consistent with the depth selected because the defaults are based on impacts to a 30 cm depth.

It is possible to use a soil C model to derive steady state soil C stocks indicative of the soil reference condition for the various combinations of soil type and climate that exist within a country. However, this would require sufficient testing of the model used to provide evidence that the model is adequate for this purpose (See Section 2.5.2 for more information). Further information related to soil sampling strategies and how to derive soil reference C stocks can be found in Batjes (2011), as well as in a range of soil sampling and analysis texts (e.g. Carter & Gregorich 2008; de Gruijter *et al.* 2006)

4) *Stock change factors*. An important advancement for a Tier 2 method is the estimation of country-specific stock change factors (F_{LU}, F_{MG} and F_I). The derivation of country-specific factors can be accomplished using experimental/measurement data and computer model simulation. In practice, deriving stock change factors involves estimating a response ratio for each study or observation (i.e., the C stocks in different input or management classes are divided by the value for the nominal practice, respectively).

Optimally, stock change factors are based on experimental/measurement data in the country or surrounding region, by estimating the response ratios from each study and then analysing those values using an appropriate statistical technique (e.g., Ogle *et al.* 2003 and 2004; VandenBygaart *et al.* 2004). Studies may be found in published literature, reports and other sources, or inventory compilers may choose to conduct new experiments. Regardless of the data source, it is *good practice* that the plots being compared have similar histories and management as well as similar topographic position, soil physical properties and be located in close proximity. Studies should provide soil C stocks (i.e., mass per unit area to a specified depth) or the information needed to calculate soil C stocks (i.e., percent organic carbon together with bulk density; proportion of rock in soil, which is often measured as the greater than 2mm fraction and by definition contains negligible soil organic C). If percent organic matter is available instead of percent organic carbon, a conversion factor of 0.58 can be used to estimate the C content. Moreover, it is *good practice* that the measurements of soil C stocks are taken on an equivalent mass basis (e.g., Ellert *et al.* 2001; Gifford & Roderick, 2003). In order to use this method, the inventory compiler will need to determine a depth to measure the C stock for the nominal land use or practice, such as native lands or conventional tillage. This depth will need to be consistent with the depth for the reference C stocks. The soil C stock for the land-use or management change is then measured to a depth with the equivalent mass of soil. Box 2.2b provides further information on issues associated with conducting an inventory on an equivalent mass basis.

Another option for deriving country-specific values is to simulate stock change factors from advanced models (Bhatti *et al.*, 2001). To demonstrate the use of advanced models, simulated stock change factors can be compared to with measured changes in C stocks from experiments. It is *good practice* to provide the results of model evaluation, citing published papers in the literature and/or placing the results in the inventory report. This approach is considered a Tier 2 method because it relies on the stock change factor concept and the C estimation method elaborated in the Tier 1 method.

Derivation of country-specific management factors (F_{MG}) and input factors (F_I), either with empirical data or advanced models, will need to be consistent with the management system classification. If more systems are specified for the inventory, unique factors will need to be derived representing the finer categories for a particular land use.

Another consideration in deriving country-specific stock change factors is their associated time dependence (D in Equation 2.25), which determines the number of years over which the majority of a soil C stock change occurs, following a management change. It is possible to use the default time dependence (D) for the land-use sector (e.g., 20 years for cropland), but the dependence can be changed if sufficient data are available to justify a different time period. In addition, the method is designed to use the same time dependence (D) for all stock change factors as presented in Equation 2.25. If different periods are selected for F_{LU}, F_{MG} and F_I, it will be necessary to compute the influence of land use, management and inputs separately and divide the associated stock change dependence. This can be accomplished by modifying Equation 2.25 so that SOC at time T and 0-T is computed individually for each of the stock change factors (i.e., SOC is computed with F_{LU} only, then computed with F_{MG}, and finally computed with F_I). The differences are computed for the stocks associated with land use, management, and input, dividing by their respective D values, and then the changes are summed.

Changes in soil C stocks normally occur in a non-linear fashion, and it is possible to further develop the time dependence of stock change factors to reflect this pattern. For changes in land use or management that cause a decrease in soil C content, the rate of change is highest during the first few years, and progressively declines with time. In contrast, when soil C is increasing due to land-use or management change, the rate of accumulation tends to follow a sigmoidal curve, with rates of change being slow at the beginning, then increasing and finally decreasing with time. If historical changes in land-use or management practices are explicitly tracked by re-surveying the same locations (i.e., Approach 2 or 3 activity data, see Chapter 3), it may be possible to implement a Tier 2 method that incorporates the non-linearity of changes in soil C stock.

BOX 2.2A (NEW)

USING EQUIVALENT MASS METHODS TO DERIVE MINERAL SOIL ORGANIC CARBON STOCK CHANGE FACTORS

Soil carbon stock estimates may be improved when deriving country-specific factors for F_{LU} and F_{MG}, by expressing carbon stocks on a soil-mass equivalent basis rather than a soil-volume equivalent (i.e. fixed depth) basis. This is because the soil mass to a certain soil depth changes in response to altered management practices associated with land use change (e.g. uprooting forest vegetation, land levelling, and rain compaction due to the disappearance of the cover of tree canopy). In addition, soil bulk density may be affected differently by particular management practices within a given land use (e.g. tillage and machinery traffic within cropping systems or the extent of compaction induced by different animal at stocking rates within pasture systems). Where the soil bulk density changes due to land use and/or management, the comparison of the soil carbon stocks between the cropland, settlements, grassland, wetlands, or forest land to the same depth introduces changes to soil carbon stocks as a direct consequence of changes in soil bulk density (Ellert & Bettany 1995). With a management induced change in soil bulk density, it is possible to calculate a change in soil carbon stock to a fixed depth in the absence of any change in soil carbon content. Therefore, it is more robust to calculate soil carbon stock change on an equivalent mass basis rather than on a fixed-depth basis (Toriyama et al. 2011; Bruun et al. 2013; Halvorson et al. 2016; Hu et al., 2016). The equivalent mass approach has more rigorous comparability when the bulk density between cropland, grassland, wetland, settlements and forest land is markedly different even if the site is within close proximity. It is important to realise that comprehensive data of soil carbon concentration and soil bulk density would be required to derive stock change factors across all land uses. The changing mass of organic carbon itself will affect the equivalent soil mass and therefore equivalent mass basis is not appropriate for organic soils. There are proposals for methods based on only equivalent mass of the mineral soil portion (McBratney & Minasny 2010) that would reduce the effect of changing soil organic mass distorting the equivalent soil mass. Adopting an equivalent-mass based carbon stock inventory requires thorough consideration of the challenges.

The impact of biochar C amendments on mineral soils can also be estimated with a Tier 2 method for mineral soils using Equation 2.25A and adding this estimate to the result in Equation 2.25.[7]

[7] Biochar is a solid carbonised product from thermochemical conversion through pyrolysis (heating with limited air). The term biochar is used herein only to refer to materials that have been produced under process conditions in which relatively easily mineralisable organic materials are converted to more persistent forms by heating to above 350 °C with limited air through a

EQUATION 2.25A
ANNUAL CHANGE IN BIOCHAR CARBON STOCK IN MINERAL SOILS RECEIVING BIOCHAR ADDITIONS

$$\Delta BC_{Mineral} = \sum_{p=1}^{n} \left(BC_{TOT_p} \bullet F_{C_p} \bullet F_{perm_p} \right)$$

Where:

$\Delta BC_{Mineral}$ = the total change in carbon stocks of mineral soils associated with biochar amendment, tonnes sequestered C yr^{-1}

BC_{TOT_p} = the mass of biochar incorporated into mineral soil during the inventory year for each biochar production type p , tonnes biochar dry matter yr^{-1}

F_{C_p} = the organic carbon content of biochar for each production type p, tonnes C $tonne^{-1}$ biochar dry matter

F_{perm_p} = fraction of biochar carbon for each production type p remaining (unmineralised) after 100 years, tonnes sequestered C $tonne^{-1}$ biochar C

n = the number of different production types of biochar

Country-specific values the C content of the forms of biochar included in the inventory (F_{C_p} in units of tonnes C $tonne^{-1}$ biochar on a dry mass basis) can be measured directly from representative samples of biochar. Country-specific values may also be based on published data on carbon content of biochar produced using the same feedstock and process conditions as the biochar that is applied to soils in the country.

The fraction of biochar C remaining after 100 years is defined by the parameter F_{perm_p} . It is not possible to measure this value directly due to the time scales involved. So, this parameter is estimated from other data. The elemental composition of biochar, specifically the ratio of hydrogen to organic carbon (H/C_{org}) or ratio of oxygen to organic carbon (O/C_{org}), has been shown to correlate non-linearly with biochar residence time (Spokas 2010; Lehmann *et al.* 2015). Therefore, country-specific Tier 2 estimates of F_{perm_p} can be based on H/C_{org} or O/C_{org} measured directly from representative samples of biochar, or from published data for biochar produced using similar process conditions as the biochar that is applied to soils in the country. This parameter can also be derived from the biochar elemental composition using published equations relating this composition to mean residence time or half-life (for example H/C_{org}, Lehmann *et al.* 2015; or O/C_{org}, Spokas 2010), and extrapolated to the permanence time frame assuming one-, two-, or three-pool exponential decay (Zimmerman 2010; Herath *et al.* 2015; Lehmann *et al.* 2015). A justification should be provided if a permanence time frame other than 100 years is used.

Since the impact of biochar amendments is a separate calculation and summed with the result from Equation 2.25 in the Tier 2 method, it is essential that biochar C is not included as an organic amendment in the estimates of $SOC_{Mineral}$ in Equation 2.25.

gasification or pyrolysis process. This guidance does not deal with pyrolytic organic materials that result from wild fires or open fires, and is only applicable for biochar added to mineral soils.

BOX 2.2B (NEW)
GHG EMISSION SOURCES WITH BIOCHAR PRODUCTION

Biochar production involves emissions from several different sectors and source categories. All GHG emissions and removals are reported in a greenhouse gas inventory, but estimation and reporting is done based on sources in which the activity occurs. The guidance in this section is addressing C stock changes associated with the end-product use of biochar amendments to mineral soils. However, other emissions do occur along the biochar feedstock supply chains that are estimated in other source categories. For example, the harvesting and use of forest wood biomass for biochar production would be part of reported C stock changes in *Forest Land Remaining Forest Land* (Volume 4). Moreover, biomass may be grown specifically as a feedstock and the C stock changes are estimated and reported under the appropriate source categories for land use associated with feedstock production (Volume 4). For plant residues and manures, their utilisation as feedstock reduces input of organic amendments to soil and thereby affects soil C stocks in cropland and grassland, and possibly other land uses receiving manure amendments (Volume 4). For waste materials, their utilisation as feedstock reduces input to waste streams and is addressed in the calculation of emissions from waste management (Volume 5). There may also be use of fossil fuels in the harvesting, transport and pyrolysis of the feedstock and a potential release of other non-CO_2 greenhouse gases during the heating process that would be included in the energy sector (Volume 2).

Organic soils

No refinement. See Chapter 2, Section 2.2 of the *2013 Wetlands Supplement.*

Soil inorganic C

No refinement.

Tier 3: Advanced estimation systems

Tier 3 approaches for soil C involve the development of an advanced estimation system that will typically better capture annual variability in fluxes, unlike Tier 1 and 2 approaches that mostly assume a constant annual change in C stocks over an inventory time period based on a stock change factor. Essentially, Tiers 1 and 2 represent land-use and management impacts on soil C stocks as a linear shift from one equilibrium state to another. To understand the implications better, it is important to note that soil C stocks typically do not exist in an absolute equilibrium state or change in a linear manner through a transition period, given that many of the driving variables affecting the stocks are dynamic, periodically changing at shorter time scales before a new “near” equilibrium is reached. Tier 3 approaches can address this non-linearity using more advanced models than Tiers 1 and 2 methods, and/or by developing a measurement-based inventory with a monitoring network. In addition, Tier 3 inventories are capable of capturing longer-term legacy effects of land use and management. In contrast, Tiers 1 and 2 approaches typically only address the most recent influence of land use and management, such as the last 20 years for mineral C stocks. See Section 2.5 (Generic Guidance for Tier 3 methods) for additional discussion on Tier 3 methods beyond the text given below.

Mineral soils

Model-based approaches can use mechanistic simulation models that capture the underlying processes driving carbon gains and losses from soils in a quantitative framework, such as the influence of land use and management on processes controlling carbon input resulting from plant production and litter fall as well as microbial decomposition (e.g., McGill, 1996; Smith *et al.*, 1997b; Smith *et al.*, 2000; Falloon and Smith, 2002; Tate *et al.*, 2005; Campbell&Paustian, 2015). Note that Tier 3 methods provide the only current opportunity to explicitly estimate the impact of soil erosion on C fluxes (Box 2.2d). In addition, Tier 3 model-based approaches may represent C transfers between biomass, dead biomass and soils, which are advantageous for ensuring conservation of mass in predictions of C stock changes in these pools relative to CO_2 removals and emissions to the atmosphere.

Tier 3 modelling approaches are capable of addressing the influence of land use and management with a dynamic representation of environmental conditions that affect the processes controlling soil C stocks, such as weather, edaphic characteristics, and other variables. The impact of land use and management on soil C stocks can vary as environmental conditions change, and such changes are not captured in lower Tiers, which may create biases in those results. Tier 3 methods can also include lateral flows of C associated with erosion and deposition (See Box 2.2c). Consequently, Tier 3 approaches are capable of providing a more accurate estimation of C stock changes associated with land-use and management activity if the modelling approach has been calibrated to the range of environmental conditions, soil properties and management practices to which the model will subsequently be applied (See Section 2.5 for more information).

For Tier 3 approaches, a set of benchmark sites will be needed to evaluate model results. Ideally, a series of permanent, benchmark monitoring sites would be established with statistically replicated design, capturing the major climatic regions, soil types, and management systems as well as system changes, and would allow for repeated measurements of soil organic C stocks over time (Smith, 2004a). Monitoring is based on re-sampling plots every 3 to 5 years or each decade; shorter sampling frequencies are not likely to produce significant differences due to small annual changes in C stocks relative to the large total amount of C in a soil (IPCC, 2000; Smith, 2004b).

BOX 2.2C (NEW)
REPRESENTING THE IMPACT OF SOIL EROSION AND DEPOSITION ON SOIL CARBON STOCK CHANGES

Soil erosion and/or deposition can have marked effect on measured carbon stocks (Chappell *et al.* 2016). Soil carbon stock changes due to soil erosion/deposition are not considered to be embedded in factors for land-use change or land management. In practice, it is difficult to determine whether soil erosion/deposition effects are or are not included in stock change factors derived from empirical data. Different land use changes and subsequent management practices could result in different extents of soil movement. For example, land-use change from forest or grassland to cropland, or land management change from no-till to full tillage are typically associated with increased soil movement. The amounts of soil erosion or deposition are rarely measured or documented in datasets that have quantified soil carbon stock changes.

One option to include the effects of soil erosion and deposition is using well-tested models that capture these dynamics with required input data to make estimates of the effect of past erosion/deposition on soil carbon stocks (Van Oost *et al.* 2005; Causarano *et al.* 2007). However, use of such models also requires having empirical data on erosion/deposition effects on carbon stocks for evaluation of the model predictions. Another option is to consistently apply a rationale that identifies measured data of soil carbon stock changes that are affected by erosion/deposition for the development of Tier 2 or 3 methods, developing factors related to erosion/deposition impacts, and then applying these factors in areas affected by erosion/deposition.

In addition to model-based approaches, Tier 3 methods afford the opportunity to develop a measurement-based inventory using a similar monitoring network as needed for model evaluation. However, measurement networks, which serve as the basis for a complete inventory, will have a considerably larger sampling density to minimise uncertainty, and to represent all management systems and associated land-use changes, across all climatic regions and major soil types (Sleutel *et al.*, 2003; Lettens *et al.*, 2004). Measurement networks can be based on soil sampling at benchmark sites or flux tower networks. Flux towers, such as those using eddy covariance systems (Baldocchi *et al.*, 2001), constitute a unique case in that they measure the *net* exchange of CO_2 between the atmosphere and land surface. Thus, with respect to changes in C stocks for the soil pool, flux tower measurement networks are subject to the following caveats: 1) towers need to occur at a sufficient density to represent fluxes for the entire country; 2) flux estimates need to be attributed to individual land-use sectors and specific land-use and management activities; and 3) CO_2 fluxes need to be further attributed to individual pools including stock changes in soils (also biomass and dead organic matter). Additional considerations about soil measurements are given in the previous section on Tier 2 methods for mineral soils (See stock change factor discussion).

It is important to note that measurement-based inventories represent full C estimation approaches, addressing all influences on soil C stocks. Partial estimation of only land-use and management effects may be difficult, however. Examples in Box 2.2d provide illustrations of Tier 3 methods for estimating change in mineral soil C stocks, including information such as type of data required, brief description of the models and methods that are used to apply the models. For Tier 3 methods, it is important to calibrate and test models against field measurements that reflect the variability in climate, soil type and land use over which the model will be applied (See Section 2.5.2 for more information). Application of the equivalent mass approach may be possible for calculating soil C stocks with Tier 3 models, and is discussed in Box 2.2e.

BOX 2.2D (NEW)
EXAMPLES OF TIER 3 MINERAL SOIL C STOCK CHANGE METHODS

Four examples of Tier 3 model applications for soil organic C stock changes are elaborated in this section based on government reporting to the UNFCCC by the Australia, Finland, Japan and United States.

Australia

Australia has implemented a Tier 3 inventory approach based on the use of the FullCAM model (Richards 2001; Richards & Evans 2004) to estimate management induced changes in the stock of organic carbon held in the 0-30 cm soil depth layer over time. Australian lands included in the inventory were allocated to forest land, cropland, grassland, deforested land, forest land converted to cropland and grassland, grassland converted to forest land, and land with sparse woody vegetation based on national land use mapping (ABARES 2016) and remote sensing protocols (Caccetta *et al.* 2012) Detailed presentations of the soil carbon accounting processes under all land uses can be found in the National Inventory Reports (NIR) (http://www.environment.gov.au/climate-change/greenhouse-gas-measurement/publications/national-inventory-report-2015). Here a summary is provided of the Tier 3 approach as applied to soil organic carbon stocks for cropland and grassland.

The FullCAM model simulates soil carbon stock change in 25m x 25m areas across Australia. This size was selected as it represented the finest scale to which the remote sensing process (Caccetta *et al.* 2012; Tupek *et al.* 2016) can detect land use change and quantify movement of lands between the various classes included in the inventory. The data requirements and processes used to quantify the impact of management on Australia's 0-30 cm stock of soil organic carbon can be summarised as follows:

1) Spatially explicit daily and monthly climatic data (average temperature, total rainfall and total pan evaporation) are extracted from the Australian Bureau of Meteorology database and then interpolated using thin plate smoothing splines according to (Kesteven & Lansberg 2004). Additionally, spatially explicit estimates of soil clay content and water holding capacity are extracted from the Soil and Landscape Grid of Australia (www.clw.csiro.au/aclep/soilandlandscapegrid/). These data represent required inputs the modelling described in steps 4 and 5.

2) The initial 0-30 cm total soil organic carbon stock is defined using a national map derived by Viscarra Rossel *et al.* (2014). This total stock is then allocated to three measurable organic carbon fractions (particulate, humus and resistant forms) that provide estimates for the respective stocks of resistant plant material, humus and inert carbon required to initialize the FullCAM model (Baldock *et al.* 2013; Skjemstad *et al.* 2004; Viscarra Rossel & Hicks 2015).

3) The types of crops and pastures grown, the applied management practices (e.g. tillage and residue management) and their relative allocations within defined land areas are calculated using national agricultural statistics derived from censuses conducted every five years (http://www.abs.gov.au/Agriculture).

4) For the bulk of Australian crops and pastures, total growth is defined by the availability of water received as rainfall. Thus, a plant growth model applying species specific transpiration efficiency terms to the amount of water made available to growing plants is used to estimate above ground dry matter production. This production is then used along with plant species specific harvest indices (Unkovich *et al.* 2010) and root:shoot ratios to define the mass of carbon entering the soil and/or deposited on the soil surface for each monthly time step within the FullCAM simulation model. Within irrigated systems, plant growth attains defined plant specific maximum values each year.

5) The FullCAM model is then initialized and run on a monthly time step. During each step, decomposition of decomposable and resistant plant materials and humus pools of C occurs according to first order decay equations. The values of the decomposition rate constants associated with the resistant plant material and humus pools of carbon within the model were calibrated to Australian conditions to the corresponding measured stocks of soil carbon fractions

BOX 2.2D (NEW) (CONTINUED)

EXAMPLES OF TIER 3 MINERAL SOIL C STOCK CHANGE METHODS

5) (continued) of soil temperature and water content on decomposition is modelled through the application of decomposition rate constant modifiers as done in the Rothamsted Carbon Model (RothC) soil carbon model (Jenkinson 1990).

The impact of management on soil carbon stocks is quantified by running the described modelling process forward from 1970 under two scenarios. In both scenarios, the same relative spatial allocation of regimes (combinations of crop or pasture species and management practice) is used from 1970 to 1990. From 1990 onwards, the relative spatial allocation of regimes is held constant at 1990 values in the first scenario. For the second scenario, the regimes are varied from 1991 onwards to reflect the temporal variations in regimes defined within the available data. The first scenario thus estimates the soil carbon stock that would have been attained with no change in management from that present in 1990; while the second scenario estimates the soil carbon stock attained when management changes over time are accounted for. The net impact of management since 1990 is then calculated as the difference in the soil organic carbon stock between the two scenarios.

Finland

Finland uses Yasso07 soil carbon model as a Tier 3 method to report carbon stock changes on forest and agricultural lands as well as in the cases of land use change (Statistics Finland 2017). Yasso07 is based on a few explicit assumptions on soil carbon cycling and these assumptions form a conceptual model further formulated into mathematical equations (Tuomi *et al.* 2011b; US EPA 2017). The model has four state variables based on the solubility of the organic material (acid-, water-, ethanol- and non-soluble and in addition, there is a humus pool that has the lowest decay rate.

The model is used in the NGHGI to generate annual C stock change rates per hectare based on regional estimates of organic matter input (forest and crop statistics) and annual climate parameters. Litter input is given in the four solubility fractions based on laboratory measurements. Organic matter decays in the five model fractions driven by temperature and precipitation. The resulting C stock change rates are applied on the respective land areas to produce regional estimates of C stock change. The model is used consistently across different land use categories so that e.g. the initial C allocation to different model compartments in forest land converted to cropland is based on the results of the simulation of forest soil remaining forest soil.

Model parameters rely on a large global database of measurements of litter decay, wood decay and soil carbon and all parameter values have been estimated using Markov chain Monte Carlo method. Alternative details in the model structure have been evaluated using Bayesian criteria (Tuomi *et al.* 2011a). The results of Yasso07 model are characterized by statistical probability distributions that represent uncertainty about the parameter values. The Yasso07 approach makes it possible and easy to add new data to the database and develop the model continuously (model-data-fusion). The model has been extensively tested against independent data on forest land (Dalsgaard *et al.* 2016; Lehtonen *et al.* 2016; Rantakari *et al.* 2012; Tupek *et al.* 2016) and also on cropland (Karhu *et al.* 2012). Yasso07 is a standard component of Max Planck Institute Earth System Model (Goll *et al.* 2017) and the model is used for UNFCCC reporting in several countries (e.g. Austria, Benin, Czech Republic, Estonia, Ireland, Finland, Latvia, Norway, Romania and Switzerland), see Hernandez *et al.* (2017). The model is widely used because it is simple, transparent, verifiable, freely available and easy to apply. For more information, consult http://en.ilmatieteenlaitos.fi/yasso.

BOX 2.2D (NEW) (CONTINUED)

EXAMPLES OF TIER 3 MINERAL SOIL C STOCK CHANGE METHODS

Japan

Japan uses a Tier 3 method to estimate soil organic C stock changes in agriculture land (cropland and managed grassland) based on RothC. RothC model is a soil carbon dynamic model validated by using long-term field experiments (Coleman & Jenkinson 1996). In order to apply the model to Japanese agricultural condition, the model was tested against long-term experimental data sets in Japanese agricultural lands. It was found that the original model could apply for non-volcanic upland soils without any modification or calibration (Shirato & Taniyama 2003), however, the model required modification for Andosols and paddy soils by taking unique mechanisms of soil C dynamics in these soils into account. For Andosols, the decomposition rate constant of the HUM (humified organic matter) pool of RothC was reduced because the presence of Al-humus complexes enhances its stability and resistance to decomposition (Shirato *et al.* 2004). For paddy soils, the decomposition rate constants of all four active C pools was reduced on the basis of differences in organic matter decomposition rates between upland and paddy (submerged in the rice growing season) soil conditions (Shirato & Yokozawa 2005). Model performance was verified by comparing the model output with measured soil C stock data under various climate condition, soil types and land uses.

The model is applied at the country scale (Yagasaki & Shirato 2014) using weather data (monthly average temperature, precipitation, and open-pan evaporation), soil property data (soil clay content, depth of surface soil, carbon content at the starting year, and bulk density), land use data and other activity data (carbon input from crop residue and organic manure) and calculated at each standard mesh (100 x 100m). The weather, soil property and land use data are available as spatially explicit data set, while carbon input from crop residue and organic manure are calculated by statistical data and survey data available based on public administration boundary basis. The all obtained data are allocated to each standard mesh and then run the model.

In the NGHGI, the model is used to generate average C stock change rates per hectare in each prefecture and in each sub-category (rice field, upland crop fields, orchards and managed grassland). This is because the land use data used for the model estimation (grid-based data set) and used for the official land classification in the NGHGI (statistical data) are not consistent very much and so Japan put its priority using a consistent land area data among every estimate relating to agriculture land in AFOLU sector. This is one of the key challenges of the model application to the NGHGI and the development of a standard spatially explicit land use data set is needed for the further improvement of estimations.

United States of America

The United States uses a Tier 3 method based on the DayCent Ecosystem Model to estimate soil C stock changes in cropland and grassland (Ogle *et al.* 2010, US EPA 2017). DayCent is a process-based model that simulated soil organic matter dynamics using a three-pool structure originally developed for the Century Model (Parton *et al.* 1998; Parton *et al.* 1987). Model testing and parameterisation of DayCent has been conducted across a wide range of cropland and grassland sites globally. For the inventory, the model is applied using land use data that are compiled through a national survey, National Resources Inventory (NRI) (Nusser *et al.* 1998; Nusser & Goebel 1997). The NRI has a two-stage sample with recorded history, starting in 1979, for approximately 400,000 survey locations that are cropland or grassland throughout the conterminous United States. Each survey location that is identified as cropland also has the specific crop rotation histories that were grown by the farmer. Daily weather and soils data are needed to drive the model, and this information is based on national datasets. Remote sensing data is used to inform production estimates based on MODIS Enhanced Vegetation Index products. Other data are also incorporated into the analysis, such as N fertilization rate data compiled through surveys.

BOX 2.2D (NEW) (CONTINUED)

EXAMPLES OF TIER 3 MINERAL SOIL C STOCK CHANGE METHODS

One of the key challenges in developing a Tier 3 method is to robustly address uncertainties. Compilers in the United States have addressed uncertainties in model inputs (e.g., fertilization rates, tillage practices and organic amendments), model structure and parameterization, and propagate uncertainty through the model application using an Approach 2 method (i.e., Monte Carlo Analysis) (Ogle et al. 2010). Model structure and parameterization is addressed using an empirically-based method in which observed experimental data are compared to simulation results, and predictive ability of the model is quantified using statistical methods (Ogle et al. 2007). These experimental observations are independent from the data that are used to parameterise the model. The resulting statistical equation is applied to adjust for biases in model results, if needed, and address the precision of the model C stock changes. The major advantage of the Tier 3 method is that the results are much more precise than Tier 1 and 2 methods, with uncertainty ranging from ±60% in the Tier 1 method to about ±20% for the Tier 3 method (US-EPA 2017). The improved precision is due to the process-based framework in the DayCent model that incorporates more drivers of soil C stock changes than lower Tier methods. However, without adequate activity data or a model with sufficient prediction capability, a Tier 3 method could produce less precise results than lower-tier methods.

BOX 2.2E (NEW)
CONSIDERATION OF EQUIVALENT MASS METHODS WITHIN TIER 3 MODELLING APPROACHES

Process models that are used to estimate carbon stock changes over time, such as Century (Parton et al. 1987) and RothC (Coleman & Jenkinson 1996) can also be affected by changing soil bulk density by the nature of the carbon stock data used for model parameterisation. These types of models simulate the mass balance of organic carbon over time to a defined soil depth (e.g., 30 cm or an alternative). The models require initialisation at which point an initial carbon stock is determined along with an initial soil mass in some cases (although the soil mass is rarely determined explicitly, it is implicit in the model application). The models therefore use an equivalent soil mass approach to simulate changes in carbon stocks since the estimated carbon stocks are unaffected by concurrent soil bulk density changes. If the models are parameterised to carbon stocks on an equivalent mass basis, then the carbon stock changes estimated by the parametrised model, and for a factor derived from those modelled estimates, will be for soil carbon change on an equivalent mass basis. However, the carbon stock change calculated from carbon stock measurements for a fixed depth is the net effect of the effect of soil bulk density changes on carbon stocks and the effect of biochemical processes on carbon stocks. Therefore, when parameterised using fixed-depth carbon stock data, the model will be estimating the net effect of these processes, so the modelled carbon stock estimates only will be appropriate for the fixed depth and cannot address changes in mass of the soil over time. Careful consideration of the effects of model assumptions and choice of data used for model parametrisation and testing is required to understand and properly report the basis of the carbon stock changes that are estimated directly or indirectly by a model based on parameterisation with data from fixed depths.

Tier 3 methods can be used to model the loss of biochar C over time after its application to mineral soils and to account for GHG sources and sinks not captured in Tier 2, to address changes to N_2O or CH_4 fluxes from soils[8], to estimate changes to net primary production (and associated C inputs to soil organic C pool), the mechanisms and effects underlying interactions with soil, climate and other environmental variables. Although positive priming of labile soil organic matter is not expected to have a significant impact in the long term (Annex 2A.2), negative priming leading to an increase in soil organic carbon stocks could have a substantial impact in soils amended with biochar (Woolf *et al.* 2012). Similarly, to the extent that there are reductions in net emissions of N_2O and CH_4 from soil and increases in plant growth, there could be a larger impact of biochar additions on reducing greenhouse gas emissions (Gaunt & Lehmann 2008; Woolf *et al.* 2010; Hammond *et al.* 2011). It is also important to recognise

[8] Impacts of biochar amendments on N_2O are estimated in the methods for soil N_2O emissions (Chapter 11), and impacts on CH_4 emissions are estimated from specific land uses in the inventory, such as Rice Cultivation (Chapter 5) and Wetlands (Chapter 7).

that the dynamic nature of biochar decomposition is important because its net impact on soil C stocks and GHG emissions varies with time, which can be better addressed with a Tier 3 model.

Examples of advanced modelling approaches include representing the dynamic impact of biochar decomposition over long time scales (Lenton & Vaughan 2009), and process-based modelling using biochar-specific LCA models (e.g. Roberts *et al.* 2010; Hammond *et al.* 2011; Shackley *et al.* 2012; Sparrevik *et al.* 2013). There are also applications that have focused on soil greenhouse gas emission balances, together with modelling of decomposition rates (H/C_{org} ratio; Lehmann *et al.* 2015) and priming (Woolf & Lehmann, 2012; Wang *et al.* 2016). In addition, models have been used to simulate nitrous oxide reductions (Cayuela *et al.* 2013, 2014) as a function of H/C_{org} ratio (Cayuela *et al*. 2015) and feedbacks to primary plant productivity (Jeffery *et al.* 2011, 2015) and associated impacts on SOC stocks (Whitman *et al.* 2010, 2011).

Organic soils

No Refinement. *See Chapter 2 of the 2013 Wetlands Supplement.*

Soil inorganic C

No Refinement.

2.4 NON-CO_2 EMISSIONS

There are significant emissions of non-greenhouse gases from biomass burning, livestock and manure management, or soils. N_2O emissions from soils are covered in Chapter 11, where guidance is given on methods that can be applied nationally (i.e., irrespective of land-use types) if a country chooses to use national scale activity data. The guidance on CH_4 and N_2O emissions from livestock and manure are addressed only in Chapter 10 because emissions do not depend on land characteristics. A generic approach to estimating greenhouse gas emissions from fire (both CO_2 and non-CO_2 gases) is described below, with land-use specific enhancements given in the Forest Land, Grassland and Cropland chapters. It is *good practice* to check for complete coverage of CO_2 and non-CO_2 emissions due to losses in carbon stocks and pools to avoid omissions or double counting.

Emissions from fire include not only CO_2, but also other greenhouse gases, or precursors of greenhouse gases, that originate from incomplete combustion of the fuel. These include carbon monoxide (CO), methane (CH_4), non-methane volatile organic compounds (NMVOC) and nitrogen (e.g., N_2O, NO_x) species (Levine, 1994). In the *1996 IPCC Guidelines* and *GPG2000*, non-CO_2 greenhouse gas emissions from fire in savannas and burning of crop residues were addressed along with emissions from Forest Land and Grassland conversion. The methodology differed somewhat by vegetation type, and fires in Forest Land were not included. In the *GPG-LULUCF*, emissions (CO_2 and non-CO_2) from fires were addressed, particularly in the chapter covering Forest Land (losses of carbon resulting from disturbances). In the Cropland and Grassland chapters, only non-CO_2 emissions were considered, with the assumption that the CO_2 emissions would be counterbalanced by CO_2 removals from the subsequent re-growth of the vegetation within one year. This assumption implies maintenance of soil fertility – an assumption which countries may ignore if they have evidence of fertility decline due to fire. In Forest Land, there is generally a lack of synchrony (non-equivalence of CO_2 emissions and removals in the year of reporting).

These Guidelines provide a more generic approach for estimating emissions from fire. Fire is treated as a disturbance that affects not only the biomass (in particular, above-ground), but also the dead organic matter (litter and dead wood). The term `biomass burning` is widely used and is retained in these Guidelines but acknowledging that fuel components other than live biomass are often very significant, especially in forest systems. For Cropland and Grassland having little woody vegetation, reference is usually made to biomass burning, since biomass is the main pool affected by the fire.

Countries should apply the following principles when estimating greenhouse gas emissions resulting from fires in Forest Land, Cropland and Grassland:

- Coverage of reporting: Emissions (CO_2 and non- CO_2) need to be reported for all fires (prescribed fires and wildfires) on managed lands (the exception is CO_2 from Grassland, as discussed below). Where there is a land-use change, any greenhouse gas emission from fire should be reported under the new land-use category (transitional category). Emissions from wildfires (and escaped prescribed fires) that occur on unmanaged lands do not need to be reported, unless those lands are followed by a land-use change (i.e., become managed land).
- Fire as a management tool (prescribed burning): greenhouse gas emissions from the area burnt are reported, and if the fire affects unmanaged land, greenhouse gas emissions should also be reported if the fire is followed by a land-use change.
- Equivalence (synchrony) of CO_2 emissions and removals: CO_2 net emissions should be reported where the CO_2 emissions and removals for the biomass pool are not equivalent in the inventory year. For grassland

biomass burning and burning of agriculture residues, the assumption of equivalence is generally reasonable. However, woody vegetation may also burn in these land categories, and greenhouse gas emissions from those sources should be reported using a higher Tier method. Further, in many parts of the world, grazing is the predominant land use in Forest Land that are regularly burnt (e.g., grazed woodlands and savannas), and care must be taken before assuming synchrony in such systems. For Forest Land, synchrony is unlikely if significant woody biomass is killed (i.e., losses represent several years of growth and C accumulation), and the net emissions should be reported. Examples include: clearing of native forest and conversion to agriculture and/or plantations and wildfires in Forest Land.

- Fuels available for combustion: Factors that reduce the amount of fuels available for combustion (e.g., from grazing, decay, removal of biofuels, livestock feed, etc.) should be accounted for. A mass balance approach should be adopted to account for residues, to avoid underestimation or double counting (refer to Section 2.3.2).
- Annual reporting: despite the large inherent spatial and temporal variability of fire (in particular that from wildfires), countries should estimate and report greenhouse gas emissions from fire on an annual basis.

These Guidelines provide a comprehensive approach for estimating carbon stock changes and non-CO_2 emissions resulting from fire in the Forest Land (including those resulting from forest conversion), and non-CO_2 emissions in the Cropland and Grassland. Non-CO_2 emissions are addressed for the following five types of burning: (1) grassland burning (which includes perennial woody shrubland and savanna burning); (2) agricultural residues burning; (3) burning of litter, understory and harvest residues in Forest Land, (4) burning following forest clearing and conversion to agriculture; and (5) other types of burning (including those resulting from wildfires). Direct emissions of CO_2 are also addressed for items (3) and (4) and (5). Since estimating emissions in these different categories have many elements in common, this section provides a generic approach to estimate CO_2 and non-CO_2 emissions from fire, to avoid repetition in specific land-use sections that address emissions from fire in these Guidelines.

Prescribed burning of savannas is included under the grassland biomass burning section (Chapter 6, Grassland, Section 6.3.4). It is important to avoid double counting when estimating greenhouse gas emissions from savannas that have a vegetation physiognomy characteristic of Forest Land. An example of this is the cerradão (dense woodland) formation in Brazil which, although being a type of savanna, is included under Forest Land, due to its biophysical characteristics.

In addition to the greenhouse gas emissions from combustion, fires may lead to the creation of an inert carbon stock (charcoal or char). Post-fire residues comprise unburned and partially burnt components, as well as a small amount of char that due to its chemical nature is highly resistant to decomposition. The knowledge of the rates of char formation under contrasting burning conditions and subsequent turnover rates is currently too limited (Forbes *et al.*, 2006; Preston and Schmidt, 2006) to allow development of a reliable methodology for inventory purposes, and hence is not included in these Guidelines. A technical basis for further methodological development is included in Appendix 1.

Additionally, although emissions of NMVOC also occur as a result of fire, they are not addressed in the present Guidelines due to the paucity of the data and size of uncertainties in many of the key parameters needed for the estimation, which prevent the development of reliable emission estimates.

METHOD DESCRIPTION

Each relevant section in these Guidelines includes a three-tiered approach to address CO_2 (where applicable) and non-CO_2 greenhouse gas emissions from fire. The choice of Tier can be made following the steps in the decision tree presented in Figure 2.6. Under the Tier 1 approach, the formulation presented in Equation 2.27 can be applied to estimate CO_2 and non-CO_2 emissions from fire, using the default data provided in this chapter and in the relevant land-use sections of these Guidelines. Higher Tiers involve a more refined application of Equation 2.27.

Since Tier 1 methodology adopts a simplified approach to estimating the dead organic matter pool (see Section 2.3.2), certain assumptions must be made when estimating net greenhouse gas emissions from fire in those systems (e.g. Forest Land, and Forest Land converted to another land use), where dead organic matter can be a major component of the fuel burnt. Emissions of CO_2 from dead organic matter are assumed to be zero in forests that are burnt, but not killed by fire. If the fire is of sufficient intensity to kill a portion of the forest stand, under Tier 1 methodology, the C contained in the killed biomass is assumed to be immediately released to the atmosphere. This Tier 1 simplification may result in an overestimation of actual emissions in the year of the fire, if the amount of biomass carbon killed by the fire is greater than the amount of dead wood and litter carbon consumed by the fire.

Non-CO_2 greenhouse gas emissions are estimated for all fire situations. Under Tier 1, non-CO_2 emissions are best estimated using the actual fuel consumption provided in Table 2.7, and appropriate emission factors (Table 2.8) (i.e., not including newly killed biomass as a component of the fuel consumed). Clearly, if fire in forests contributes significantly to net greenhouse gas emissions, countries are encouraged to develop a more complete methodology (higher tiers) which includes the dynamics of dead organic matter and improves the estimates of direct and post-fire emissions.

For Forest Land converted to other land uses, organic matter burnt is derived from both newly felled vegetation and existing dead organic matter, and CO_2 emissions should be reported. In this situation, estimates of total fuel consumed (Table 2.6) can be used to estimate emissions of CO_2 and non- greenhouse gases using Equation 2.27. Care must be taken, however, to ensure that dead organic matter carbon losses during the land-use conversion are not double counted in Equations 2.27 (as losses from burning) and Equation 2.23 (as losses from decay).

A generic methodology to estimate the emissions of individual greenhouse gases for any type of fire is summarised in Equation 2.27.

EQUATION 2.27
ESTIMATION OF GREENHOUSE GAS EMISSIONS FROM FIRE

$$L_{fire} = A \bullet M_B \bullet C_f \bullet G_{ef} \bullet 10^{-3}$$

Where:

L_{fire} = amount of greenhouse gas emissions from fire, tonnes of each GHG e.g., CH_4, N_2O, etc.

A = area burnt, ha

M_B = mass of fuel available for combustion, tonnes ha^{-1}. This includes biomass, ground litter and dead wood. When Tier 1 methods are used then litter and dead wood pools are assumed zero, except where there is a land-use change (see Section 2.3.2.2).

C_f = combustion factor, dimensionless (default values in Table 2.6)

G_{ef} = emission factor, g kg^{-1} dry matter burnt (default values in Table 2.5)

Note. Where data for M_B and C_f are not available, a default value for the amount of fuel actually burnt (the product of M_B and C_f) can be used (Table 2.4) under Tier 1 methodology.

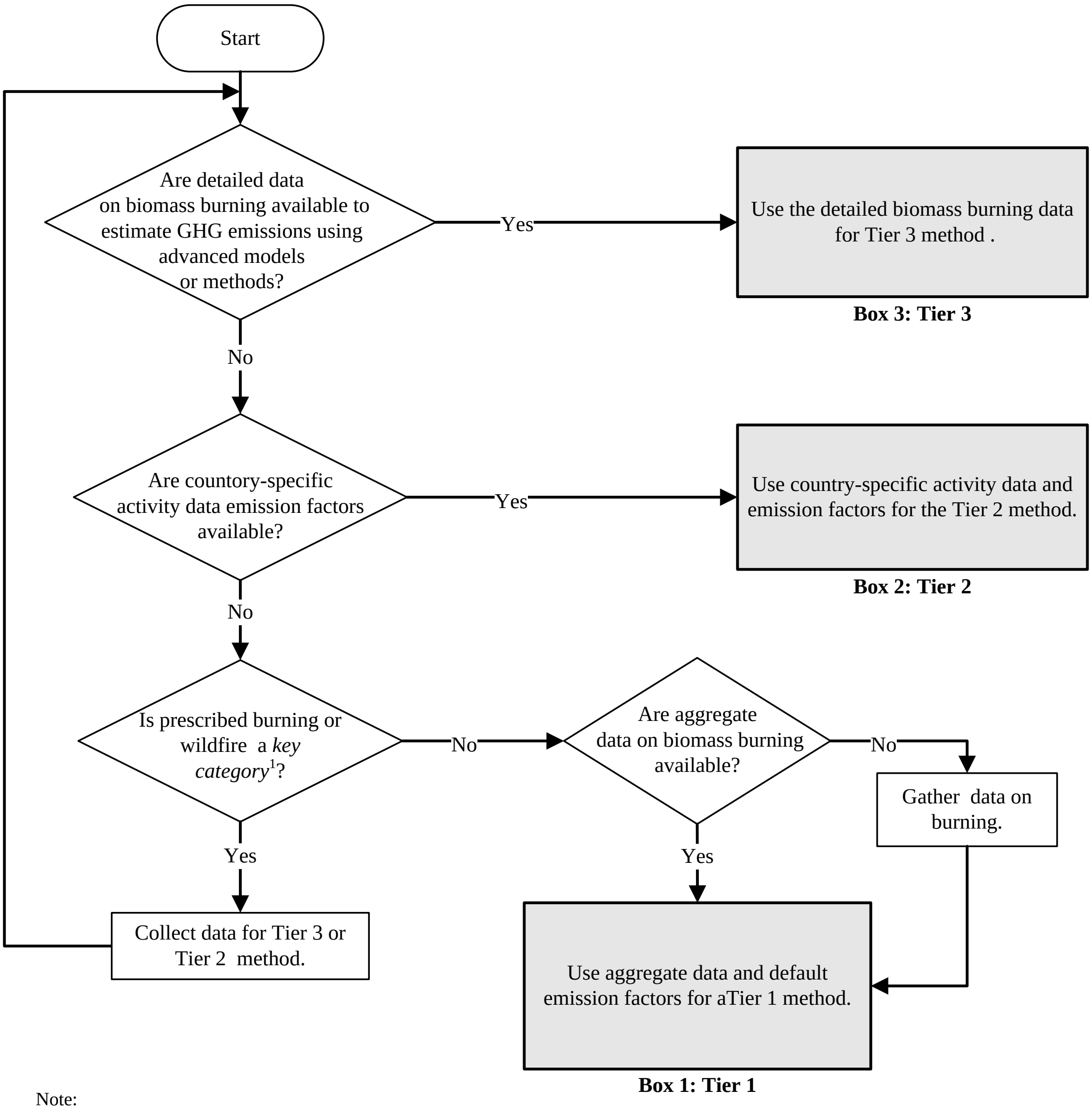
For CO_2 emissions, Equation 2.27 relates to Equation 2.14, which estimates the annual amount of live biomass loss from any type of disturbance.

The amount of fuel that can be burnt is given by the area burnt and the density of fuel present on that area. The fuel density can include biomass, dead wood and litter, which vary as a function of the type, age and condition of the vegetation. The type of fire also affects the amount of fuel available for combustion. For example, fuel available for low-intensity ground fires in forests will be largely restricted to litter and dead organic matter on the surface, while a higher-intensity 'crown fire' can also consume substantial amounts of tree biomass.

The combustion factor is a measure of the proportion of the fuel that is actually combusted, which varies as a function of the size and architecture of the fuel load (i.e., a smaller proportion of large, coarse fuel such as tree stems will be burnt compared to fine fuels, such as grass leaves), the moisture content of the fuel and the type of fire (i.e., intensity and rate of spread which is markedly affected by climatic variability and regional differences as reflected in Table 2.4). Finally, the emission factor gives the amount of a particular greenhouse gas emitted per unit of dry matter combusted, which can vary as a function of the carbon content of the biomass and the completeness of combustion. For species with high N concentrations, NO_x and N_2O emissions from fire can vary as a function of the N content of the fuel. A comprehensive review of emission factors was conducted by Andreae and Merlet (2001) and is summarised in Table 2.5.

Tier 2 methods employ the same general approach as Tier 1 but make use of more refined country-derived emission factors and/or more refined estimates of fuel densities and combustion factors than those provided in the default tables. Tier 3 methods are more comprehensive and include considerations of the dynamics of fuels (biomass and dead organic matter).

Figure 2.6 Generic decision tree for identification of appropriate tier to estimate greenhouse gas emissions from fire in a land-use category



Note:
1. See Volume 1 Chapter 4, Methodological Choice and Identification of Key Categories (noting Section 4.1.2 on limited resources), for discussion of *key categories* and use of decision trees.

TABLE 2.4 (UPDATED)
FUEL (DEAD ORGANIC MATTER PLUS LIVE BIOMASS) BIOMASS CONSUMPTION VALUES (TONNES DRY MATTER HA^{-1}) FOR FIRES IN A RANGE OF VEGETATION TYPES
(To be used in Equation 2.27, to estimate the product of quantities '$M_B \bullet C_f$', i.e., an absolute amount)

Vegetation type	Subcategory	Mean	SE	References
Primary tropical forest (slash and burn)	Primary tropical forest	83.9	25.8	7, 15, 66, 3, 16, 17, 45
	Primary open tropical forest	163.6	52.1	21,
	Primary tropical moist forest	160.4	11.8	37, 73
	Primary tropical dry forest	-	-	66
All primary tropical forests		**119.6**	**50.7**	
Secondary tropical forest (slash and burn)	Young secondary tropical forest (3-5 yrs)	8.1	-	61
	Intermediate secondary tropical forest (6-10 yrs)	41.1	27.4	61, 35
	Advanced secondary tropical forest (14-17 yrs)	46.4	8.0	61, 73
All secondary tropical forests		**42.2**	**23.6**	66, 30
All Tertiary tropical forest		**54.1**	-	66, 30
Boreal forest	Wildfire (general)	52.8	48.4	2, 33, 66
	Crown fire	25.1	7.9	11, 43, 66, 41, 63, 64
	Surface fire	21.6	25.1	43, 69, 66, 63, 64, 1
	Post logging slash burn	69.6	44.8	49, 40, 66, 18
	Land clearing fire	87.5	35.0	10, 67
All boreal forest		**41.0**	**36.5**	43, 45, 69, 47
Eucalypt forests	Wildfire	53.0	53.6	66, 32, 9
	Prescribed fire – (surface)	16.0	13.7	66, 72, 54, 60, 9
	Post logging slash burn	168.4	168.8	25, 58, 46
	Felled, wood removed, and burned (land-clearing fire)	132.6	-	62, 9
All Eucalypt forests		**69.4**	**100.**	
Other temperate forests	Wildfire	19.8	6.3	32, 66
	Post logging slash burn	77.5	65.0	55, 19, 14, 27, 66
	Felled and burned (land-clearing fire)	48.4	62.7	53, 24, 71
All "other" temperate forests		**50.4**	**53.7**	43, 56
Shrublands	Shrubland (general)	26.7	4.2	43
	Calluna heath	11.5	4.3	26, 39
	Sagebrush	5.7	3.8	66
	Fynbos	12.9	0.1	70, 66
All Shrublands		**14.3**	**9.0**	

TABLE 2.4 (UPDATED) (CONTINUED)
FUEL (DEAD ORGANIC MATTER PLUS LIVE BIOMASS) BIOMASS CONSUMPTION VALUES (TONNES DRY MATTER HA^{-1}) FOR FIRES IN A RANGE OF VEGETATION TYPES
(To be used in Equation 2.27, to estimate the product of quantities '$M_B \bullet C_f$', i.e., an absolute amount)

Vegetation type	Subcategory	Mea	SE	References
Savanna woodlands (early dry season burns)*	Savanna woodland	2.5	-	28
	Savanna parkland	2.7	-	57
All savanna woodlands (early dry season burns)		**2.6**	**0.1**	
Savanna woodlands (mid/late dry season burns)*	Savanna woodland	3.3	-	57
	Savanna parkland	4.0	1.1	57, 6, 51
	Tropical savanna	6	1.8	52, 73
	Other savanna woodlands	5.3	1.7	59, 57, 31
All savanna woodlands (mid/late dry season burns)*****		**4.6**	**1.5**	
Savanna Grasslands/ Pastures (early dry season burns)*	Tropical/sub-tropical grassland	2.1	-	28
	Grassland	-	-	48
All savanna grasslands (early dry season burns)*		**2.1**	**-**	
Savanna Grasslands/ Pastures (mid/late dry season burns)*	Tropical/sub-tropical grassland	5.2	1.7	9, 73, 12, 57
	Grassland	4.1	3.1	43, 9
	Tropical pasture~	23.7	11.8	4, 23, 38, 66
	Savanna	7.0	2.7	42, 50, 6, 45, 13, 65
All savanna grasslands (mid/late dry season burns)*		**10.0**	**10.1**	
Other vegetation types	Peatland	41	1.4	68, 33
	Tundra	10	-	33
Agricultural residues (post-harvest field burning)	$M_B = AGR_{(T)}$ x $Frac_{Brunt(T)}$			See Equation 11.6 in Chapter 11, Volume 4 for $AGR_{(T)}$ calculation

* Surface layer combustion only

~ Derived from slashed tropical forest (includes unburned woody material)

[a] For sugarcane, data refer to burning before harvest of the crop.

[b] Expert assessment by authors.

TABLE 2.5
EMISSION FACTORS (g kg^{-1} DRY MATTER BURNT) FOR VARIOUS TYPES OF BURNING. VALUES ARE MEANS ± SD AND ARE BASED ON THE COMPREHENSIVE REVIEW BY ANDREAE AND MERLET (2001)
(To be used as quantity 'G_{ef}' in Equation 2.27)

Category	CO_2	CO	CH_4	N_2O	NO_X
Savanna and grassland	1613 ± 95	65 ± 20	2.3 ± 0.9	0.21 ± 0.10	3.9 ± 2.4
Agricultural residues	1515 ± 177	92 ± 84	2.7	0.07	2.5 ± 1.0
Tropical forest	1580 ± 90	104 ± 20	6.8 ± 2.0	0.20	1.6 ± 0.7
Extra tropical forest	1569 ± 131	107 ± 37	4.7 ± 1.9	0.26 ±0.07	3.0 ± 1.4
Biofuel burning	1550 ± 95	78 ± 31	6.1 ± 2.2	0.06	1.1 ± 0.6

Note: The "extra tropical forest' category includes all other forest types.

Note: For combustion of non-woody biomass in Grassland and Cropland, CO_2 emissions do not need to be estimated and reported, because it is assumed that annual CO_2 removals (through growth) and emissions (whether by decay or fire) by biomass are in balance (see earlier discussion on synchrony in Section 2.4.

TABLE 2.6 (UPDATED)
COMBUSTION FACTOR VALUES (PROPORTION OF PREFIRE FUEL BIOMASS CONSUMED) FOR FIRES IN A RANGE OF VEGETATION TYPES
(Values in column 'mean' are to be used for quantity Cf in Equation 2.27)

Vegetation type	Subcategory	Mean	SD	References
Primary tropical forest (slash and burn)	Primary tropical forest	0.32	0.12	7, 8, 15, 56, 66, 3, 16, 53, 17, 45,
	Primary open tropical forest	0.45	0.09	21
	Primary tropical moist forest	0.50	0.03	37, 73
	Primary tropical dry forest	-	-	66
All primary tropical forests		**0.36**	**0.13**	
Secondary tropical forest (slash and burn)	Young secondary tropical forest (3-5 yrs)	0.46	-	61
	Intermediate secondary tropical forest (6-10 yrs)	0.67	0.21	61, 35
	Advanced secondary tropical forest (14-17 yrs)	0.50	0.10	61, 73
All secondary tropical forests		**0.55**	**0.06**	56, 66, 34, 30
All tertiary tropical forest		**0.59**	**-**	66, 30
Boreal forest	Wildfire (general)	0.40	0.06	33
	Crown fire	0.43	0.21	66, 41, 64, 63
	surface fire	0.15	0.08	64, 63
	Post logging slash burn	0.33	0.13	49, 40, 18
	Land clearing fire	0.59	-	67
All boreal forest		**0.34**	**0.17**	45, 47
Eucalyptus forests	Wildfire	-	-	
	Prescribed fire – (surface)	0.61	0.11	72, 54, 60, 9
	Post logging slash burn	0.68	0.14	25, 58, 46
	Felled and burned (land-clearing fire)	0.49	-	62
All Eucalyptus forests		**0.63**	**0.13**	
Other temperate forests	Post logging slash burn	0.62	0.12	55, 19, 27, 14
	Felled and burned (land-clearing fire)	0.51	-	53, 24, 71
All "other" temperate forests		**0.45**	**0.16**	53, 56

TABLE 2.6 (UPDATED) (CONTINUED)
COMBUSTION FACTOR VALUES (PROPORTION OF PREFIRE FUEL BIOMASS CONSUMED) FOR FIRES IN A RANGE OF VEGETATION TYPES
(Values in column 'mean' are to be used for quantity C_f in Equation 2.27)

Vegetation type	Subcategory	Mean	SD	References
Shrublands	Shrubland (general)	0.95	-	44
	Calluna heath	0.71	0.30	26, 56, 39
	Fynbos	0.61	0.16	70, 44
All shrublands		**0.72**	**0.25**	
Savanna woodlands (early dry season burns)*	Savanna woodland	0.22	-	28
	Savanna parkland	0.73	-	57
	Other savanna woodlands	0.37	0.19	22, 29
All savanna woodlands (early dry season burns)		**0.40**	**0.22**	
Savanna woodlands (mid/late dry season burns)*	Savanna woodland	0.72	-	66, 57
	Savanna parkland	0.82	0.07	57, 6, 51
	Tropical savanna	0.73	0.04	52, 73, 66, 12
	Other savanna woodlands	0.68	0.19	22, 29, 44, 31, 57
All savanna woodlands (mid/late dry season burns)*		**0.74**	**0.14**	
Savanna Grasslands/ Pastures (early dry season burns)*	Tropical/sub-tropical grassland	0.74	-	28
	Grassland	-	-	48
All savanna grasslands (early dry season burns)*		**0.74**	-	
Savanna Grasslands/ Pastures (mid/late dry season burns)*	Tropical/sub-tropical grassland	0.92	0.11	44, 73, 66, 12, 57
	Tropical pasture~	0.35	0.21	4, 23, 38, 66
	Savanna	0.86	0.12	53, 5, 56, 42, 50, 6, 45, 13, 44, 65, 66
All savanna grasslands (mid/late dry season burns)*		**0.77**	**0.26**	
Other vegetation types	Peatland	0.50	-	20, 44
	Tropical Wetlands	0.70	-	44
Agricultural residues (Post-harvest field burning)	Wheat residues	0.90	-	see Note b
	Maize residues	0.80	-	see Note b
	Rice residues	0.80	-	see Note b
	Sugarcane a	0.80	-	see Note b
	Other Crops	0.85	-	see Note b

* Surface layer combustion only; ~ Derived from slashed tropical forest (includes unburned woody material); [a] For sugarcane, data refer to burning before harvest of the crop; [b] Expert assessment by authors.

2.5 ADDITIONAL GENERIC GUIDANCE FOR TIER 3 METHODS

Tier 3 inventories are advanced systems using measurements and/or modelling, with the goal of improving the estimation of greenhouse gas (GHG) emissions and removals, beyond what is possible with Tier 1 or 2 methods.

In this section, guidelines are elaborated that provide a sound scientific basis for the development of Tier 3 Inventories in the AFOLU sector. These guidelines do not limit the selection of Tier 3 sampling schemes or modelling methods but provide general guidance to assist the inventory developer in their implementation. AFOLU inventory compilers are advised to read this section in conjunction with general guidance for Tier 3 methods relevant to all sectors found in Volume 1, Chapter 6.

2.5.1 Measurement-based Tier 3 inventories

Inventories can be based on direct measurements from which emissions and removals of carbon are estimated. Purely measurement-based inventories, e.g., based on repeated measurements using a national forest inventory or similar estimation methods can produce carbon stock change estimates but still rely on appropriate statistical models, such as allometric models or volume and wood density functions. Inventories using measurement-based methods also need to select appropriate statistical sampling estimators to produce a national inventory from the plot estimates. Moreover, inventory plot remeasurements will typically require additional data or methods to arrive at estimates of GHG emissions from disturbance events, in particular for non-CO_2 GHG. Measurement of non-CO_2 greenhouse gas emissions is possible, but because of the high spatial and temporal variability, Tier 3 methods for estimating non-CO_2 emissions typically use a combination of models (see Section 2.5.2) and measurements.

Many countries using a measurement-based Tier 3 method will already have well established national inventories. Typically, these inventories have been established for purposes other than collecting data for estimating carbon stock changes and non-CO_2 emissions (e.g., National Forest Inventories for timber resource assessments or soil resource mapping for agricultural planning). In general, the following six steps should be considered when implementing a measurement-based Tier 3 inventory.

Step 1. Develop a sampling scheme, including sample unit (plot) design and measurements to be collected.

Sampling schemes can be developed using a variety of methods such as simple random, stratified random, systematic or model-based sampling. When designing a sampling scheme, countries often also consider factors such as spatial variability and temporal dynamics of carbon stocks, key environmental variables (e.g., climate) and management systems (e.g., harvested forest land, grazed grassland).

When using a repeated measurement design, the timing of re-measurement may be influenced by the rate of change experienced. For example, re-measurement periods in boreal and some temperate regions, where trees grow slowly and DOM pools change little in single years, can be longer than in environments where carbon dynamics are more rapid. When implementing a measurement-based Tier 3 inventory, the inventory compiler should take into consideration that it will not be possible to estimate emissions and removals using the stock-difference method until a minimum of two measurement cycles have been conducted (often 10 years or longer in total).

Some sampling schemes do not include re-sampling of the same sites (e.g., temporary inventory plot designs). Such designs may limit the statistical power of the analysis when estimating change, and therefore lead to greater uncertainty in estimates of carbon stock change. Repeated measurement designs with permanent plot locations typically provide a better basis for estimating carbon stock changes or emissions. The utility of permanent plots is often greater if they are accurately georeferenced to facilitate the use of spatial auxiliary variables, such as from remote sensing (GFOI, 2016).

For some carbon pools, such as soil carbon, litter and woody debris, it is not necessarily possible to remeasure the same material through time (i.e., if taking a soil core, that soil has been removed from the site and cannot be remeasured, unlike measuring the same trees through time). However, multiple samples can be taken at each time step to capture local site scale heterogeneity in the carbon stock and detect changes over time with each re-sampling of a site (Ellert et al., 2002, Conant et al., 2003). Where countries use direct measurement methods for soil C, the sampling design needs to ensure that a sufficient number of samples are taken at each measurement time for estimating stock change (Spencer et al., 2011).

Inventory and plot designs should consider the practicality of implementation given country circumstances (e.g., terrain, access, safety, vegetation type). The types and number of measurements will depend on the plot design, the underlying population of carbon pools to be reported and the data requirements of methods adopted to estimate carbon stocks and stock changes from the plot data.

It is *good practice* to develop a methodology handbook (e.g., Canadian Forest Service, 2008; US Forest Service, 2006) explaining the entire sampling scheme as part of Step 1. This handbook can be useful for those involved with the measurements, laboratory analyses and other aspects of the process, as well as possibly providing supporting material for documentation purposes. The handbook should document the plot design, in particular how plots are to be located and, in the case of repeated measurement designs, re-located for future measurements (Vidal et al., 2016).

Step 2. Select sample sites.

Specific sampling sites will be located based on sampling design. It is *good practice* to have an appropriate process in place for selecting alternative sites in case it is not possible to sample some original locations. In a repeated measurement design, the sites will become a monitoring network that is periodically re-sampled.

Determining sampling locations will likely involve the use of a geographic information system. A geographic database may include information on land use and land-use changes (i.e., activity data) as well as a variety of environmental and management data, such as climate, soils, land use, and livestock operations, depending on the source category and stratification. If key geographic data are not available at the national scale, or are spatially inconsistent, the inventory developer may either 1) re-evaluate the design and stratification (if used) in Step 1 and possibly modify the sampling design or 2) re-develop the geographic data to meet the inventory requirements.

Normally the sampling intensity should be the same within a stratum but not necessarily between strata. However, where the stratification is based on land use and is updated for each inventory, changes in land use between measurement periods can complicate the estimation of changes in carbon stocks over time. As such, it is *good practice* to use stratification methods that do not lead to bias or time-series inconsistencies due to changes in land use.

Sampling may require coordination among different national ministries, provincial or state governments, corporate and private land owners. Establishing relationships among these stakeholders can be undertaken before collecting initial samples. Informing stakeholders about ongoing monitoring may also be helpful and lead to greater success in implementing monitoring programs.

Step 3. Collect initial samples.

Once the plot locations have been determined, a measurement team can visit those locations, establish plots and collect initial measurements and samples. It is helpful to take geographic coordinates of plot locations or sample points with a global positioning system (GPS) to help relocate them later, noting that GPS readings are often not accurate enough to relocate the exact plot location, especially under dense forest canopies. As such, if repeated measurements are planned, it is *good practice* to permanently mark the location for ease of finding and re-sampling the site in the future. Where possible these markers should not be visible to the land owner (e.g., utility ball markers that can be buried in the soil and re-located precisely over time).

It is *good practice* to take relevant measurements and notes of the environmental conditions and management at the site. This will confirm that the conditions were consistent with the design of the sampling scheme, and also may be used in data analysis (Step 5). If a stratified sampling approach is used, and it becomes apparent that many or most sites are not consistent with the expected environmental conditions and management systems, it is *good practice* to repeat Step 1, re-evaluating and possibly modifying the sampling scheme based on the new information.

Step 4. Re-sample the monitoring network on a periodic basis.

For repeated measurement designs, sampling sites will be periodically re-sampled with the time between re-measurement dependant on the rate of stock changes or the variability in emissions, the resources available for the monitoring program, and the design of the sampling scheme. It is *good practice* to avoid any impact of measurement techniques on C stocks and their dynamics (i.e. no destructive sampling) where permanent sample plots are used.

If destructive sampling is involved, such as removing a soil core or dead organic matter sample, it is *good practice* to re-sample at the same site but not at the exact location in which the sample was removed during the past. Destructive sampling the exact location is likely to create bias in the measurements. Such biases would compromise the monitoring and produce results that are not representative of national trends. When destructive sampling of trees is undertaken, for example to develop or validate allometric equations, the samples are usually taken from locations or species that are considered representative of the trees in the plots.

Step 5. Analyse data and determine carbon stock changes/non-CO_2 emissions, and infer national emissions and removal estimates and their uncertainty.

A well-designed sampling scheme will provide an unbiased estimate and variance for the measured quantities (See Volume I, Chapter 3 for more information). The overall result of the statistical analysis will be estimates of carbon stock changes or measurements of emissions from which the national emission and removal estimates can be derived.

To derive estimates of carbon stock changes or emissions from measurements collected on the plots typically requires the use of models that relate these measurements to carbon stocks. The types of models and the uncertainty associated with them vary depending on measurements taken and the carbon pools being estimated. Examples of these models include allometric equations for estimating tree and deadwood biomass, root:shoot ratios for estimating belowground biomass (Mokany et al., 2006) and the use of spectral signatures to estimate soil carbon (Baldock et al., 2013).

When estimating uncertainty for carbon stock changes and/or emissions it is *good practice* to include all relevant sources of uncertainty, including the sampling scheme, plot measurements and model parameters and structure and laboratory processing methods (see discussion for each source category later in this volume in addition to the uncertainty chapter in Volume 1). Overall uncertainty can be reduced by increasing the sampling intensity, using additional strata or covariates to explain more of the variance or improving the models. Model uncertainty may be relatively small, at least in situations with well-developed models calibrated for national situations, or relatively large where global models are applied.

To obtain national estimates of carbon stock changes or emission of non-CO_2 greenhouse gases, it may be necessary to interpolate or extrapolate measurements using spatial statistical analyses and models that take into consideration environmental conditions, management and other activity data. Such models are necessary because of the expense and difficulty in obtaining a sufficient sampling intensity to infer C stock changes or emissions directly from the survey sample. For example, CH_4 and N_2O emissions from forest fires are typically inferred from data on the area burnt, and fuel consumption estimates derived from specific case studies. In a similar fashion, soil N_2O emissions could be readily estimated using chambers, but this can be very expensive to establish a network with the sampling intensity needed to provide national emission estimates based solely on measurements without use of models for extrapolation. Alternatively, compilers may use a model-based approach in these cases, which is informed by the limited sample of C stock or emission measurements (See Section 2.1.2).

It is *good practice* to analyse emissions relative to environmental conditions in addition to the contribution of various management practices to those trends. Interpretation of the patterns will be useful in evaluating possibilities for future mitigation.

Step 6. Reporting and Documentation.

It is *good practice* to assemble inventory results in a systematic and transparent manner for reporting purposes.

Documentation typically includes a description of the sampling scheme and statistical methods, sampling schedule (including re-sampling), stock change and emissions estimates and the interpretation of emission trends (e.g., contributions of management activities). In addition, QA/QC should be completed and documented in the report. For details on QA/QC, reporting and documentation, see the section dealing with the specific source category later in this volume, as well as information provided in Volume 1, Chapter 6.

When developing/collating documentation for reporting Tier 3 measurement-based methods it is *good practice* to:

- describe the sampling design and/or measurements;
- describe any changes in the design or measurements through time and how these changes are addressed to ensure time series consistency in carbon stocks or emissions;
- describe the models used to calculate carbon stock changes and non-CO_2 emissions from the measurements, including the uncertainty;
- describe how area estimates are derived from the survey, such as a national forest inventory, and harmonized with land representation data for other land-uses;
- discuss the influence of time periods between measurement cycles on estimated C stock changes or emission estimates, and how this impact is incorporated into the uncertainty analysis; and
- document, if applicable, how Tier 3 measurement methods are applied consistently with Tier 2 or Tier 3 model-based methods to prevent errors of omission or commission in reported carbon stock changes or emissions for the entire spatial and temporal domain of the country.

TABLE 2.6A (NEW) EXAMPLES OF DOCUMENTATION TO ASSEMBLE IN SUPPORT OF TRANSPARENT REPORTING OF TIER 3 MEASUREMENT BASED INVENTORIES	
Step 1. Develop sampling scheme, including sample size and design and measurements to be collected.	A description of the sampling scheme including size and design and measurements to be collected Reason for adopting the selected sampling scheme
Step 2. Select sample sites.	Description of the process for selecting sample sites and processes for dealing with exclusions/replacements
Step 3. Collect initial samples.	Sample collection and quality assurance / quality control protocols.
Step 4. Re-sample the monitoring network on a periodic basis.	Description of re-sampling strategy and reasoning for adopted resampling period
Step 5. Analyse data and determine carbon stock changes and other sources of emissions, and infer national emissions and removals estimates and measures of uncertainty.	Data processing and quality assurance / quality control protocols including how adopted re-sampling period is handled when making carbon stock change estimates and their associated uncertainty.
Step 6. Reporting and Documentation	All of the above material summarised into a report for third party review.

2.5.2 Model-based Tier 3 inventories

Model-based Tier 3 inventories are developed using empirical (e.g. forest growth curves that represent carbon stock increase with tree age.), process-based (e.g. model representation of underlying physiological, biophysical, and management processes that drive carbon dynamics in ecosystems), hybrid (e.g. the development of forest growth curves from empirical data combined with a process model calibrated from research data on dead organic matter dynamics) and/or other types of models. Just as Tier 3 measurement-based methods typically also require models to estimate carbon stock changes (see Section 2.1.1), Tier 3 model-based inventories require measurements to calibrate and validate the models used to estimate carbon stock changes.

It is unlikely that one single model will be suitable for estimating emissions and removals for all carbon pools and non-CO_2 gases across all land uses, land-use changes and management actions. Therefore, inventory compilers will need to select a suite of different models to develop estimates of interest. In many cases existing models need to be adapted, coupled and/or integrated to provide a complete estimate of emissions and removals in the source categories of interest.

When selecting a model, it is important to consider how it will be used and interact with other models. This is particularly important when using Tier 3 mass-balance models in combination with Tier 1 or 2 emissions factors (e.g. if different soil carbon models or methods are used for different land-uses, how will the carbon pools be transferred between them in the case of land-use change). If changes in modelling methods within the reporting time series occur adequate steps should be taken to ensure time series consistency.

Models may be run individually for different land uses and carbon pools and the results combined or brought together in a single framework using coupling and integration techniques. Individual model simulations are typically used where multiple agencies are responsible for developing different parts of the inventory (e.g., the forest agency responsible for forest lands, the agriculture agency responsible for cropland and grassland).

Coupling different models is a convenient strategy for addressing effects with different time and space scales. In contrast, model integration links different modelling approaches to elucidate the complex dimension of time and space dynamics (Panichelli & Gnansounou, 2015), helping ensure consistency in land representation, carbon pools and input variables (Brack et al., 2006). Integration frameworks can also help organize data and estimation methods at any level of methodological complexity and facilitate the systematic progression from simpler to more complex methods (GFOI, 2016).

In all cases, models used in Tier 3 methods ensure higher accuracy only when they are correctly implemented and capable of representing the population of interest. In general, the following seven steps are used to correctly implement a Tier 3 model-based inventory (see also Figure 1, Volume 1, Chapter 6, Section 2.4).

Step 1. Model selection or development

Inventory compilers can choose from a wide range of model types depending on reporting needs, data availability and capacity. As part of model selection or development, it is *good practice* to consider if the model/s:

- adequately represent the range of land uses, ecosystems and management practices in the region or country;

- allow for the quantification of uncertainty;
- reduce uncertainty relative to other available methods (e.g., Tier 1 methods) or estimates are improved in other ways (e.g., more complete coverage of carbon pools or lands);
- can be run and maintained in an operational context with available time and resources (e.g., input data is readily available, staff have sufficient experience and knowledge, suitable compute infrastructure is available);
- produce outputs that can be used for reporting emissions and removals by relevant land-use categories;
- produce time-series consistent results;
- are compatible with other existing models used in the inventory; and
- are well documented and tested.

Multiple models will likely be selected as potentially suitable as part of Step 1. These models can then be tested prior to implementation using steps 2 and 3 below. Therefore, before moving to Step 2, at least a sub-set of the input data required to run the model should be collected or collated, including input variables (such as forest species or type, climate, soil characteristics), and any existing parameters and data required for further model calibration and evaluation. In some cases, input data may be a limiting factor in model selection or development, requiring some models to be discarded or modified to accommodate the available activity and/or environmental data.

Step 2. Model Calibration

Model calibration (i.e. parameterisation) is the process of selecting or adjusting model parameters to obtain results that best represent the processes of interest in the region (and time period) for which the model will be applied. The model calibration procedure readies a model for its further use in analyses. For example, replacing default growth curves with those specific to the tree species or site conditions to which the model will be applied or replacing climate averages with regional climate data are examples of model parameterisation.

Calibration data should represent the population. In practice, this does not mean that all environmental conditions are covered, but that the calibration data includes a range of the conditions existing the country that is representative of national circumstances.

Model sensitivity analyses may be used to determine the most important parameters for calibration. In a sensitivity analysis, parameter values are varied through a series of simulations to determine the associated change in model output. The parameters are ranked from most to least sensitive based on the level of change in model output. Some techniques also incorporate measurements into the sensitivity analysis (Sobol, 2001). The most sensitive parameters are typically calibrated to improve the agreement between modelled and measured carbon stocks, stock changes or non-CO_2 greenhouse gas emissions.

There are multiple methods for calibrating models. Simpler empirical models (e.g., empirical forest growth models based on forest age or site indices) are commonly developed by fitting functions to data on carbon stocks or stock changes using standard statistical methods and software. More advanced models (e.g., hybrid or process-based models) typically have numerous, interrelated parameters. For these models calibration is often completed using parameter optimisation methods that vary the model parameters within known ranges to best match known results (e.g., carbon stocks). There are several methods for doing this, including generic algorithms, machine learning and Bayesian. The methods may also be used to propagate error through the inventory analysis (e.g., Hararuk et al., 2017).

In all cases it is *good practice* to document the calibration procedure and results.

Re-calibration of the model or modifications to the structure may be necessary if the model does not capture general trends or there are large systematic biases. Full evaluation of the model is described in Step 3. See Box 2.2f for examples of model calibration.

BOX 2.2F (NEW)
AN EXAMPLE OF MODEL CALIBRATION, EVALUATION AND IMPROVEMENT THROUGH DATA ASSIMILATION

The development of Canada's Carbon Budget Model for the Canadian Forest Sector started in 1989 and is continually being improved through new data collection, analysis and model enhancements. As part of this process, Shaw et al., (2014) assessed CBM-CFS3's ability to predict ecosystem carbon stocks in independent plots established as part of Canada's national forest inventory (NFI). The study demonstrated close agreement in the predictions of total ecosystem carbon stocks (within 1percent) but found some compensating errors (bias) in specific pools, ecozones, and plots with different tree species.

To further improve the CBM-CFS3 performance in Canadian forest ecosystems, a Bayesian Markov Chain Monte Carlo (MCMC) technique was used to calibrate 45 model parameters by assimilating carbon stocks of six deadwood and soil carbon pools estimated from 635 plots from Canada's National Forest Inventory (Hararuk et al., 2017). These plots were randomly split into two groups; calibration (n = 326), used to calibrate the parameters, and validation (n = 309), used to evaluate the performance of the model with calibrated parameters.

Calibration led to most improvement in the simulation of carbon stocks in small and fine woody debris, reducing RMSE by 54.3 percent, followed by the snag stems (RMSE reduced by 23.2 percent), and coarse woody debris (13 percent). Twenty of the 45 parameters were well constrained by the available data. The calibrated parameters resulted in increased rates of carbon cycling in fine and coarse woody debris and the soil organic layer, distinct carbon dynamics in hardwood and softwood dominated stands, and increased temperature sensitivity of the carbon contained in the mineral soil.

While parameter calibration considerably improved the simulation of the small and fine woody debris and snags stem pools, model representation of the branch snag, coarse woody debris, soil organic layer, and mineral soil pools were not substantially improved. This indicated the need for the inclusion of additional processes in carbon dynamics simulation or a change in the modelling paradigm. Model improvements may be achieved by including a lignin effect on deadwood decay and by including the effects of tree species, soil types, and mosses (see Box 2.2g) in the CBM-CFS3. Further data assimilation analyses are ongoing.

Step 3. Evaluation of Model Behaviour

Once the model has been calibrated, it should be evaluated to demonstrate that the model effectively simulates measured trends for the source category of interest. Evaluation can also support the justification for selecting, developing or possibly improving a particular model for the inventory analysis.

It is *good practice* to use measurements independent of those used for model calibration when evaluating model behaviour and to confirm that the model is capable of estimating emissions and removals in the source categories of interest (Falloon and Smith, 2002; Prisley and Mortimer, 2004). In practice, this is typically achieved by setting aside a subset of data collected for model calibration to be used exclusively for model evaluation. Comparisons between model output and independent measurements can be made using statistical tests and/or graphically. In addition to evaluation with independent data, other evaluation checks may be useful, including:

- range checks to show that estimates of carbon stocks and changes in all pools do not exceed pre-defined expected limits;
- in models that track both stocks and flows between carbon pools and the atmosphere, that mass-balance is been maintained through all simulations;
- use of other statistical methods for assessing model behaviour, such as resampling methods (e.g., bootstrapping); and
- assessment of the sensitivity of various parameters in the model (sensitivity analysis).

It is *good practice* to ensure that the model responds appropriately to variations in activity data and environmental conditions occurring in the spatial and temporal domain where the model will be applied. Re-calibration of the model or modifications to the structure (i.e., algorithms) may be necessary if the model does not capture general trends or there are large systematic biases. In some cases, a new model may be selected or developed based on this evaluation. Evaluation results are an important component of the reporting documentation. See Box 2.2g for examples of model evaluation and improvement.

BOX 2.2G (NEW)
EXAMPLE OF MODEL EVALUATION AND IMPROVEMENT

Finland

The sample sizes in soil carbon inventories are usually not adequate for national level soil carbon stock change assessment with few exceptions (e.g., Sweden, and Germany, see Gamfeldt et al., 2014 and Grüneberg et al., 2014). As such, most countries use soil carbon models to estimate carbon stock changes then evaluate the results using repeated soil inventories. In general, it has been shown that models can estimate soil carbon stock change in the same magnitude as that measured, but uncertainties of both measurements and model estimates are often higher than actual measurements (Ortiz et al., 2009; Rantakari et al., 2012). This makes the evaluation of model outputs challenging.

Two soils carbon models are commonly used in Finland: Yasso07 and ROMULv. An evaluation of the performance of these models against forest soil carbon stock measurements was undertaken by Lehtonen et al. (2016). Both models require estimates of carbon input from vegetation. Litter input from trees was estimated using litter production rates from research sites and stem volume maps from the National Forest Inventory. Inputs from understorey vegetation were estimated using new biomass models.

To evaluate the models, both were applied across Finland and run until steady state was achieved; thereafter, measured soil carbon stocks were compared with model estimates. The evaluation showed that the role of understorey litter input was underestimated by Yasso07, especially in northern Finland, and the inclusion of soil water holding capacity in the ROMULv model improved predictions, especially in southern Finland. Simulations and measurements indicated that models using only litter quality and quantity and weather data underestimate soil carbon stock in southern Finland, and this underestimation is due to omission of the impact of droughts on the decomposition of organic layers. The model evaluation results imply improving estimates of understorey litter production in the northern latitudes would be an area for improvement in greenhouse gas inventories (Lehtonen et al., 2016).

Canada

An evaluation of CBM-CFS3 ability to predict ecosystem carbon stock estimates derived from an entirely independent data set from the initial establishment of Canada's new National Forest Inventory (Gillis et al., 2005) was undertaken (Stinson et al., 2016). Estimates of aboveground biomass, dead organic matter and soil carbon stocks from up to 696 ground plots were compared to model-derived estimates (Shaw et al., 2014). Model simulations for each ground plot used only the type of input data available to the NFCMARS for the NIR in 2010.None of the model's default parameters were altered. Ecosystem total C stocks estimated by CBM-CFS3 were unbiased (mean difference = 1.9 Mg ha^{-1}, $p = 0.397$), and significantly correlated ($r = 0.54$, $p > 0.001$) with ground plot-based estimates. Although the overall C stock estimates were within 1 percent of the observed values, detailed analyses also revealed compensating biases specific to pools, ecozones or leading species. Contribution to ecosystem total C stocks error from soil was large, and from deadwood and aboveground biomass small. Results for percent error in the aboveground biomass (7.5 percent) and deadwood (30.8 percent) pools compared favourably to the *GPG-LULUCF* standards of 8 percent and 30 percent, respectively. Further details are provided in Shaw et al. (2014).

Subsequent analyses assessed the reasons for the consistent under prediction of organic carbon stocks in low productivity boreal sites, in which mosses can contribute 30 percent or more of total ecosystem Net Primary Production (Bona et al., 2013). Although mosses are not a carbon stock that is included in the IPCC pools, it is increasingly evident that omitting them will result in significant under prediction of both carbon stocks and fluxes in forest ecosystems with high moss cover. Bona et al. (2016) estimated that in poorly drained upland black spruce forests of boreal Canada as much as 31–49 percent of the total carbon stocks are potentially contributed by mosses alone. A new moss module was developed and added to the CBM-CFS3 and off-line comparisons indicate that representing moss carbon stocks and inputs will reduce bias in organic carbon stock estimates (Bona et al., 2016).

Step 4. Collect and collate require model data inputs

Models require specific input data to estimate greenhouse gas emissions and removals associated with a source category. These inputs may range from weather and soils data to livestock numbers, forest types, natural disturbances or cropping management practices. While much of this data may have been collected as part of the model selection process (Step 1), additional data may need to be collected prior to full implementation. For example, the climate data used in model selection may have only been for specific points, while for implementation the model will require the data spatially over large areas. In these cases, the new spatial input data may need to be developed to implement the model at the desired spatio-temporal scale.

Step 5. Model Implementation

The major consideration when implementing the model is to obtain enough computing resources and personnel time to prepare the input data, conduct the model simulations, and analyse the results. In some cases, limitations in computing resources may constrain the complexity and range of spatial or temporal resolution that can be used in implementing the model at the national scale (i.e. simulating at finer spatial and temporal scales will require greater computing resources). An initial analysis of computing needs should be explored during model selection and development (Step 1). It may be possible to increase the efficiency of this process using programming scripts, re-coding parts of the model and adjusting the spatial and temporal extent and resolution of the simulations. It may also be possible to implement the model on computing resources that are outside the agency (e.g. cloud-based computing).

Step 6. Assess uncertainty

Uncertainty analysis should not be confused with sensitivity analysis. Uncertainty analysis determines the probabilities of a range of estimates that can be used to derive confidence intervals for the estimates, and to develop plans to further reduce uncertainties. Sensitivity analysis is conducted to determine the relative change in model output given changes in model input values, which can be informative for model calibration (See Step 3).

In many Tier 3 models, Monte Carlo analyses can be used to simulate the uncertainty arising from the large number of possible parameters in the systems. Empirical analyses may also be an option to quantify uncertainty in model structure and parameterization based on an evaluation of model prediction error for sites with known inputs (See Box 2.2h). In general, uncertainties are quantified at national scales on annual time steps for reporting but may also be estimated at finer spatial and temporal scales. However, it may not be feasible or sensible to apply full Monte Carlo simulations to, for example, every spatial unit in a country. Given the computing resource and time requirements, it may also not be necessary to repeat a full Monte Carlo analysis every year. For example, in the case where only the activity data time series has been updated, but no other material changes to the inventory have been made, uncertainty estimates can be extrapolated to the additional years in the time series. A smaller test may also be run to demonstrate there has been no material change in uncertainty.

BOX 2.2H (NEW)

EXAMPLES OF QUANTIFICATION OF MODEL UNCERTAINTY

This box is provided for information purposes and for the presentation of examples of quantification of uncertainties in Tier 3 modelling approaches.

Canada

Both uncertainty and sensitivity analyses were conducted on Canada's CBM-CFS3 integration framework (Metsaranta et al., 2017) and uncertainty analysis results are summarized below.

A wide range of factors that contribute to the uncertainty in the model estimates were varied using Monte-Carlo simulations using the entire national system. These factors include the processes used to initialize dead organic matter and soil carbon pools, biomass increment data (a multiplier with a range of ±50 percent was applied to net biomass increment), activity data (wildfire (±10 percent), insects (±25 percent), and harvest (range varies by jurisdiction)), selection of stands during the allocation of natural disturbances to affected stands, and parameters defining litter input and dead organic matter pool dynamics. Parameter ranges for 32 biomass turnover and dead organic matter carbon modelling parameters were obtained from the literature and used as minimum and maximum values of triangular distributions (with mode set to the CBM-CFS3 default value). All parameter values and input data were varied independently, because the correlation structure among parameters could not be estimated.

Input data for Canada's 230 million ha of managed forest are contained in 20 CBM-CFS3 databases, each representing a specific region in Canada. Monte Carlo simulations for each of

BOX 2.2H (NEW) (CONTINUED)

EXAMPLES OF QUANTIFICATION OF MODEL UNCERTAINTY

these 20 databases were conducted independently and the sample size for national totals was increased by summing random combinations of the 100 Monte Carlo runs from the 20 projects to generate 1000 randomly recombined estimates of national totals. The approximated 95 percent confidence interval (CI) was defined from the 2.5th and 97.5th percentiles of these national estimates.

Under the assumptions of this analysis, the 95 percent confidence interval width averaged 32.2 Tg C·year^{-1} (+16.6 and –15.6 Tg C·year^{-1}) for net biome production (total stock changes) relative to an overall simulation median of –0.8 Tg C·year^{-1} from 1990 to 2014. The largest sources of uncertainty were related to factors determining biomass increment and the parameters used to model soil and dead organic matter carbon dynamics. Some of these processes also vary in their intrinsic degree of predictability (Luo et al., 2015), and some factors causing large contributions to uncertainty may prove difficult to reduce (e.g., fine root turnover and its spatial and temporal variations).

United States of America

Uncertainty analysis for agricultural soil carbon and N_2O emissions have been conducted for the US greenhouse gas inventory (Ogle et al. 2010; Del Grosso et al. 2010; US EPA, 2017). A Tier 3 method is applied to generate emissions estimates with application of the DayCent ecosystem model. This process-based model simulates plant production, soil organic matter formation, nutrient cycling, water flows, and temperature regimes (Parton et al. 1998). Uncertainty is quantified through a combination of Monte Carlo simulations, an empirical analysis of model prediction error, and propagation of variance associated with the land representation survey data.

The inventory is compiled by simulating plant production and soil processes based on land use histories at about 400,000 locations that are part of a national survey, the National Resources Inventory (NRI) (Nusser et al. 1998, Nusser and Goebel 1997). The major input uncertainties in the Tier 3 model application are associated with fertilization and tillage management and are quantified in probability distribution functions (PDFs), representing the likelihood of different fertilization rates, tillage practices and manure amendments. The model is applied using a Monte Carlo Analysis in a series of 100 simulations for each NRI survey locations based on random draws from the PDFs. In turn, the analysis produces 100 estimates of soil C stock changes and N_2O emissions for each survey location.

Model prediction error, including bias and precision, is quantified in statistical models with an empirical analysis based on a comparison of model output to measured observations of soil C stocks and N_2O emissions from experimental sites (Ogle et al. 2007). The model inputs are mostly known for the DayCent model simulations of the experimental sites and so the primary sources of uncertainty that are quantified in this analysis are associated with model structure and parameterisation, in addition to the variance in measured observations. Moreover, the experimental sites are independent from model calibration allowing for an independent evaluation of model prediction error. The resulting empirical model is applied to the DayCent model output to adjust for biases, to the extent needed, and to quantify precision in model results.

In a final step, variance associated with the NRI is derived based on the standard variance estimator for a stratified two-stage sample design (Särndal et al. 1992) and propagated through calculations to estimate national totals for the inventory (Ogle et al. 2010). The largest source of uncertainty in the analysis is associated with model structure and parameterization, as quantified in the empirical analysis. This source accounts for more than 80 percent of the total uncertainty in soil carbon stock change and N_2O emission estimates at the national scale, highlighting the importance of further improving the model to reduce uncertainty.

Step 7. Verification of inventory estimates with independent data

NGHGI estimates from Tier 3 models can be difficult to verify because alternative measurements often do not exist at the national scale. This is not unique to the AFOLU sector. There may however, be opportunities to verify component estimates against independent data. For example, model derived estimates of crop yield, or timber harvest can be compared against independent data such as crop or timber production statistics. Such comparisons require a good understanding of the methods used for both the Tier 3 and the comparative estimates, to avoid interpreting possible discrepancies as an indicator of problems in the Tier 3 model, when the discrepancy is in fact due to methodological differences.

Another useful step in verification of inventory estimates is to compare current estimates against those in the inventory submissions of prior years. Changes in time series estimates that are not consistent with changes in activity or other input data should be examined and understood as these could be indicative of a variety of problems, including errors in data processing. Developing quality assurance/quality control (QA/QC) procedures that document the changes in estimates attributed to each change in input data, model parameters, or other methodological changes can assist inventory compilers in the verification of inventory estimates.

Verification of inventory estimates can also be based on measurements from a monitoring network or from research sites that were not used to calibrate model parameters or evaluate model behaviour. The network would be similar in principle to a series of sites that are used for a measurement-based inventory. However, the uncertainty of the estimates (output) from a model-based approach does not depend directly on the sample size and therefore the sampling need not be as dense. In some cases, verification may demonstrate that the model-based estimation system is inappropriate due to large and unexplainable differences between model results and the measured trends from the monitoring network. Problems may stem from one of three possibilities: errors in the implementation step, poor input data, or an inappropriate model. Implementation problems typically arise from computer programming or data input errors, while model inputs may generate erroneous results if these data are not representative of management activity or environmental conditions. In these cases, it is *good practice* for the inventory compiler to return to either Steps 2 or 5 depending on the issue. It seems less likely that the model would be inappropriate if Step 2 was deemed reasonable. However, if this is the case, it is *good practice* to return to the model selection/development phase (Step 1) or to further refine the existing model.

In addition to verifying inventory estimates, independent data may also be used to check areas estimates for land-use and land use change including

- that land area is conserved over time;
- changes between land-use types are logical in terms of the type, frequency and time periods between changes, defined by the country;
- consistency between input data (e.g. area to be disturbed by disturbance type X) and model simulation results (e.g., area actually disturbed in the model by disturbance type X).

Step 8. Reporting and Documentation

It is *good practice* to assemble inventory results in a systematic and transparent manner for reporting purposes. Documentation of model-based Tier 3 inventory systems should include those items listed in Table 2.6b. For further details on QA/QC, reporting and documentation, see the sections dealing with the specific source categories later in this volume, as well as information provided in Volume 1, Chapter 6.

TABLE 2.6B (NEW)
EXAMPLES OF DOCUMENTATION TO ASSEMBLE IN SUPPORT OF TRANSPARENT REPORTING OF TIER 3 MODEL-BASED INVENTORIES

Step 1 – Model selection or development	• A description of the model • Reason for choosing or designing the model demonstrating applicability • Discussion of any likely consequences if the model is used outside the domain that the model is parameterised to simulate.
Step 2 - Model calibration	• Description of the process undertaken to calibrate the model and documentation of the data sources informing the manual or automated calibration.
Step 3 – Evaluate model behaviour	• Results of the analysis verifying model behaviour using independent measurements to confirm that the model is capable of estimating carbon stocks, stock changes and/or emissions and removals in the source/sink categories of interest. The sources of independent data should also be documented.
Step 5 - Implement the model	• Overview of procedures that are used to apply the model.
Step 6 - Quantify uncertainties	• Description of the approach taken to estimate uncertainty in the model outputs.
Step 7 - Verification of inventory estimates	• Summary of the verification results for the inventory.
Step 8 – Reporting and Documentation	• Information on QA/QC steps

2.6 INTER-ANNUAL VARIABILITY

In the AFOLU sector, the management of land is used as the best approximation of human influence and thus, estimates of emissions and removals on managed land are used as a proxy for anthropogenic emissions and removals on the basis that the preponderance of anthropogenic effects occurs on managed lands (see Vol. 4 Chapter 1). This allows for consistency, comparability, and transparency in estimation. Referred to as the Managed Land Proxy (MLP), this approach is currently recognised by the IPCC as the only universally applicable approach to estimating anthropogenic emissions and removals in the AFOLU sector (IPCC 2006, IPCC 2010). However, it is also recognised that the estimated emissions and removals on managed lands can represent a combination of both anthropogenic (direct and indirect) and natural effects (Vol. 4 Chapter 1 p1.5; IPCC 2010; see Fig. 2.6A).

Some of the emissions and removals from managed land are characterised by high interannual variability. Interannual variability (IAV) refers to the variability in the annual emissions and removals (E/R) estimates between years within a time series. In the AFOLU sector, the application of the MLP means that IAV can be caused by both anthropogenic and natural causes. The three main causes of IAV in GHG emissions and removals in the AFOLU sector are (1) natural disturbances (such as wildfires, insects, windthrow, and ice storms), which can cause large immediate and delayed emissions and kill trees; (2) climate variability (e.g. temperature, precipitation, and drought), which affects photosynthesis and respiration (Ciais *et al.* 2005; Aragão *et al.* 2018); and, (3) variation in the rate of human activities, including land use (such as forest harvesting), and land-use change (Stinson *et al.* 2011; Pilli *et al.* 2016; Kurz *et al.* 2018).

In some countries IAV in emissions from natural disturbances can be larger than the IAV of emissions caused by human activities such as forest management. For example, IAV in Canada's 1990 to 2016 time series of annual emission and removals due to natural disturbances is much larger than the IAV in the emissions and removals on the remaining managed forest land (Figure 2.6C). The NGHGIs for Portugal (Figure 6-32 of Portugal's NIR 2018 (Portuguese Environmental Agency 2018)) and Australia (Table 6.21 of Australia's NIR 2016 Volume 2 (Commonwealth of Australia 2018)) are two other examples of time series with high IAV. In some countries, the areas burned by wildfires can vary by two orders of magnitude between years (Stinson *et al.* 2011; Miller *et al.* 2012; Genet *et al.* 2018). In other countries, the majority of IAV may be due to human activities.

When the MLP is used and the IAV in emissions and removals due to natural disturbances is large, it is difficult to gain a quantitative understanding of the role of human activities compared to the impacts of natural effects. In such situations, disaggregating[9] MLP emissions and removals into those that are considered to result from human activities and those understood to result from natural effects may provide increased understanding of the emissions and removals that are due to human activities such as, land use (including harvesting) and land-use change. In this way, disaggregation can contribute to improved understanding of the trends in emission and removals due to human activities and mitigation actions that are taken to reduce anthropogenic emissions and preserve and enhance carbon stocks.

Disaggregating emissions and removals according to anthropogenic and natural effects has been recognised as a scientific challenge (Canadell *et al.* 2007; Vetter *et al.* 2008; IPCC 2010; Kurz 2010; Smith 2010; Brando *et al.* 2014; Henttonen *et al.* 2017). It is not yet possible to fully and accurately separate emissions and removals associated with human activity from those associated with natural effects. The last IPCC Expert Meeting Report on this topic encouraged further development of scientific methods (IPCC 2010).

Recognizing that some but not all countries may choose to address emissions and removals from natural disturbances on managed land outside the inventory process, this guidance is provided as an option that may be used by countries that choose to disaggregate their reported MLP emissions and removals (i.e. all emissions and removals on managed land) into those that are considered to result from human activities and those that are considered to result from natural disturbances. These supplementary approaches may be of interest to countries with AFOLU sector emissions where IAV due to natural effects is large. The section first addresses definitional issues, followed by a description of whether or not different methodological approaches used to estimate C stock changes quantify the IAV of emissions and removals. A generic approach to report on disaggregation of the contribution of natural disturbances in reporting on total emissions and removals on managed lands is then provided, along with country-specific examples of methodological approaches to disaggregating anthropogenic effects and natural disturbances on managed lands.

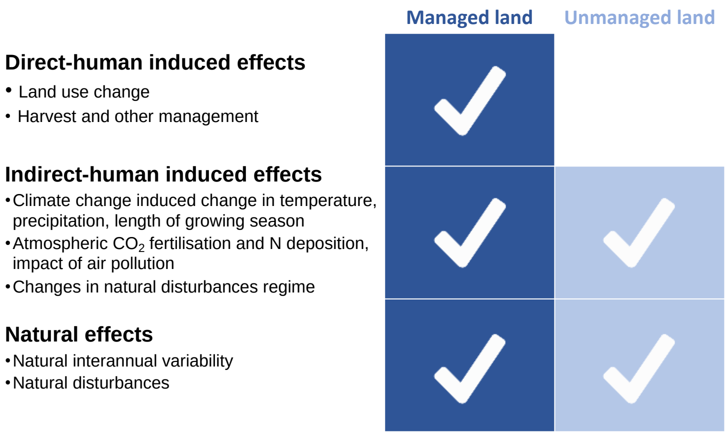
[9] Disaggregating means that an estimate is separated into its component parts.

2.6.1 Definitional issues

2.6.1.1 DIRECT AND INDIRECT HUMAN EFFECTS, AND NATURAL EFFECTS

Anthropogenic (i.e., direct and indirect human) effects and natural effects are described in Vol. 4 Chapter 1. Figure 2.6a summarizes the main factors that cause these effects and their occurrences in managed and unmanaged lands. The specific effects included in estimates reported in NGHGIs depend on the estimation method and data used, which differ in approach and complexity among countries (see Table 2.6c). Describing how the various effects are reflected in the estimates of emissions and removals, based on the estimation method and data used, increases the transparency of the NGHGI and its understanding by the scientific and policy communities (Grassi *et al.* 2018, section 2.6.2). Useful information may include definition and spatial maps of managed land, information on areas of forest being harvested and those subject to other management, and information on the main determinants of the GHG fluxes (e.g., forest age structure, harvested volumes, harvest cycle).

Figure 2.6a: Conceptual illustration of how various anthropogenic (direct and indirect) and natural factors affect land-related GHG emissions and removals in managed and unmanaged lands (Source: Grassi *et al.* (2018)).



Direct human-induced effects of any management activity on emissions or removals, by definition, only occur on managed lands. Indirect human-induced effects (i.e., the second order impacts of human activities on emissions or removals mediated through environmental change) and natural effects can occur on both unmanaged and managed lands. The *"anthropogenic GHG emissions and removals by sinks are defined as all those occurring on 'managed land'"* (Vol. 4, Ch. 1). The natural effects *"tend to average out over time and space"* (Vol. 4, Ch. 1), provided that there are no trends in disturbance rates, such as increased annual area burned as a result of climate change. Nonetheless, their IAV in emissions and removals can have an important impact on annual NGHGIs. Depending on the estimation method and data used, GHG estimates for managed land may capture all or only some of this IAV (see Section 2.6.2).

The IPCC describes the MLP as a method to approximate estimates of anthropogenic emissions and removals, but this proxy estimate also contains emissions and removals resulting from natural disturbances (IPCC 2006; IPCC 2010). This section introduces an approach that countries can apply on a voluntary basis within the MLP in order to indicate those emissions and removals considered to result from human activity, and those that are understood to result from natural disturbances. This is achieved by disaggregating the estimated emissions and removals due to natural disturbances (ND E/R) within the estimated total MLP emissions and removals. This remaining aggregate of emissions and removals associated with human activity might still include some effects of IAV of natural disturbances and other natural effects on anthropogenic emissions and removals.

2.6.1.2 NATURAL DISTURBANCES

Disturbances, in particular wildfires, can contribute to large IAV in emissions. The number, frequency and intensity of fire events are strongly controlled by climate and weather, fuels, ignition sources, and human activities. High temperatures, past levels of fire suppression, and persistent drought events are key drivers of forest fires, for instance in the Western US (Westerling 2016), in the Amazon region (Morton *et al.* 2013) or in Indonesia (Schimel *et al.* 2015). However, land use and land-use change such as deforestation and peatland drainage can influence the likelihood and impacts of fire (Page & Hooijer 2016). In the Brazilian Cerrado, severe drought events explain the loss of almost 30 percent of aboveground woody biomass (de Miranda *et al.* 2014). Other natural disturbances with large IAV include storm damage (Yamashita *et al.* 2002; Lindner *et al.* 2010). Insects tend to follow outbreak cycles, thus causing more long-term trends that contribute to interdecadal rather than interannual variations (Kurz *et al.* 2008; Hicke *et al.* 2012). However, like IAV, the inter-decadal variability can also make it difficult to identify trends in emissions and removals that result from human activities.

Definition of natural disturbances

Natural disturbances in the context of the AFOLU sector are non-anthropogenic events or non-anthropogenic circumstances that cause significant emissions and are beyond the control of, and not materially influenced by a country. These include wildfires, insect and disease infestations, extreme weather events and/or geological disturbances, beyond the control of, and not materially influenced by a country. Natural disturbances exclude human activities such as harvesting, prescribed burning and fires associated with activities such as slash and burn.[10]

Non-anthropogenic events refer to non-human induced events (e.g. fire initiated by lightening, damage by wind storms), non-anthropogenic circumstances refer to non-human induced conditions that exacerbate these disturbances (e.g., fire occurring during particularly harsh conditions like strong winds, high temperature, drought, etc.). For information on how to document that disturbances are beyond the control of and not materially influenced by the country, see Section 2.6.4 below.

The methodological guidance provided in this section is aimed at disaggregating emissions and removals in ecosystems where natural disturbances cause large IAV in emissions within the MLP and where subsequent removals occur over a multi-year period of time. Therefore, this methodological guidance is applicable to natural disturbances in forests, and in woody grassland, undrained wetlands or undrained peatlands, but not in other land categories where human actions materially determine and/or deeply influence the conditions and circumstances associated with significant emissions by disturbances (such in drained peatlands and in cropland).

Balance of emissions and subsequent removals

A fundamental assumption under the MLP is that carbon emissions and removals associated with natural effects will average out over space and time (see also Volume 4, Chapter 1). Therefore, consistent with this assumption, the CO_2 emissions (from above and below ground biomass, dead organic matter and soil carbon) from areas affected by natural disturbances are expected to be balanced by subsequent removals across the landscape at some future point in time. This expectation has no established time limit because the time to balance depends on the types of ecosystems affected by disturbances and their rates of regrowth.

At stand level, changes in growing conditions could affect this expectation, in particular if environmental conditions contribute to regeneration failure of stands that were affected by natural disturbances, e.g. landslides and erosion after wildfire, making it more difficult to achieve the balance. Conversely, if environmental changes contribute to increased growth rates or reduced mortality rates, then the balance will be achieved faster. In the case of repeated disturbances on the same area, the time to reach balance for that area may increase.

2.6.2 Relationship between different methodological approaches and the representation of emissions and removals from interannual variability

The choice of estimation method and data affects the extent to which the IAV of different drivers is reflected in reported estimates (see Table 2.6c). Countries can apply different estimation methods to report their emissions and removals capturing the anthropogenic components with different temporal resolution and disaggregation of variables (annual to periodic, averaged or disaggregated by drivers). Table 2.6c provides information on how the choice of estimation method affects whether or not factors contributing to IAV of reported emissions and removals are captured in NGHGIs. This table may help countries in understanding and describing how the various effects are reflected in the estimates of emissions and removals, therefore increasing the understanding of NGHGIs by the scientific and policy communities.

[10] Information on natural disturbance definitions and approaches applied in the Kyoto Protocol accounting can be found in IPCC. (2014) In: *2013 Revised Supplementary Methods and Good Practice Guidance Arising from the Kyoto Protocol*, eds. T. Hiraishi, T. Krug, K. Tanabe, N. Srivastava, J. Baasansuren, M. Fukuda & T. G. Troxler, IPCC, Switzerland.

TABLE 2.6C (NEW)
GENERAL GUIDANCE ON WHETHER OR NOT THE ESTIMATION METHOD IS ABLE TO DISTINGUISH BETWEEN THE IMPACT OF THE INDIVIDUAL DRIVERS BELOW ON THE INTERANNUAL VARIABILITY OF REPORTED ANNUAL EMISSION AND REMOVAL ESTIMATES - NOTE THAT SOME EXCEPTIONS MAY OCCUR, DEPENDING ON THE DATA USED

			Drivers			
Method			**Direct Human**	**Indirect Human**	**Natural climate variability**	**Natural Disturbances**
Stock Difference[11] Periodic measurements (multi-year)			No	No	No	No
Stock Difference[12] Annual measurements			Yes	Yes	Yes	Yes
Gain-Loss[13]	Live biomass pools	Biomass growth based on Emission Factors or empirical yield tables	Yes	No	No	Yes
		Growth based on process (or hybrid) model	Yes	Yes	Yes	Yes
	Dead and soil organic matter pools	Dead and soil organic matter dynamics based on Emission Factors	Yes	No	No	No
		Dead and soil organic matter dynamics with constant climate	Yes	No	No	Yes
		Dead and soil organic matter dynamics with variable climate	Yes	Yes	Yes	Yes

The Stock Difference method calculates net emissions/removals (E/R) as the difference in estimated C stocks for relevant pools measured at two points in time. Average annual net E/R can be calculated by dividing the C stock difference of a period by the number of years between the two observations. Periodic stock assessments without auxiliary data therefore do not allow the quantification of the IAV of emissions and removals and its relation to the various drivers.

With annual measurements of ecosystem carbon stocks, e.g. via subsets of annual plot measurements in a continuous forest inventory, the quantification of IAV of emissions and removals becomes possible. Periodic or annual subsets of inventories can by themselves not detect IAV unless auxiliary data – such as area annually burned, harvest rates or other specific plot-level measurements on the timing of tree mortality – are used to inform about IAV (Röhling *et al.* 2016). For non-CO_2 emissions (e.g., CH_4 and N_2O from fires), auxiliary data on the type of disturbance that caused carbon losses would be required when the stock difference method is used.

The Gain-Loss method requires annual data on forest management, land-use change and natural disturbances and when these are available it can provide estimates of the IAV of net emissions. Depending on the estimation methodology and the data sets used, it may capture some or all of the impacts of drivers of the IAV of annual emissions and removals. A Gain-Loss approach utilising yield tables or constant emission factors (EF) will be insensitive to natural climate variability and, therefore, will only be able to distinguish between the direct human impact and natural disturbance impacts on IAV of emissions and removals. Gain-Loss methods that utilise climate-sensitive growth and mortality models (Richards & Evans 2004; Waterworth *et al.* 2007; Hember *et al.* 2018), or

[11] Forest inventories with multi-year period remeasurement and no auxiliary data cannot detect IAV. In some cases, periodic measurements on permanent sample plots are augmented with additional annual data thus increasing the ability to estimate IAV.

[12] Forest inventories with annual remeasurements for the same plots can detect IAV but are rarely implemented.

[13] The assumption for the Gain-Loss method is that activity data such as harvest, land-use change, and natural disturbances are available annually.

climate sensitive models of dead and soil organic matter dynamics (see Figure 6 in Liski *et al.* (2006)) can, in addition, estimate the indirect human and natural climate variability impacts on the IAV of emissions and removals.

2.6.3 Optional approach for reporting of emissions and removals from Natural Disturbances

It is *good practice* for countries to apply the MLP and to estimate and report all emissions and removals that occur on managed lands. This section describes a generic approach for use by countries that choose to report on the further disaggregation of emissions and subsequent removals from natural disturbances from the total emissions and removals estimated using the MLP. As discussed above, disturbances may have a natural and an anthropogenic component. This reporting guidance aims to assist countries choosing to report on the disaggregation of emissions and subsequent removals associated with human activity and those associated with natural disturbances within the total emissions and subsequent removals estimates of the MLP.

The elements of a generic approach are provided below, followed by examples of how the approach has been implemented to date:

1. **Quantification of the total emissions and removals from Managed Lands (consistent with MLP)**

   Estimate total E/R consistent with the MLP. Guidance provided by the IPCC for each relevant land category applies for the estimation of associated emissions and subsequent removals due to regrowth within the MLP. This is the total MLP flux, i.e. the first order approximation of the anthropogenic emissions and removals, which also includes emissions and subsequent removals from areas that are identified as subject to natural disturbances.

2. **Reporting on the country-specific approach to applying the definition of natural disturbances**

   Consistent with the generic definition of natural disturbances provided in section 2.6.1.2, countries describe their approach when applying the definition of natural disturbances consistently over time. The country description includes the types of disturbances for which the disaggregation of emissions and subsequent removals is implemented. The description also explains how the country excludes from natural disturbances the impacts of human activities, e.g., salvage logging, prescribed burning, slash and burn and deforestation.

3. **Identification of emissions and removals due to natural disturbances**

   The emissions and subsequent removals associated with natural disturbances are identified by applying the ND definition to either the individual (stand-level) disturbed areas or the total (landscape-level) emissions from all disturbances in the year[14]. In identifying those emissions and removals, it is *good practice* to avoid the inclusion of emissions and removals that are materially affected by human actions[15]. Both approaches provide for the:

   (i) Identification of the lands and area of land affected by each disturbance, as well as a description of the methods and criteria applied.

   (ii) For those lands, estimation of the emissions and subsequent removals associated with natural disturbances only (e.g. salvage logging emissions and associated subsequent removals are not included), as well as a description of the methods and criteria applied.

   If a country chooses to disaggregate ND emissions and removals, then it is *good practice* to disaggregate as anthropogenic the emissions and subsequent removals associated with management activities occurring on land affected by natural disturbances, including salvage logging and deforestation. Consequently, subsequent removals are disaggregated between human activities and natural disturbances, proportionally to the C stock losses these activities have caused, until the CO_2 emissions from natural disturbances are balanced by removals.

   For example, if salvage logging follows wildfire, and the wildfire caused instant emissions of 20 t CO_2 per hectare and subsequent salvage logging caused an additional 40 t CO_2, then 20 t CO_2 of subsequent removals are disaggregated as natural disturbances, and all remaining removals are disaggregated as anthropogenic effects. This could be implemented sequentially (i.e. the first 20 t CO_2 removals are disaggregated as due to natural causes, and all subsequent removals to anthropogenic causes) or in parallel (i.e. in this example, for every tonne of CO_2 removal, one third is disaggregated as due to natural causes, and the remaining two thirds to anthropogenic causes). In both cases, once natural emissions are balanced by removals disaggregated as natural causes, the remaining removals are considered anthropogenic.

[14] Methodological guidance on quantification of associated emissions and removals are given in the chapters with general guidance (Chapter 2 and 3) as well in the category-specific chapters (Chapter 4 and 6)".

[15] Noting that a portion of the emissions and removals considered to be associated with natural disturbances may be affected by human actions.

Disaggregation of CO_2 removals following natural disturbances can be implemented at the landscape level by apportioning these based on, for instance, the proportion of area disturbed of total forest area and the proportion of C stock lost of total C stock. For example, if in a year X in a country Y, Z ha of forest land is subject to wildfires, representing 0.1percent of the total forest area and 25percent of the total carbon stock present in the burned area is lost; the percentage of total CO_2 removals in the entire forest land apportioned to natural disturbances in this example is 0.025percent (i.e., 0.1percent*25percent) for year X. If the emissions from natural disturbances in year X were 25 Mt CO_2, then the removals in subsequent years are considered natural until the sum of the removals equals that amount.

Although the different approaches above (i.e., sequential or parallel disaggregation of removals subsequent to natural disturbances, stand vs. landscape level) affect the annual disaggregation, as long as the expectation of the balance between emissions from natural disturbances and the subsequent removals is fulfilled (see Section 6.2.1.2), and as long as emissions and subsequent removals are treated consistently, in the long term the totals are the same. Furthermore, in all cases it is *good practice* to report information on assumptions and methods implemented to disaggregate subsequent CO_2 removals.

When land-use change (e.g., forest land converted to cropland) follows a natural disturbance (e.g., wildfire), then emissions associated with land-use changes after natural disturbances as well as the emissions from the prior natural disturbance, are considered to be anthropogenic emissions. If regrowth occurs on that land, then any subsequent removals are also considered anthropogenic.

4. **Disaggregation of the MLP**

The natural disturbance component is subtracted from the total estimate of MLP emissions and removals, yielding an estimate of the emissions and removals associated with human activity on managed land. Both components are estimated and reported as part of the total MLP emissions and removals. In countries where natural disturbance contributes large IAV to E/R, the component of the MLP emissions and removals identified as associated with human activity is expected to have a lower IAV than the MLP emissions and removals because the variability resulting from natural disturbances has been disaggregated.

Given the expectation of the balance described above (Section 2.6.1.2), when emissions from natural disturbances are disaggregated, it is *good practice* that subsequent removals are also disaggregated until the balance has been reached. In this case, it is also *good practice* to disaggregate to the natural disturbance component those removals in each inventory year that are contributed by lands that were affected by natural disturbances prior to the start of the time series. In many ecosystems it may take decades for removals following natural disturbances to balance emissions from the disturbances. If it is not possible to estimate directly the amount of emissions that need to be balanced, for example if natural disturbances occurred before the reporting period, the time when the balance is expected can be approximated based on the estimated length (years) of the recovery period (see example in Box 2.2j). This ensures a consistent application of the balance principle throughout the time series.

In addition to CO_2 emissions, natural disturbances may cause non-CO_2 emissions, e.g. wildfires cause N_2O and CH_4 emissions. While CO_2 emissions are assumed to average out across time because of vegetation regrowth after disturbance, non-CO_2 emissions are not taken up by vegetation and therefore there is no expectation that these emissions will be balanced by removals because the biological, chemical and physical processes that result in the complete decay of CH_4 and N_2O in the atmosphere are not captured in existing IPCC inventory methods.

Examples of methodological approaches that have been developed are presented for Australia (Box 2.2i), Canada (Box 2.2j) and for an EU country (Box 2.2k).

BOX 2.2I (NEW)
AUSTRALIAN APPROACH TO ESTIMATING INTERANNUAL VARIABILITY DUE TO NATURAL DISTURBANCES

This box is for information only and neither adds guidance nor overrules guidance provided.

In Australia, all lands are considered managed lands. All areas and carbon stock changes on managed land from anthropogenic and 'natural disturbances'[16] are reported, consistent with the MLP. 'Natural disturbance' emissions and removals are considered to be caused by non-anthropogenic events and circumstances beyond the control of, and not materially influenced by, human activity despite extensive efforts by emergency management organizations to prevent, manage and control such events.

Both initial carbon losses and subsequent recoveries in carbon stocks are modelled as part of the disturbance event, and carbon stocks are spatially tracked until pre-disturbance levels are reached to ensure completeness and balance in reporting. Most Australian wildfires are not stand-replacing and carbon stocks typically recover after 11 years (Roxburgh *et al.* 2015). Estimates are prepared using a process (hybrid) model with DOM/SOM dynamics with variable climate (FullCAM).

'Natural disturbances' are defined as occurring in a year which is an outlier (exceeding the 95percent probability level) in the series of annual carbon stock losses due to wildfire at the national level and, spatially, as fires in those regions (States) experiencing abnormal fire activity in that year. (A full description of the method to identify outliers can be found in Volume 2 of Australia's NIR 2016 - Section 6.4.1.3)

'Natural disturbance' emissions and removals are modelled on a spatial basis and, consistent with the MLP, included in reporting after averaging out initial carbon stock losses and subsequent recovery[17]. This leaves the trend in carbon stock changes as the dominant result of human activity (e.g. from prescribed burning, normal seasonal wildfires – see "B" in Figure 2.6B).

The approach ensures that Australia's modelled implementation of the MLP is comparable with estimates generated using other methods, such as Tier 3 stock-difference approaches, that tend to average out IAV due to natural causes over space (scaling from plots to region) and time (averaging between periodic re-measurements). All carbon stock changes on managed land from anthropogenic and natural disturbances are transparently reported in Australia's NIR.

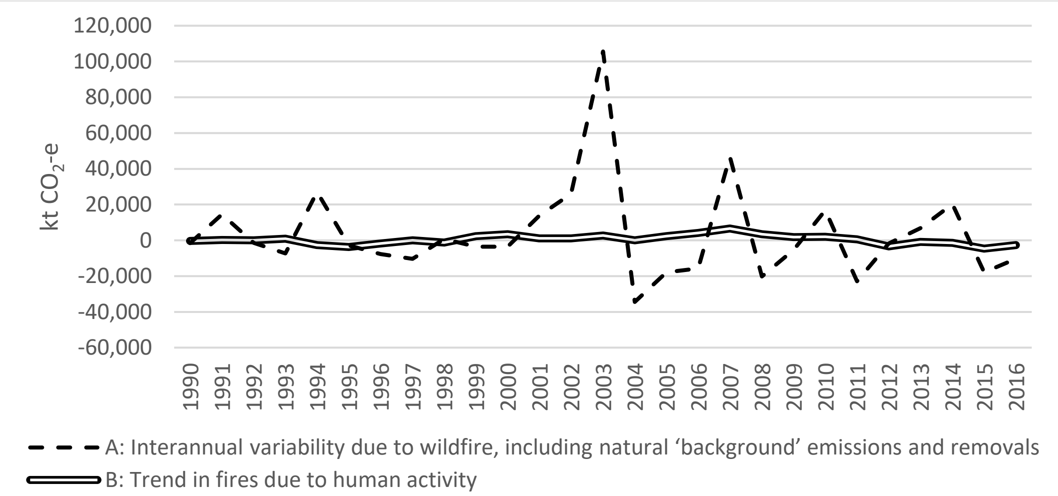


Figure 2.6b: Example of the disaggregation of wildfire emissions in Australia into 'natural disturbance' emissions and removals and the emissions and removals from fires due to human activity.

[16] References to 'natural disturbances' in this box refer to the *natural 'background' of greenhouse gas emissions and removals by sinks* described in *2006 IPCC Guidelines* Vol 4, page 1.5: (Managed land proxy) "Finally, while local and short-term variability in emissions and removals due to natural causes can be substantial (e.g. emissions from fire – footnote 1), the natural 'background' of greenhouse gas emissions and removals by sinks tends to average out over time and space."

[17] *2006 IPCC Guidelines* Vol 4, page 1.5: (Managed land proxy) "Finally, while local and short-term variability in emissions and removals due to natural causes can be substantial (e.g. emissions from fire – footnote 1), the natural 'background' of

BOX 2.2J (NEW)
CANADA'S APPROACH TO ESTIMATING INTERANNUAL VARIABILITY FROM NATURAL DISTURBANCES

This box is for information only and neither adds guidance nor overrules guidance provided.

In the 2017 National GHG Inventory Report[18] Canada revised its reporting approach to increase the transparency of the reporting of anthropogenic emissions and removals on Forest Land remaining Forest Land (FL-FL). The new approach disaggregated the emissions and subsequent removals on managed lands affected by natural disturbances from those on the remaining lands subject to forest management. The concept of the MLP was maintained: the sum of these two emission and removal components are identical to the total emissions and removals for FL-FL under the MLP. Canada's 2018 National GHG Inventory Report[19] further refined the approach. The methods are described in detail by (Kurz *et al.* 2018) and are summarized here.

Canada defined natural disturbances as all stand-replacing wildfires and all disturbances of other natural causes (insects, windthrow etc.) that result in more than 20 percent tree mortality (biomass) in affected stands. The threshold of 20 percent was selected because large areas of forests are affected by insects that cause low levels of mortality and/or growth reductions. Disturbances with impacts below this threshold are considered part of the natural, small-scale forest mortality that affect stand dynamics such as self-thinning.

For all areas affected by stand-replacing fire disturbances, annual CO_2 and non-CO_2 GHG emissions and subsequent CO_2 removals are summarized in the natural disturbance land category for several decades following the fire event. The time at which stands affected by natural disturbances transition back to the category of lands affected by forest management varies across Canada and is determined by the age at which stands are eligible for harvest, typically 60 to 90 years. For other natural disturbances that cause more than 20 percent biomass mortality, E/R are summarised in the natural disturbance category until the pre-disturbance biomass values are reached. For the 1990 to 2016 time series, stands regenerating following wildfire that are younger than the age at which stands are eligible for harvest is summarised in the natural disturbance category: removals that occur after 1989 in stands that have been affected by stand-replacing wildfires prior to 1990 are therefore contributing to balancing emissions from wildfires that occurred since 1990. The 56 Mha of managed forest affected by wildfire disturbances prior to 1990 contribute in 1990 estimated removals of 64 Mt CO_2e yr^{-1}. From 1990 to 1994 these cumulative annual removals are larger than the emissions from wildfires since 1990, making the lands subject to natural disturbances net sinks (Kurz *et al.* 2018). This approach contributes to balanced reporting as otherwise only removals from stands affected by natural disturbances after 1990 would appear in the natural disturbance component.

The disaggregation of fluxes improves the estimate of human impacts: reported emissions and removals without natural disturbances showed clear temporal trends that are correlated with changes in the rates of human activities such as rates of clear-cut harvesting (Figure 2.6C). In areas strongly affected by the Mountain Pine Beetle outbreak (Kurz *et al.* 2008) the trend in emissions reported for lands affected by forest management is still somewhat influenced by the impacts of the beetle because that area is decreasing (Kurz *et al.* 2018). The high IAV resulting primarily from fires is reported separately (Table 6.5 in Canada's NIR 2018). Further methodological details are provided in Canada's NIR 2018, Sections 6.3.1 and in Annex 3.5.2.3 and in (Kurz *et al.* 2018).

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greenhouse gas emissions and removals by sinks tends to average out over time and space. This leaves the greenhouse gas emission and removals from managed lands as the dominant result of human activity."

[18] http://unfccc.int/files/national_reports/annex_i_ghg_inventories/national_inventories_submissions/application/zip/can-2017-nir-13apr17.zip

[19] https://unfccc.int/documents/65715

BOX 2.2J (NEW) (CONTINUED)

CANADA'S APPROACH TO ESTIMATING INTERANNUAL VARIABILITY FROM NATURAL DISTURBANCES

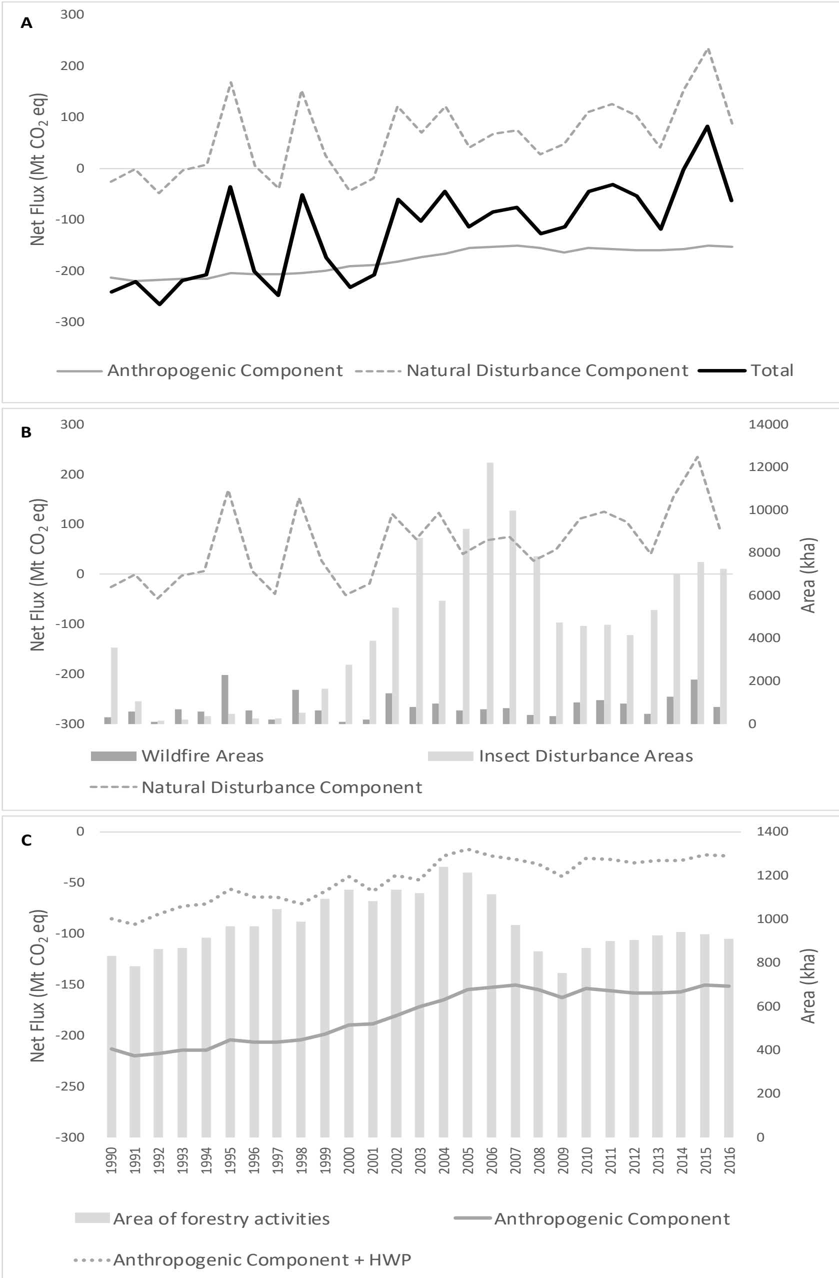

Figure 2.6c: Example of the disaggregation of Canada's FL-FL emissions and removals into those occurring on lands dominated by natural disturbance impacts and those occurring in the remaining managed forest (A). Note the high IAV in the natural disturbance fluxes (up to 250 Mt CO_2e/yr) (B) on the area affected by natural disturbances (primarily wildfires) and the low IAV of fluxes on the remaining managed forest area (C) which are correlated with forest management activities (e.g. primarily area of forest harvest). Fluxes in panel C are shown without (solid line) and with (dashed line) the emissions from harvested wood products. Data from Canada's 2018 NIR and figure from (Kurz *et al.* 2018)).

BOX 2.2K (NEW)
APPROACH TO ESTIMATING INTERANNUAL VARIABILITY FROM NATURAL DISTURBANCES BASED ON THE EU LEGISLATION[20]

This box is for information only and neither adds guidance nor overrules guidance provided. This example demonstrates a methodological approach that has not yet been implemented.

Forests of example country Z[21] are prone to wildfires that in years with extreme weather conditions (e.g. drought, especially if combined with strong winds) may cause large emissions from biomass burning and cause high IAV in the net CO_2 balance. Although, the country recognizes that most of its wildfires are human-induced either intentionally, e.g. pyromaniacs, or unintentionally, e.g. campfires, fireworks, cigarettes or other causes, some have natural causes. Consequently, emissions from wildfires have both an anthropogenic and a natural component.

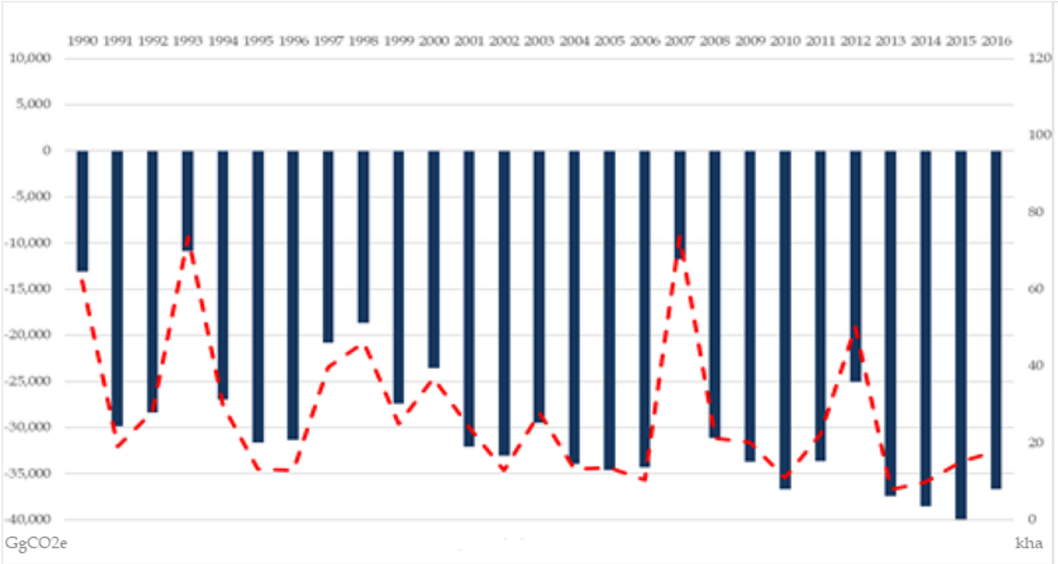

Figure 2.6d: Time series of managed forest land total GHG net emission (anthropogenic + natural disturbance (ND) and area burned. Blue bars (left Y-axis) represent annual total net GHG emission (Gg CO_2e) from managed forest land net sink. The dashed red line (right Y-axis) represents the annual area burned (kha).

To disaggregate the natural component of emissions and removals from wildfires, the country uses its national definition of natural disturbances: *Natural Disturbances are those wildfires that are non-anthropogenic events or non-anthropogenic circumstances that cause significant emissions in forests and are beyond the control of, and not materially influenced by, the Country's land use and management practices. These practices exclude salvage logging and prescribed burning*.

All wildfires are considered not materially influenced by the country's land use and management practices since the use of fire is forbidden in any forest land and the country has an advanced national fire management system for fire prevention, fire monitoring and fire suppression in all land uses, including forest land.

To identify wildfires that cause significant emissions and are beyond the control of the country's fire management system and are therefore considered natural disturbances, the country looks for statistical outliers that fall outside the 95 percent confidence interval of the variability of the historical time series of the annual GHG emissions from wildfires[22]. To do so, the distribution of emissions from wildfires is established, and it is assumed that all values within the normal

[20] The presented methodology is based on the EU Regulation 2018/841

[21] Data for this example are derived from the Italian GHG inventory

[22] Such time series do not include emissions from salvage logging nor emissions from wildfires that are followed by a deforestation event. The time series can start before the base year of the country and may include all years for which data are available. For this example, the time series starts in 1971.

BOX 2.2K (NEW) (CONTINUED)

APPROACH TO ESTIMATING INTERANNUAL VARIABILITY FROM NATURAL DISTURBANCES BASED ON THE EU LEGISLATION

distribution are exclusively associated with the anthropogenic component[23], any outlier value, in the upper tail, is considered as the signal of a disturbance event that is unlikely to have been generated by anthropogenic causes alone and therefore includes a natural component.

In practice, first a historical time series of annual emissions[24] from wildfires is constructed starting from 1971, i.e., the base year (1990) of the NGHGI of the country minus 20 years. Then, using an iterative process, outliers (if any) that are larger than the mean plus two times[25] the standard deviation are removed from the time series in successive iterations, until an outlier-free normal distribution is obtained.

The resulting time series, as well as its mean (referred to below as the background level of anthropogenic emissions from wildfires) and two times its standard deviation (referred to below as the margin) excludes all outliers. Based on these statistics, natural disturbances are those that occur in years when the total immediate emissions from wildfires are larger than the background level plus the margin and emissions from these natural disturbances are quantified as the amount exceeding the background level. This amount is disaggregated from the anthropogenic component.

To establish the balance between immediate CO_2 emissions (F) and total subsequent CO_2 removals[26] (R) due to natural disturbances, and to avoid introducing artificial trends to the time series, the country also estimates and reports removals occurring from land disturbed in the X years prior to the inventory year, where X[27] is the length of the period that is needed for forest vegetation (by relevant forest types and site types) to recover the pre-disturbance C stock. The CO_2 removals are quantified under the assumption that forest vegetation fully recovers within X years after wildfires. This assumption is based on the current legislation that forbids conversion of burnt forests to other land uses and that prescribes post-fire management activities aimed at rehabilitating the pre-fire forest vegetation. Consequently, the average amount of subsequent annual removals (R_{annual}) to be disaggregated for X years of a past ND event[28] is equivalent to $\frac{F}{X}$ and $\sum_0^X R_{annual} = R = F$ (where 0 is the year in which the natural disturbances occur and X the time needed for C stocks to recover to their pre-disturbance level).

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[23] The average value of this distribution is the so -called background level of emissions associated with disturbances and it is considered anthropogenic.

[24] The country includes the emissions of fire events only, delayed emissions associated with the decay of biomass that was killed during the fire are not considered

[25] This is an approximation of Student's t value for data series with number of data >= 30.

[26] Calculated directly from the biomass net increment (ΔC_G of IPCC equation 2.7)

[27] For this example, X has been estimated to be 20 years for the entire country's territory.

[28] This means that in any year Y of the NGHGI the amount of CO_2 removals to be disaggregated is equivalent to the $\sum_{Y-X}^{Y} \left(\frac{F}{X}\right)_{(Y-X)}$ (where $\left(\frac{F}{X}\right)_{(Y-X)}$ are the annual CO= removals occurring on all lands disturbed in the period Y-X that have not yet achieved their pre-disturbance level of C stocks.)

BOX 2.2K (NEW) (CONTINUED)

APPROACH TO ESTIMATING INTERANNUAL VARIABILITY FROM NATURAL DISTURBANCES BASED ON THE EU LEGISLATION

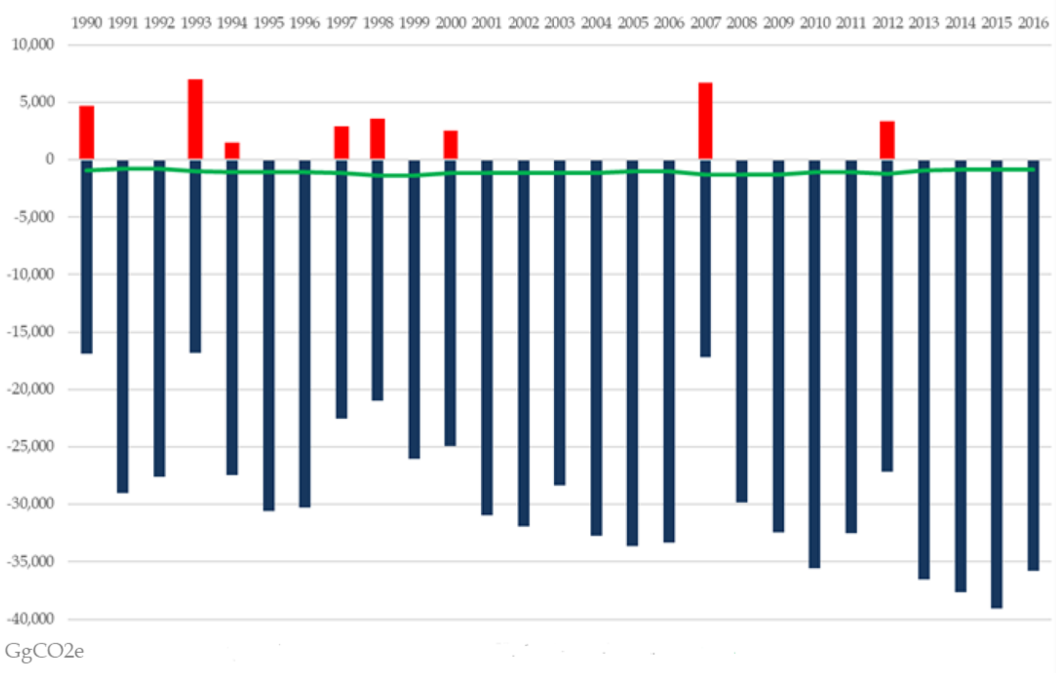

Figure 2.6e: Time series of managed forest land GHG net emissions and removals (Gg CO_2e). Blue bars (net sink) represent annual anthropogenic GHG net emissions (Gg CO_2e) from managed forest land; red bars (source and green line (sink)) disaggregated GHG emissions and subsequent CO_2 removals from natural disturbances in managed forest land, respectively. The coefficient of variation of the time series is 0.184.

2.6.4 Reporting the contribution of natural disturbances and anthropogenic effects to the emissions and removals for managed lands

Voluntary disaggregation of the total of emissions and removals in the MLP into those that are associated with human effects and those due to natural disturbances may provide a clearer picture of the impact of management activities. It is understood that a complete separation of the direct human impacts from natural impacts is, at this time, not possible due to limitations of scientific methods (IPCC 2010) but disaggregating the emissions and subsequent removals that are associated with natural disturbances on managed lands may be a helpful first step.

The MLP total is the sum of all emissions and removals on managed land. Box 2.2l describes a possible approach to reporting the total E/R from MLP plus the two components from:

1. Natural disturbances;
2. Anthropogenic activities (direct and indirect human effects).

The first component includes emissions from natural disturbances and subsequent net removals from regrowth. Emissions may include delayed emissions from dead organic matter that was added by the disturbance to the already existing dead organic matter pools.

The second component includes emissions and removals directly and indirectly associated with human activity calculated as the difference between MLP total emissions and removals minus those associated with natural disturbances.

In those cases where natural disturbance fluxes are large compared to the anthropogenic component of the MLP, the optional disaggregation of estimates of the emissions and removals associated with natural disturbances can identify the estimated trends of the emissions and removals on managed land associated with human activity, as demonstrated in recent NGHGI reports (e.g., Boxes 2.2I, 2.2J).

Transparency:

For those countries that choose to identify, quantify and report disaggregated natural disturbance emissions and subsequent removals, it is *good practice* to document disaggregated emissions and removals in the MLP, and the approaches, assumptions and methods used.

It is *good practice* to document the following:

- Consistency of the country approach with the generic definition of natural disturbances provided in Section 2.6.1.2, if any.
- The **types** of natural disturbances for which emissions and subsequent removals are identified, quantified and disaggregated within MLP reporting.
- How the **requirements** associated with the above definition of natural disturbances are met, including that the identified ND events are "non-anthropogenic events or non-anthropogenic circumstances", which can be demonstrated by providing information to show that the disturbances were **"**not materially influenced by, and beyond the control of, a country".
- How the emissions and removals that are materially influenced by human actions are excluded from the natural disturbances component.

The demonstration that natural disturbances were "not materially influenced by, and beyond the control of, a country" is based on scientific reasoning or evidence and documentation on practicable efforts to prevent, manage or control the occurrences that led to the natural disturbances. Such evidence and practicable efforts may include but are not limited to:

- Studies showing the prevalent direct cause of fires in a given region, forest type and climate zone; information on weather conditions related to the disturbance events or to the cumulative affected areas;
- Application of preventative measures or modifying factors related to the occurrence or propagation of the disturbances that may reduce the likelihood and/or magnitude of the disturbances occurring;
- Efforts to manage or control the disturbances when they occur, to the extent possible.

It is *good practice* to document the **methods** used to identify, quantify and disaggregate the impact of ND on GHG emissions and removals, including information on:

- How the method is consistent with the expectation that the CO_2 emissions from areas affected by natural disturbance will be balanced by subsequent removals.
- The methods by which GHG fluxes are disaggregated from total MLP fluxes.
- For lands subject to ND, documentation on how subsequent land use and land-use change, if any, is identified and how GHG fluxes previously disaggregated as associated with natural disturbances are re-assigned to the anthropogenic component following land-use change.

Documentation on the manner in which emissions associated with human activities that occur after the natural disturbance event (such as salvage logging and site rehabilitation or other activities that do not cause a land-use to change), and subsequent removals, are estimated and disaggregated.

BOX 2.2L (NEW)
EXAMPLE OF THE TABLE FORMAT THAT COULD BE USED FOR VOLUNTARY DISAGGREGATION OF TOTAL ESTIMATED FLUXES ON MANAGED LANDS INTO ANTHROPOGENIC AND NATURAL DISTURBANCE COMPONENTS

Land-use category	**e.g. Forest land remaining forest land**					
Years		**Start year†**	**…**	**…**	**…**	**Inventory year**
Total Area under the MLP (kha)						
Carbon stock change	Gains					
	Losses					
	Net					
non-CO_2 emissions	Emissions					
Net E/R plus non-CO_2	Total*					
Annual area of natural disturbances (kha)[29]						
Area subject to natural disturbances (kha)[30]						
Carbon stock change	Gains					
	Losses					
	Net					
non-CO_2 emissions	Emissions					
Net E/R plus non-CO_2	Total					
Remaining area of managed land (kha)						
Carbon stock change	Gains					
	Losses					
	Net					
non-CO_2 emissions	Emissions					
Net E/R plus non-CO_2	Total #					

† This is the first year in the inventory time series, e.g. 1990.

* This is the total MLP estimate of net emissions and removals, i.e. the first order approximation of the anthropogenic emissions and removals

This is the optional disaggregated estimate of the anthropogenic emissions and removals

[29] The area of natural disturbance in the year it first occurs.

[30] The cumulative area which has been subject to natural disturbances up to and including the current inventory year, minus the area of natural disturbances on which past CO_2 emissions are considered to be balanced by subsequent removals since the occurrence of the natural disturbance. In the cumulative area totals, areas affected multiple times are included only once.

Annex 2A.1 Default Mineral Soil Reference C Stocks

Data presented in Table 2.3 were derived from Batjes (2011) and Batjes (2010) unless no values were available for particular combinations of IPCC Climate Zones and IPCC soil types. Where no values were available, values were taken from the *2006 IPCC Guidelines for National Greenhouse Gas* or the *1996 IPCC Guidelines*.

Reference C Stocks for the mineral soils C method were derived for IPCC climate zones (IPCC 2006 p. 3.39) and IPCC soil classes (IPCC 2006 pp. 3.40-3.41). Soil data are from the ISRIC-WISE database (10250 profiles) complimented with 1900 additional geo-referenced profiles from under represented temperate and boreal sites. Data from all soils were screened and where organic carbon contents were determined using the Walkley Black analysis, values were adjusted based on a conversion factor of 1.3 to estimate corresponding values that would have been obtained by dry combustion analysis. Profiles were collected between 1925 and 2010 with two-thirds of the pedons sampled between 1955 and 1995. Profiles were classified as “cultivated or disturbed” vs “(semi)natural”. Only profiles flagged as being under native vegetation (classified as “(semi)natural”) were included (a total of 5560 profiles equating to approximately 1.6 times that used in the *2006 IPCC Guidelines*). The profiles also had a better geographical distribution across the globe compared to those use to derive reference carbon stock values within the *2006 IPCC Guidelines*.

The following equation was used to compute SOC stocks:

EQUATION 2A.1.1

ESTIMATION OF SOIL ORGANIC CARBON STOCKS

$$T_d = \sum_{i=1}^{k} (\rho_i \bullet P_i \bullet D_i) \bullet (1 - S_i)$$

Where:

T_d = total amount of organic carbon over depth, d, (in kg m^{-2})

ρ_i = bulk density of layer i (Mg m^{-3})

P_i = the proportion of organic carbon in layer i (g C Kg^{-1})

D_i = thickness of the layer (m)

S_i = volume of the fraction of fragments >2 mm

Gaps in bulk density and coarse fragment >2mm content data were filled using pedo(taxo)-transfer functions presented by Batjes *et al.* (2007) on the basis of soil type, soil textural class and soil depth. IPCC Tier 1 methods consider changes in 0-30 cm soil depth layer; however, best-estimates were also derived for 0-50 and 0-100 cm soil depth layers.

Annex 2A.2 Additional Information for the Estimation of Soil Carbon Stock Change from Biochar Amendments to Mineral Soils Using Tier 2 and 3 Methods

Thermochemical Conversion Technologies

For the purpose of this methodology, biochar is defined as a solid material generated by heating biomass to a temperature in excess of 350 °C under conditions of controlled and limited oxidant concentrations to prevent combustion. These processes can be classified as either pyrolysis (in which oxidants are excluded), or gasification (in which oxidant concentrations are low enough to generate syngas).

Torrefaction and hydrothermal carbonisation (also called liquefaction) are not included because they do not generate solid products that are significantly more persistent in soil than the original organic feedstock material (Libra *et al.* 2011; Kammann *et al.* 2012). Both of these processes typically utilise temperatures below 350°C, with torrefaction operating under dry feedstock conditions in ambient pressure, while hydrothermal carbonisation uses pressurised wet aqueous slurries. In contrast, pyrolysis operates at temperatures at 350°C and above (typically but not always below 700°C) under variable times, and gasification utilises temperatures between 500 and 1500°C and typically short times (Boateng *et al.* 2015), both in dry conditions. Dry conditions are defined here in terms of the feedstock moisture, whereby feedstocks can have moisture up to 20percent after pre-drying; in comparison, wet slurries typically have liquid water contents above 80percent.

Priming of native soil organic carbon by biochar amendments

Mineralisation of native soil organic carbon is on average reduced by 4 percent (95 percent CI = -8.1–0.8percent) after biochar additions to soil (Wang *et al.* 2015). Similar to laboratory trials (Kuzyakov *et al.* 2014), field trials also show reductions in mineralisation of native soil organic carbon close to a decade after biochar additions (Weng *et al.* 2017) as well as in biochar-rich soils after several millennia (Liang *et al.* 2010). Known mechanisms that would cause an increase in mineralisation involve co-metabolism (Whitman *et al.* 2015) that operates over the short term by supplying easily mineralisable organic matter as a source of energy to metabolise native organic matter (Zimmerman *et al.* 2011). Conservatively, we assume no effect of biochar on existing soil organic matter in the long term.

Nitrous oxide emissions from soil after biochar amendments

Meta-analyses have found that nitrous oxide emissions are on average reduced between 54 percent (Cayuela *et al.* 2014), 38 percent (Borchard *et al.* 2018), 32 percent (Liu *et al.* 2018) to 0 percent (Verhoeven *et al.* 2017) after addition of biochar to soil. Any reductions in nitrous oxide emissions due to biochar additions typically decline over several years after application (Fungo *et al.* 2017). Furthermore, assessments of nitrous oxide emissions several years after biochar additions are indicative of long-term emission reductions although at lower rates, since changes in biochar properties occur slowly over long periods of time (decades and centuries) compared to changes observed during the initial days to years (Nguyen *et al.* 2008).

High-N feedstocks generate biochar with some microbially available N (Wang *et al*. 2012) and can lead to short-term (days to weeks) increases in total nitrous oxide emissions if produced at lower temperatures (< 600 °C) (Cayuela *et al.* 2013). However, charring consistently reduces nitrous oxide emissions originating from the nitrogen in nitrogen-rich organic materials (Rose *et al.* 2016), as easily mineralisable amino-groups are converted to polyaromatic nitrogen-carbon structures (Knicker 2007).

Due to limiting evidence demonstrating the long-term persistence of soil nitrous oxide emission reductions, it is conservatively assumed that biochar does not reduce nitrous oxide emissions from soil in the Tier 1 method. However, any bioavailable N additions associated with biochar amendments should be included in the calculations of direct and indirect soil nitrous oxide emissions (Volume 4, Chapter 11) as part of organic N inputs. This approach will be conservative in terms of the influence of biochar on greenhouse gas emissions for the Tier 1 method.

Biochar Amendments to Organic Soils

No methods are provided in this guidance for estimating the impact of amending organic soils with biochar. Compilers may be able to develop a Tier 3 method for estimating the impact of biochar C amendments to organic soils, but it is important to recognise that the dynamics may be different, particularly with respect to priming. Few studies have investigated the impact of priming by biochar on organic soils. However, one study that has investigated priming of organic horizons in a forest soil found substantial losses of soil C over a ten-year period with charcoal additions (Wardle *et al*. 2008). Wardle *et al*. (2008) did not use isotopes and were therefore unable to attribute these losses unequivocally to the organic soil C or to the charcoal. Nor was their study able to determine the extent to which enhanced mass loss of organic soil carbon was due to mineralisation, or was due to vertical transport of the C into the soil column as dissolved or colloidal organic carbon (Lehmann & Sohi 2008). Nonetheless, the Wardle *et al*. (2008) study did indicate the possibility that priming of soil organic matter decomposition by biochar may lead to a net loss of soil C in organic soils.

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