CHAPTER 2

GENERIC METHODOLOGIES APPLICABLE TO MULTIPLE LAND-USE CATEGORIES

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2.1 INTRODUCTION

No refinement

2.1.1 Inventory Framework

Elaboration in a box concerning the consistency between AFOLU projects or activities and IPCC Inventory Guidelines.

NEW- BOX 2.0A

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 national GHG inventory. 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, boundaries, double-counting, leakage, and attribution. Moreover, projects and activities may use different definitions and sources of data compared to the data used for the NGHGI, including different sources of activity data and data for emissions estimation methods such as EFs or model parameters. The project or activity may also use different Approaches for land representation and Tiers compared to the NGHGI, impacting the consistency between the two. These need to be considered when applying the IPCC Guidelines outside of national GHG inventories (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[2];

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.

For example, 1) REDD+ activities could be identified in the national 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[3] for ensuring consistency in emissions estimation between AFOLU project-level mitigation activities and Australia's NGHGI. This framework includes integrity standards[4] to ensure emissions estimation methods are consistent with IPCC guidelines, and consequently estimated GHG reductions are fungible with trends of times series of relevant NGHGI categories.

Emissions and removals estimates for activities are likely to apply 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 GHGI categories/subcategories into subdivisions helps avoid double counting of emissions and removals from a single category that is impacted by more than an activity.

[2] 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 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.

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

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

NEW- BOX 2.0A (CONTINUED)

CONSISTENCY BETWEEN AFOLU PROJECTS OR ACTIVITIES AND IPCC INVENTORY GUIDELINES

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 national GHGI 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 EF 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;

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

2.2 GENERIC METHODS FOR CO_2 EMISSIONS AND REMOVALS

No refinement

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

No refinement

2.2.1.1 LAND REMAINING IN A LAND-USE CATEGORY

No refinement

2.2.1.2 LAND CONVERTED TO A NEW LAND-USE CATEGORY

No refinement

2.2.1.3 ADDITIONAL GENERIC GUIDANCE FOR TIER 2 METHODS

This is a new section.

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[5] 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.

[5]The term "allometric equation" is used also 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.

NEW - BOX 2.0B

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.

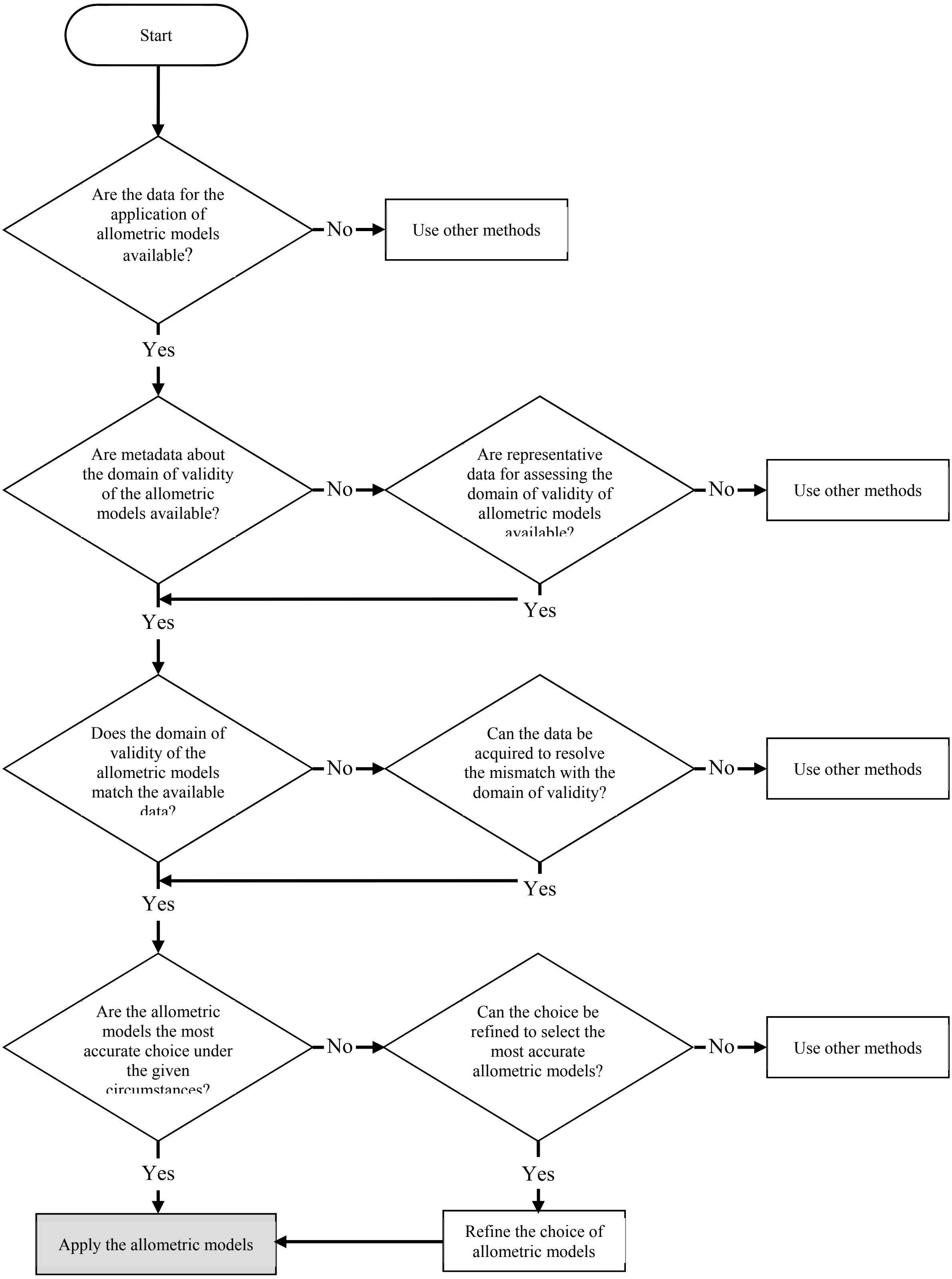
Allometric model: An allometric model is a formula that quantitatively describes an allometric relationship. The basic form is an equation: $y=f(x)$ where y and x are the dependent and independent variables. Often the equation is linear, $y = a*x^b + c$, where a, b and c are parameters. The parameter "c" is only used in relations where the value of Y is greater than zero when X is zero (e.g., tree height as function of DBH, when height is below breast height). 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, 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 second predictor variable (e.g. Ketterings et al. 2001). Models are usually provided with a residual error term (e.g., $y = f(x) + \varepsilon$), set in the model fitting; it is *good practice* to consider the residual error, calculated for each model, 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 in terms of accuracy under the given circumstances (Figure 2.2A). The accuracy of the models may be lower than e.g. available BEFs, so it is *good practice* to test for and chose the method delivering better 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 diameter at breast height (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.

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



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) Individual size range sampled to develop the model is representative of the population it will be applied to, as the model may not be valid for individuals that fall outside the 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

These conditions 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. In the absence of sufficient metadata, information about the applicability of a model may also be obtained from model validation using a representative data set (e.g. Youkhana et al 2017). The goodness of the allometric model fitting should be taken into account, by evaluating the related statistical indicators (i.e. R square, Kolmogorov-Smirnov test, chi-square etc.).

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 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) 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 find in the 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 m 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. In this case, using the new model for recalculations will cause an error.

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).

NEW - BOX 2.0C

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 national GHG inventories. The errors of biomass predictions from terrestrial laser scanning does not increase with increasing diameter or more complex tree and canopy structures (often an issue with destructive measurements or allometric relationships), and, thus, have proven useful for large and complex tropical trees in particular (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 A 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 (that also depict carbon stocks) for woody plants and trees.

Consideration when developing biomass density maps

Biomass density maps are constructed by combining remotely sensed data 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 national GHG inventories 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 national GHG inventory.
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 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 national GHG inventories (see Volume IV, Chapter 3).

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 primary variable predicted from remotely sensed data, additional information such as country-specific data for root-to-shoot ratios may be needed to estimate carbon stocks in other pools.

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).

SAR and LiDAR are active sensors 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 signal of reflected pulses, volume or biomass of woody plants and trees can be predicted (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).

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 2.0D).
2) Estimate biomass change directly from multi-temporal biomass density maps. Such 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 national GHG inventories 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 GHG inventory 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.

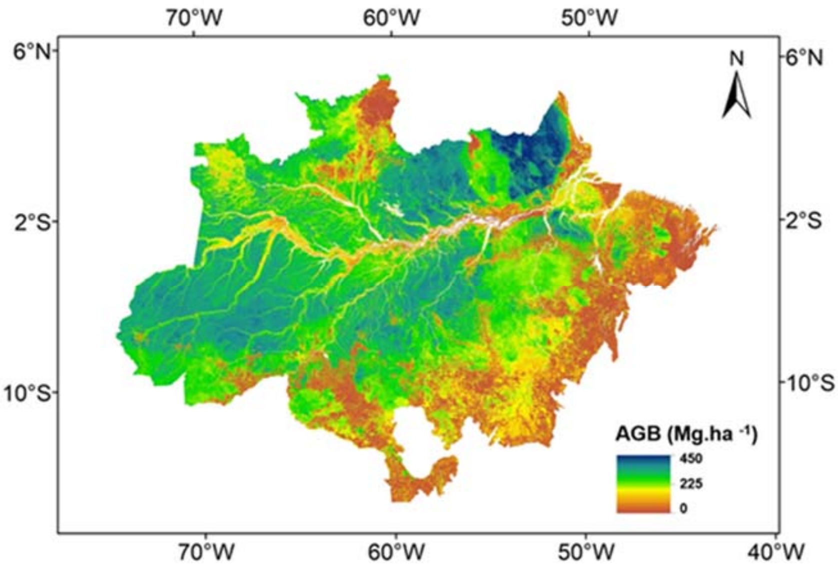
The application of such approaches requires maps well-calibrated for national circumstances. Many available large-area biomass maps might not be consistent with national definitions of forest and/or biomass pools, and often exhibit large systematic errors in the estimation of carbon stock and changes for national and local assessments (Avitabile et al., 2016). They 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 GHG inventories, 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.

NEW - BOX 2.0D

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. Aim for using the biomass map for the national GHG inventory 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 derive the biomass was based on 1,000 LiDAR transects randomly distributed across 3.5 million km2 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 equations 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=0.8059 and 20.58 MgCha-1, respectively. In this process, the SRTM elevation data was 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 propagating the uncertainties through the different levels of biomass estimation, 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.



Biomass map of the Amazon biome in Brazil

The PRODES system monitors clear cut deforestation in the Brazilian Amazon, and has been producing annual deforestation rates since 1988. PRODES is the basis for calculating carbon emissions in the Amazon region for the UNFCCC reporting and REDD+ mechanism, as well for public policies on defining goals to reduce deforestation. The map presented here is then incorporated with PRODES in the national inventory of GHG emissions and used for future planning of emissions reduction activities.

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2.2.2 Change in carbon stocks in dead organic matter

No refinement in Introduction

2.2.2.1 LAND REMAINING IN A LAND-USE CATEGORY

This section includes an elaboration of the development of equation 2.18 for estimating DOM out and associated updated default values in Table2.2

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 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 2.4 provides the decision tree for identification of the appropriate tier to estimate changes in carbon stocks in dead organic matter.

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}

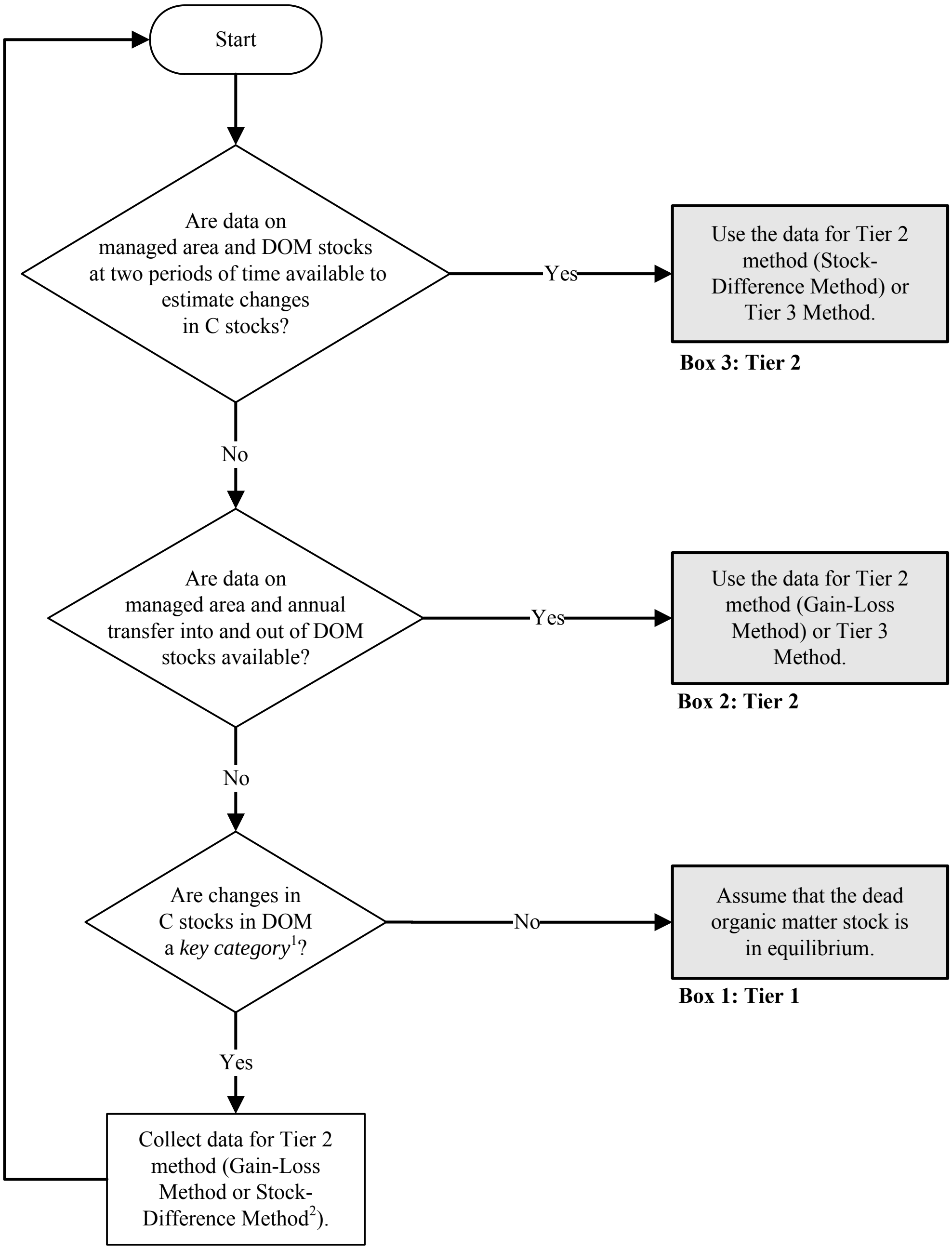
A = area of managed land, ha

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.)$^{-1}$

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.

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. 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 DOMout is estimated. DOMout using the second approach is the product of the rate-constant describing the proportion lost per year and the stock of DOM (e.g., DOMout = 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 the woodiness (i.e., wood and bark versus foliage), size, and position (i.e., standing versus downed dead wood) as well as the species of the material decomposing, state of decomposition (i.e., fresh versus highly decomposed), the decomposers present (e.g., the presence of termites and/or soil biota) and their activity, openness of the canopy and albedo as controlled by disturbances, and climate (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). 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_{t1} = dead wood/litter stock at time t_1 for managed land, tonnes d.m. ha^{-1}

DOM_{t2} = 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 = 0.37 for litter (Smith & Heath 2002), 0.5 for dead wood, temperate species (Harmon et al. 2013), 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 noncommercial 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)

$L_{disturbances}$ = 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% 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.

2.2.2.2 LAND CONVERSION TO A NEW LAND-USE CATEGORY

This section includes updates on default emission factors.

UPDATED - TABLE 2.2 TIER 1 DEFAULT VALUES FOR LITTER AND DEAD WOOD CARBON STOCKS												
FAO Ecological Zone	Forest type											
	Broadleaf deciduous		Needleleaf evergreen		All vegetation types		Broadleaf deciduous		Needleleaf evergreen		All vegetation types	
	Litter carbon stocks (tonnes C ha-1)						Dead wood carbon stocks (tonnes C ha-1)					
	Mean	**Min/Max**	**Mean**	**Min/Max**	**Mean**	**Min/Max**	**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	16.4	2.3-50.7	22.2	4.1-76.5	19.7	2.3-76.5
Boreal tundra woodland	29.3	23.7-33.7	67.4	23.7-85.1	49.5	23.7-85.1	5.7	n.a.	1.3	0.5-2.4	3.1	0.5-6.1
Polar	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	26.2	n.a.	26.2	n.a.
Subtropical desert	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	64.4	14.4-134.5	64.4	14.4-134.5
Subtropical humid forest	5.6	4.4-8.1	6.8	4.7-11.6	8.7	1.2-24.0	4.1	2.5-7.5	10.9	3.5-32.8	13.2	0.2-43.8
Subtropical mountain system	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	11.8	7.2-16.3	11.8	7.2-16.3
Subtropical steppe	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	6.8	6.0-7.7	6.8	6.0-7.7

Temperate continental forest	23.9	4.6-64.4	66.3	6.0-279.1	47.8	4.6-279.1	23.6	1.6-150.0	22.1	2.1-59.5	23.0	1.6-150.0
Temperate desert	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	10.5	n.a.	10.5	n.a.
Temperate mountain system	3.4	n.a.	3.9	n.a.	3.7	3.4-3.9	21.2	2.8-80.6	48.1	1.7-181.8	37.6	1.7-181.8
Temperate oceanic forest	n.a.	n.a.	40.5	n.a.	2.9	n.a.	40.5	2.8-95.0	24.3	n.a.	36.8	2.8-95.0
Temperate steppe	36.9	7.6-98.8	26.4	7.1-43.0	28.7	3.8-98.8	21.7	8.1-50.0	17.4	8.0-35.0	16.6	3.2-50.0
Tropical dry forest	n.a.	n.a.	n.a.	n.a.	2.4	2.1-2.7	16.0	14.7-17.3	n.a.	n.a.	9.0	1.3-17.3
Tropical moist forest	4.3	2.0-9.0	14.8	n.a.	5.9	1.9-14.8	8.4	1.2-21.2	3.4	n.a.	8.0	1.2-21.2
Tropical mountain system	n.a.	n.a.	n.a.	n.a.	n.a.		3.3	n.a.	n.a.	n.a.	3.3	n.a.
Tropical rainforest	2.5	n.a.	4.7	n.a.	4.8	2.1-16.4	17.7	0.9-218.9	1.9	n.a.	14.8	0.6-218.9
Source: See references. Note that in some cases, estimates from the 2006 Guidelines were replaced rather than expanded depending on the source of data. n.a. denotes 'not available'												

2.2.3 Change in carbon stocks in soils

No Refinement in Introduction.

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 to 20 percent organic matter 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 and 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% of the original soil C stocks can be lost (Mann, 1986; Davidson and 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.

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

This section has an elaboration of methods, new guidance and updates.

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 grasslands 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
ANNUAL CHANGE IN CARBON STOCKS IN SOILS

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

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}

$\Delta BC_{Mineral}$ = annual change organic carbon stocks with biochar amendments added to mineral 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 and 2 methods, soil organic C stocks for mineral soils are computed to a default depth of 30 cm. Greater depth can be selected and used at Tier 2 if data are available, but Tier 1 reference organic carbon stocks and stock change factors are based on 30 cm depth. Residue/litter C stocks are not included because they are addressed by estimating dead organic matter stocks (see section 2.3.2). Stock changes in organic soils are based on emission factors that represent the annual loss of organic C throughout the profile due to drainage.

The change in soil organic C stocks from biochar amendments is estimated separately from other organic amendments due to the high resistance to mineralisation exhibited by biochar carbon. Biochar is defined as 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 300°C with limited air through a gasification or pyrolysis process (Annex 2A.2). 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. A conservative approach is to be used for calculating the value of $\Delta BC_{Mineral}$ given the amount of biochar C that will remain after 1000 years. Since the impact of biochar amendments is included in Equation 2.24, it is essential that biochar is not included as an organic amendment in the estimates of $\Delta C_{Mineral}$ elsewhere in an inventory.

No Tier 1 or 2 methods are provided for estimating the change in soil inorganic C stocks 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 countries will use different tiers to prepare estimates for mineral soils, organic soils, biochar amendments and soil inorganic C, given 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). A generalised decision tree 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.

Tier 1 Approach: Default Method

Mineral soils

For mineral soils, the default method is based on changes in soil C stocks over a finite period of time. The change is computed based on C stock after the management change relative to the carbon stock in a reference condition (i.e., native vegetation that is not degraded or improved). The following assumptions are made:

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

(ii) Soil organic C stock changes during the transition to a new equilibrium SOC occurs in a linear fashion.

Assumption (i), that under a given set of climate and management conditions soils tend towards an equilibrium carbon content, is widely accepted. Although, soil carbon 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 soil 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.

821 **EQUATION 2.25**

822 **ANNUAL CHANGE IN ORGANIC CARBON STOCKS IN MINERAL SOILS**

823
$$\Delta C_{Mineral} = \frac{(SOC_0 - SOC_{(0-T)})}{D}$$

824
$$SOC = \sum_{c,s,i} \left(SOC_{REF_{c,s,i}} \bullet F_{LU_{c,s,i}} \bullet F_{MG_{c,s,i}} \bullet F_{I_{c,s,i}} \bullet A_{c,s,i} \right)$$

825 (Note: T is used in place of D in this equation if T is ≥ 20 years, see note below)

826 Where:

827 $\Delta C_{Mineral}$ = annual change in organic carbon stocks in mineral soils, tonnes C yr^{-1}

828 SOC_0 = soil organic carbon stock in the last year of an inventory time period, tonnes C

829 $SOC_{(0-T)}$ = soil organic carbon stock at the beginning of the inventory time period, tonnes C

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

831 D = Time dependence of stock change factors which is the default time period for transition between
832 equilibrium SOC values, yr. Commonly 20 years, but depends on assumptions made in computing the
833 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
834 inventory time period (0-T years).

835 *c* = represents the climate zones, *s* the soil types, and *i* the set of management systems that are present
836 in a country.

837 SOC_{REF} = the reference soil organic carbon stock for mineral soils under native vegetation, tonnes C ha^{-1}
838 (Table 2.3)

839 F_{LU} = stock change factor for land-use systems or sub-system for a particular land-use, dimensionless

840 [Note: F_{ND} is substituted for F_{LU} in forest soil C calculation to estimate the influence of natural
841 disturbance regimes.

842 F_{MG} = stock change factor for management regime, dimensionless

843 F_I = stock change factor for input of organic matter, dimensionless

844 A = land area of the stratum being estimated, ha. All land in the stratum should have common biophysical
845 conditions (i.e., climate and soil type) and management history over the inventory time period to be
846 treated together for analytical purposes.

847 Inventory calculations are based on land areas that are stratified by climate regions (see Chapter 3 Annex 3A.5,
848 for default classification of climate), and default soils types as shown in Table 2.3 (see Chapter 3, Annex 3A.5, for
849 default classification of soils). The stock change factors are very broadly defined and include: 1) a land-use factor
850 (F_{LU}) that reflects C stock changes associated with type of land use, 2) a management factor (F_{MG}) representing
851 the principal management practice specific to the land-use sector (e.g., different tillage practices in croplands), and
852 3) an input factor (F_I) representing different levels of C input to soil. As mentioned above, F_{ND} is substituted for
853 F_{LU} in Forest Land to account for the influence of natural disturbance regimes (see Chapter 4, Section 4.2.3 for
854 more discussion). The stock change factors are provided in the soil C sections of the land-use chapters. Each of
855 these factors represents the change over a specified number of years (D), which can vary across sectors, but is
856 typically invariant within sectors (e.g., 20 years for the cropland systems). In some inventories, the time period
857 for inventory (T years) may exceed D, and under those cases, an annual rate of change in C stock may be obtained
858 by dividing the product of [($SOC_0 - SOC_{(0-T)}$) ● A] by T, instead of D. See the soil C sections in the land-use
859 chapters for detailed step-by-step guidance on the application of this method.

UPDATED - TABLE 2.3

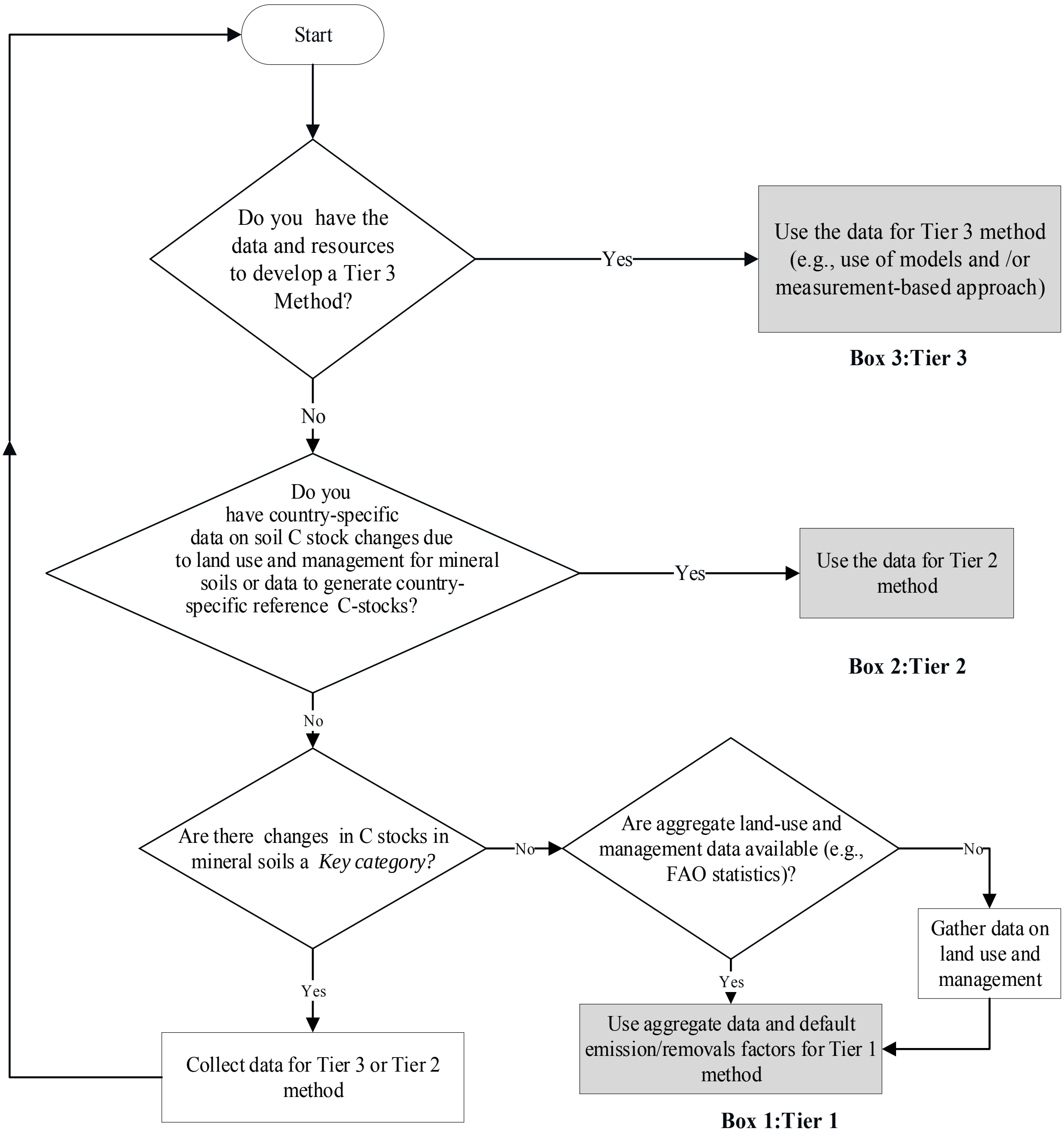
DEFAULT REFERENCE (UNDER NATIVE VEGETATION) SOIL ORGANIC CARBON STOCKS (SOCREF) FOR MINERAL SOILS (TONNES C HA-1 IN 0-30 CM DEPTH) [1, 2]

IPCC Climate Zone [5]	IPCC soil class [6]					
	High activity clay soils (HAC) [7]	**Low activity clay soils (LAC)** [8]	**Sandy soils (SAN)** [9]	**Spodic soils (POD)** [10]	**Volcanic soils (VOL)** [11]	**Wetland soils (WET)** [12]
Polar (Px - undiff)[13]	59 ± 203 (24)	NA	27 ± 210 (18)	NO	NA	NA
Boreal Bx - undiff)[13]	63 ± 106 (35)	NA	10 ± 78 [3]	117 ± 89 [4]	20 ± 88 [3]	116 ± 159 (6)
Cool temperate dry (C2)	43 ± 109 (177)	33 ± 89 [4]	13 ± 106 (10)	NO	20 ± 88 [3]	87 ± 88 [4]
Cool temperate moist (C1)	81 ± 97 (334)	76 ± 124 (6)	51 ± 150 (126)	128 ± 93 (45)	136 ± 78 (28)	128 ± 84 (42)
Warm temperate dry (W2)	24 ± 131(781)	19 ± 103 (41)	10 ± 98 (338)	NO	84 ± 205 (10)	74 ± 119 (49)
Warm temperate moist (W1)	64 ± 101(489)	55 ± 103 (183)	36 ± 142 (39)	143 ± 89 (9)	138 ± 80 (42)	135 ± 147 (28)
Tropical dry (T4)	21 ± 121 (554)	19 ± 113 (135)	9 ± 109 (164)	NA	50 ± 86 [3]	22 ± 98 (32)
Tropical moist (T3)	40 ± 108 (226)	38 ± 98 (326)	27 ± 109 (76)	NA	70 ± 90 [3]	68 ± 130 (55)
Tropical wet (T2)	60 ± 98 (137)	52 ± 94 (271)	46 ± 132 (43)	NA	77 ± 102 (14)	49 ± 108 (33)
Tropical montane (T1)	51 ± 108 (114)	44 ± 98 (84)	52 ± 113 (11)	NA	96 ± 98 (10)	82 ± 174 (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 ± $1.96\sigma/\mu$ *100). Values in parentheses are the number of soils included in the derivation of mean and standard deviation values for each combination of soil and climate types. [3] 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. [4] Indicates where no data were available from Batjes (2011) but values were presented in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories and have been used in the table. No values of n were available. [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.

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



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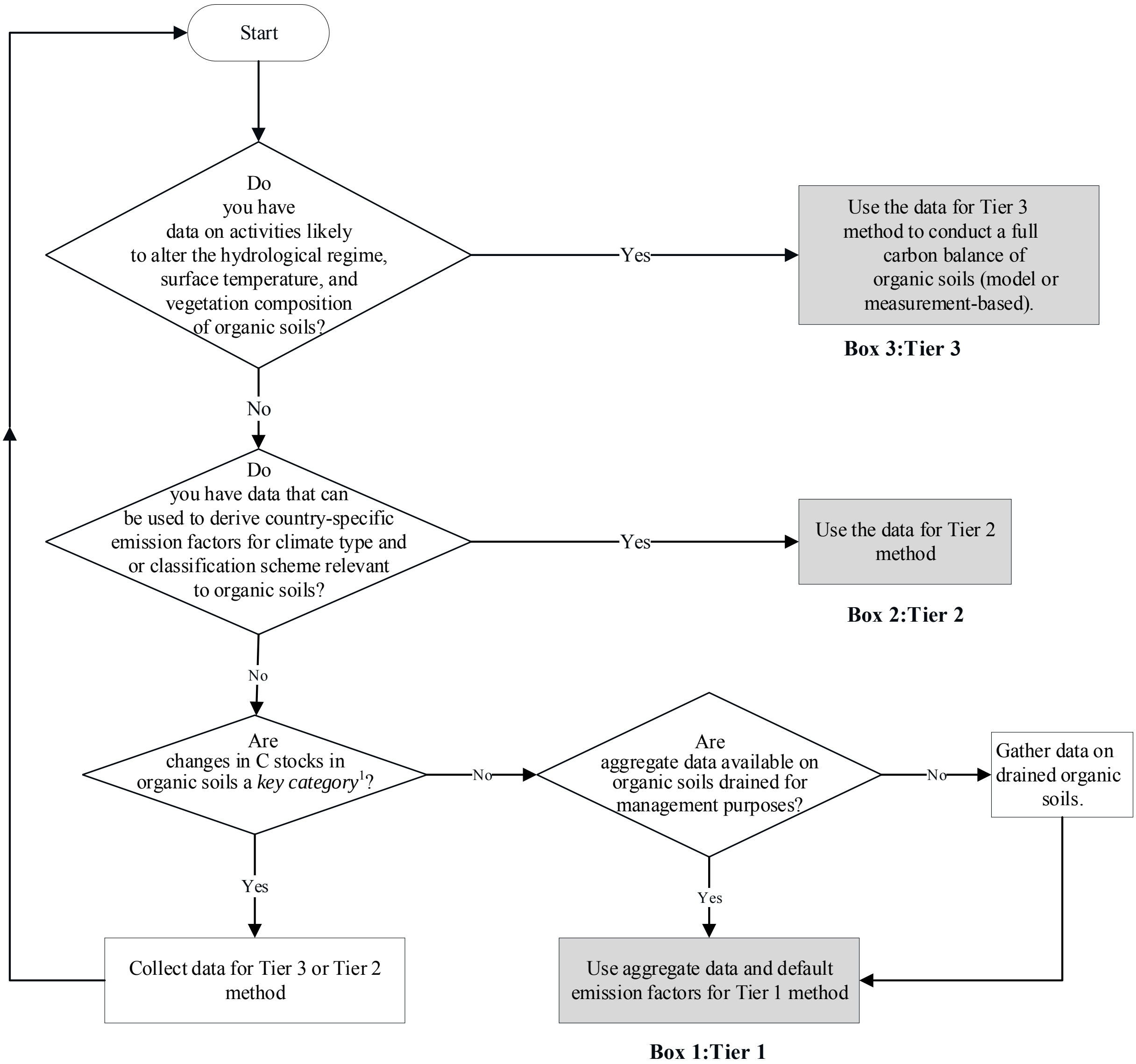
864

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



When applying the Tier 1 or even Tier 2 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). Activity data collected with Approach 1 fit with Formulation A, while activity data collected with Approach 2 or 3 will fit with Formulation B (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 and the inventory is based on activity data from 1990, 1995, 2000, 2005 and 2010,

ELABORATED - BOX 2.1
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 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.

$SOC_{(0-T)}$ 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

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

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)

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 carbon 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 carbon 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 carbon 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, carbon stocks can be computed taking into account historical changes for every individual land unit. The total carbon 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 carbon 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
$\Delta Cc_{CMineral}$ (Mt C yr^{-1})	**0.0**	**-1.1**	**-0.8**	**-0.8**	**0.4**	**0.9**	**1.0**

Both methods yield different estimates of carbon 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 carbon stocks would generally not be very different, 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 above). 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 carbon 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.

[1] A spreadsheet is available with the full set of calculations, Chap2_Spreadsheet_Box5.2 Calculations.

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.

Organic soils

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

Biochar C Amendments to Mineral Soils

The methodology used to account for biochar C additions to minerals soils is based on a top-down approach in which the total amount of biochar generated and added to mineral soil in croplands and grasslands[6] is required to estimate the contribution of biochar to annual changes in mineral soil C stocks (Equation 2.26A). Information is not needed on the application rate. Interactions between biochar fate and soil type or land management are not considered with the Tier 1 method. However, the method does require that compilers to track the source of feedstock and temperature of the pyrolysis.

The biochar-C gain is considered effectively permanent and not subject to losses. Permanence is conservatively approximated as the biochar-C remaining after 1000 years ($\mathbf{F_{perm_p}}$), so as not to over-estimate the impact of amending soils with biochar over a long-time interval. The quantity of sequestered carbon will be greater than $\mathbf{F_{perm_p}}$ for times less than 1000 years, and slowly decline below F_{PERM_P} thereafter, with F_{PERM_P} providing a conservative estimate of the sequestered carbon during long time frames. The biochar-C addition can be estimated by croplands and grasslands, or in total without disaggregation. If biochar-C is entered without disaggregation based on land use, then the C stock change should be reported in the land use receiving the majority of the biochar. Box 2.2A provides a summary of the GHG sources associated with biochar production.

NEW GUIDANCE: BOX 2.2A
GHG EMISSION SOURCES WITH BIOCHAR PRODUCTION

Biochar production involves emissions from several different sectors and source categories. The guidance in this section is addressing C stock changes associated with the end-product use associated with biochar amendments to mineral soils. However, other emissions do occur along the biochar feedstock supply chains that are estimating in other source categories. For example, the harvesting and use of forest wood biomass with 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 this organic material to soil and thereby affects soil C stocks in croplands and grasslands, 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 that would be included in the energy sector (Volume 2).

[6] A Tier 2 or 3 method is needed for application of biochar to soils in forestlands, settlements or wetlands.

EQUATION 2.26A

ANNUAL CHANGE IN BIOCHAR CARBON STOCK IN MINERAL SOILS RECEIVING BIOCHAR ADDITIONS

$$\Delta BC = \sum BC_{TOT_p} \bullet F_{C_p} \bullet F_{perm_p}$$

Where:

ΔBC = the annual change in soil carbon stocks associated with biochar amendment, tonnes sequestered C yr^{-1}

BC_{TOT_p} the total quantity of biochar incorporated into mineral soil during the inventory year by production type, tonnes biochar dry matter yr^{-1}

F_{C_p} = the organic carbon content of biochar, tonnes C $tonne^{-1}$ biochar dry matter, Table 2.3A

F_{perm_p} fraction of biochar carbon remaining (unmineralised) after 1000 years, tonnes sequestered C $tonne^{-1}$ biochar C, Table 2.3B

Priming (defined as a change in decomposition rate of non-biochar soil organic carbon, resulting from biochar additions) is assumed to have no effect on decomposition for the purpose of this Tier 1 method. This is conservative assumption because added biochar has been shown to decrease average mineralization of native organic carbon over several years, thereby reducing losses of soil organic carbon. There is currently little evidence demonstrating a significant impact in the longer term, however (Annex 2A.2). It is also assumed that there are no reductions in other soil greenhouse gas emissions (e.g., soil N_2O) for the Tier 1 method. This assumption is also a conservative because studies are demonstrating a short-term reduction in soil N_2O emissions, although there is a lack of data demonstrating the persistence of this impact in the long-term and its applicability across all forms of biochar (Annex 2A.2).

NEW GUIDANCE - TABLE 2.3A
DEFAULT VALUES FOR ORGANIC CARBON CONTENT FACTOR OF BIOCHAR BY PRODUCTION TYPE (F_{C_p}).

Feedstock	Pyrolysis Production Process	IPCC default value (F_{C_p})	Error
Animal manure	Pyrolysis[a]	0.38	±49%
	Gasification[a]	0.09	±53%
Wood	Pyrolysis	0.79	±42%
	Gasification	0.52	±52%
Herbaceous (grasses, forbs, leaves; excluding rice husks and rice straw)	Pyrolysis	0.66	±45%
	Gasification	0.28	±50%
Rice husks and rice straw	Pyrolysis	0.49	±41%
	Gasification	0.13	±50%
Nut shells, pits and stones	Pyrolysis	0.76	±39%
	Gasification	0.40	±52%
Biosolids (paper sludge, sewage sludge)	Pyrolysis	0.35	±40%
	Gasification	0.07	±50%

[a]Explanation of conversion technologies in Annex 2A.2.

NEW GUIDANCE - TABLE 2.3B
DEFAULT VALUES FOR F_{PERM_p} (FRACTION OF BIOCHAR C REMAINING AFTER 1000 YEARS)

Production	IPCC default value (F_{PERM_p})
High temperature pyrolysis and gasification (> 600 °C)	0.38 ± 0.11
Medium temperature pyrolysis (450-600 °C)	0.24 ± 0.06
Low (< 450 °C) or uncontrolled or unspecified pyrolysis temperature	0.09 ± 0.08
Data sources provided in Annex 2A.2. Determined from a review of 172 treatments from 44 studies, of which 43 treatments in 6 studies have time series data over more than one year to which a two-pool decay model could be fit.	

Soil inorganic C

No Refinement

Tier 2 Approaches

Mineral soils

A Tier 2 approach 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 approach, if possible, even if they are only able to better specify certain components of the Tier 1 default approach. For example, a country 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.

There are two options for incorporating country-specific data. One option involves deriving country-specific factors for components of the Tier 1 default equations provided for mineral and organic soils. The second option involves estimating C stock changes for mineral soils using a three-pool steady state C model that has been simplified from the Century Ecosystem Model (Ogle et al. 2012; Parton et al. 1987; Paustian et al. 1997). The second method is only applicable for croplands and grasslands.

Tier 2 - Approach 1: Developing country-specific stock change factors for the default equations

Country-specific data can be used to improve four components when applying the Tier 1 equations for estimating stock changes in mineral and organic soils that customise the application to better represent national circumstances. The components include derivation of region or country-specific stock change factors and/or reference C stocks, in addition to improving the specification of management systems, climate, or 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, Tier 2 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 C stocks (SOC_{REF}) is another possibility for improving an inventory using a Tier 2 approach (Bernoux *et al.*, 2002). Using country-specific data for estimating reference stocks will likely produce more accurate and representative values. The derivation of country-specific reference soil C stocks can be done from measurements of soils, for example, as part of a country's soil survey. It is important that reliable taxonomic descriptions be used to group soils into categories. There are three additional considerations in 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 depth increment over which the stocks are estimated. Stocks are computed by multiplying the proportion of organic carbon (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 carbon reference condition or soil depth used differ from that under native vegetation or from a depth of 30 cm, then appropriate country specific reference soil carbon stocks and stock change factors must be derived. The soil depth sampled must be at least 30 cm. It is possible to use a soil carbon model to derive steady state soil carbon stocks indicative of the reference soil carbon stock for the various combinations of soil type and climate that exist within a country. However, this approach would require sufficient testing of the Tier 3 model providing 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 reference soil carbon stocks can be found Batjes (2011), as well as in a range of soil sampling and analysis texts (e.g. Carter and Gregorich 2008; de Gruijter *et al.* 2006).

The reference condition is the 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 C storage between a reference condition, such as native lands, and another land use, such as croplands, forming the basis for F_{LU} in Equation 2.25). In the Tier 1 method, the reference condition is native lands (i.e., non-degraded, unimproved lands under native vegetation), and it is likely that many countries will use this same reference in a Tier 2 approach. However, another land use can be selected for the reference, and this would be considered *good practice* if it allows for a more robust assessment of country-specific reference stock values. The same reference stock should be used for each climate zone and soil type, regardless of the land use. The reference stock is then multiplied by land use, input and management factors to estimate the stock for each land use based on the set of management systems that are present in a country.

Another consideration in deriving country-specific reference C stocks is the possibility of estimating C storage to a greater depth in the soil (i.e., lower in the profile). Default stocks given in Table 2.3 account for soil organic C in the top 30 cm of a soil profile. It is *good practice* to derive reference C stocks to a greater depth if there is sufficient data, and if it is clear that land-use change and management have a significant impact over the proposed depth increment. Any change in the depth for reference C stocks will require derivation of new stock change factors, given that the defaults are also based on impacts to a 30 cm depth.

4) *Stock change factors.* An important advancement for a Tier 2 approach 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 C stocks (i.e., mass per unit area to a specified depth) or the information needed to estimate SOC stocks (i.e., percent organic matter 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 and 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.

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 method is considered a Tier 2 approach because it relies on the stock change factor concept and the C estimation method elaborated in the Tier 1 approach.

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 organic 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 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.

Similar to time dependence, the depth over which impacts are measured may vary from the default approach. However, it is important that the reference C stocks (SOC_{Ref}) and stock change factors (F_{LU}, F_{MG}, F_I) be determined to a common depth, and that they are consistent across each land-use sector in order to deal with conversions among uses without artificially inflating or deflating the soil C stock change estimates. It is *good practice* to document the source of information and underlying basis for the new factors in the reporting process.

In the calculation of stocks of soil carbon and changes over time either a fixed soil volume approach or an equivalent mass approach can be used. Box 2.2B provides further information on these approaches and issues that associated with conducting an inventory on an equivalent mass basis.

BOX 2.2B

USING EQUIVALENT MASS METHODS TO DERIVE MINERAL SOIL 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, settlement, grassland, wetland, or forest land to the same depth introduces changes to soil carbon stocks as a direct consequence of changes in soil bulk density (Ellert and 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, settlement 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 and 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.

Process models that are used to estimate carbon stock changes over time, such as Century (Parton et al., 1989) and RothC (Coleman and Jenkinson, 1996) can also be affected by changing soil bulk density by the nature of the carbon stock data used for model parametrisation. Both 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 defined along with an initial soil mass (although the soil mass is rarely defined, it is implicit). The models therefore use an equivalent soil mass approach to simulated 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 that parametrised model, and for a factor derived from those modelled estimates, will be for soil carbon change on an equivalent mass basis. However, fhe 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 this net effect so the modelled carbon stock estimates will be only appropriate for the fixed depth. 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 change estimated directly or indirectly by that model.

Tier 2 - Approach 2: Three-Pool Steady-State C Model for Mineral Soils

The three-pool steady-state C model is an alternative method for estimating carbon stock factors (i.e., rates of change) for determining mineral soil C stock changes in the 0-30 cm layer of the soil for cropland and grassland[7]. This is an approach with intermediate complexity between Tier 1 and Tier 3 methods, and is based on a steady-state solution to the three soil organic C pools in the Century ecosystem model (Ogle *et al.* 2012; Parton *et al.* 1987; Paustian *et al.* 1997). The approach embraces more complexity than the default method by subdividing soil C, which is a highly heterogeneous pool of C, into three separate pools with fast (Active Pool), intermediate (Slow Pool), and long turnover times (Passive Pool). Turnover time of C within each pool determines the length of time that C remains in the soil. The approach accounts for spatial and temporal variation in climate, organic carbon inputs to soils and soil properties. Moreover, this model is not a Tier 3 method because equations and a global set of default parameters are provided, similar to the gross energy intake model for livestock that provides estimates of enteric methane emissions (See Volume IV, Chapter 10). However, compilers can further develop and/or

[7] The steady-state model may be applied to other land uses, but this will require further development and parameterization than provided in this section.

parameterise this model given appropriate datasets, which would be a Tier 3 method (See Section 2.5.2 for more information about developing a Tier 3 model-based approach). See Box 2.2C for more information about the model.

The method also utilises management activity data that is typically more likely to be available in a country than the default method (which requires detailed information on the combination of crops types, tillage practices, manure amendments, mineral fertilisation, irrigation management, grazing management, green manures, and fallows for individual parcels of land in the inventory). Although several of these activity data are needed for the three-pool steady-state C model (tillage practices, manure amendments, and irrigation management), much of these data requirements are represented in the C inputs to the soil based on crop yields, grassland or forest land production, thereby eliminating several of data requirements.

The land base is stratified as fine as possible to include the spatial variation in climate and soil properties. However, there will be practical limits to the level of stratification given the resolution of data and national circumstances for inventory compilation. The method can be applied by subdividing the country into grid cells or regions, such as counties, districts or municipalities. Within each grid cell or region, the compiler will determine the C input using country-specific equations, or alternatively generic equations that are provided for cropland and grassland in Section 5.2.3.3 and 6.2.3.3, respectively. Compilers will also need values for the parameters defining the quality of the C input (lignin and nitrogen content) or use generic values available for crops and grasses in Chapters 5 and 6 in Sections 5.2.3.2 and 6.2.3.2, respectively. Monthly average temperature, precipitation and potential evapotranspiration is needed for each grid cell or region. This information is available from global datasets, such as the CRU climate dataset (https://crudata.uea.ac.uk/cru/data/hrg/), if country-specific data are not available. The average sand content is needed for each grid cell or region, which is available from Harmonized World Soil Database (http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/) or from Soil Grids (https://soilgrids.org/#!/?layer=TAXNWRB_250m&vector=1), if country-specific data are not available.

The following sections provide the equations and steps involved with application of the method within a grid cell or region (e.g., counties, districts or municipalities). The equations estimate water and temperature effects on decomposition; the amount of active, slow and passive SOC; and the change in total SOC. The values of default parameters are given in Table 2.3C. All constants in the equations are considered universally applicable (Parton et al. 1987), and should not be altered when applying this Tier 2 method.

Equations Required for the Three-Pool Steady-State C Model for Mineral Soils

Calculate SOC Stock Changes

The change in SOC stock is calculated using Equation 2.26B.

EQUATION 2.26B

ANNUAL SOC STOCK CHANGE FOR MINERAL SOILS USING THREE-POOL STEADY-STATE C MODEL

$$\Delta C_{Mineral} = SOC_Y - SOC_{Y-1}$$

$$SOC_y = ACTIVE_y + SLOW_y + PASSIVE_y$$

Where:

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

SOC_Y = SOC stock in year y, tonnes C ha^{-1}

SOC_{Y-1} = SOC stock in the previous year, tonnes C ha^{-1}

$ACTIVE_y$ = active pool SOC stock in year y, tonnes C ha^{-1} (see Equation 2.26C)

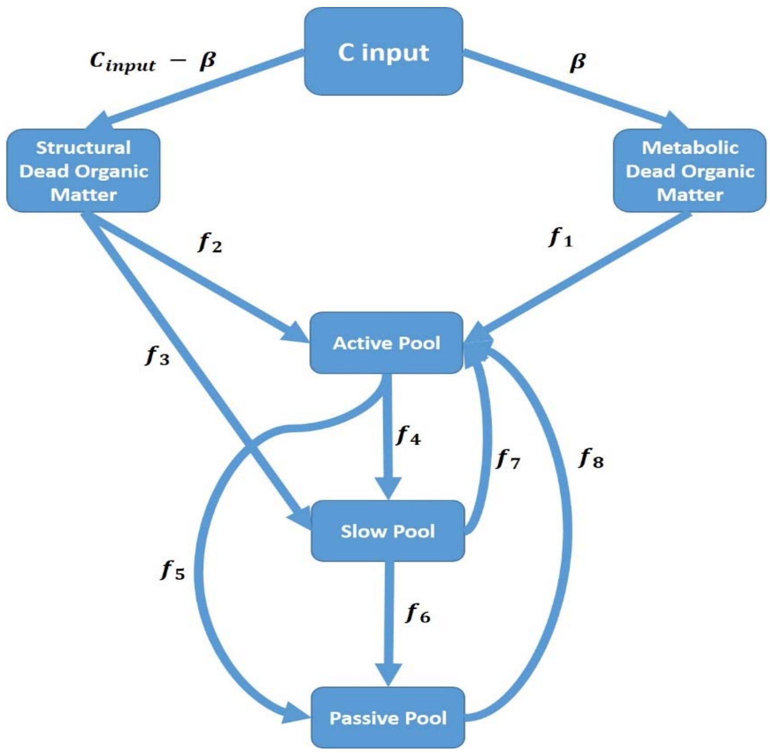
$SLOW_y$ = slow pool SOC stock in year y, tonnes C ha^{-1} (see Equation 2.26D)

$PASSIVE_y$ = passive pool SOC stock in year y, tonnes C ha^{-1} (see Equation 2.26E)

BOX 2.2C

DESCRIPTION OF THE TIER 2 THREE-POOL STEADY-STATE SOIL CARBON MODEL FOR ESTIMATING MINERAL SOIL ORGANIC CARBON STOCK CHANGES

The three-pool steady-state model is adapted from the Century Ecosystem Model (Parton *et al.* 1987) and estimates changes in soil organic C for the top 30cm of the soil profile. In this model, the stock of the soil carbon pools is initialised by running the model with climate and carbon input data associated with a period of 5-20 years prior to the start of the inventory (or longer if data are available). A proportion of biomass C (C input to the soil) is transferred to soil litter, and divided into structural and metabolic pools. The structural pool is composed of more recalcitrant, ligno-cellulose plant materials. The metabolic pool is composed of more readily decomposed organic matter. Decomposition products are transferred to soil organic matter that is composed of three pools, active, slow and passive. The active pool is microbial (bacteria and fungi) biomass and associated metabolites with a rapid turnover (months to years), the slow pool has intermediate stability and turnover (decades), and the passive pool is mineral-protected C and decomposition products with long turnover times (centuries). Irrespective of the turnover time the approach defines the stock of each pool and how they change over time. The total soil organic carbon stock and stock change is calculated as the sum of the values derived for each pool.



Decomposition rates for pools depend on the decay rate constants, temperature effects, and moisture effects. Decomposition of the active and slow pool is also influenced by the soil texture (sand content) and tillage practice. Pools with longer turnover times imply that the C remains in the soil for more years before the organic matter is decomposed and carbon is respired as CO2 by the soil decomposer community. As decomposition occurs in each pool, some of the decomposing C is transferred to other pools (arrows in the diagram) and some of the C is converted into CO2 and lost from the soil (not identified with arrows). The transfer of C to the next pool at steady state is determined by the transfer coefficients(f). Higher transfer coefficients imply that more of the C is transferred to the next pool rather than converted into CO2. The steady-state solution for this model is discussed further in Paustian et al. (1997) and Ogle et al. (2012). This method has intermediate complexity, compared to the default method, and therefore is a step towards more complicated Tier 3 methods (See Box 2.2E).

This approach is not intended to be used for estimation of dead organic matter. Compilers should apply the dead organic matter methods in section 2.3.2. Furthermore, this approach is only developed for application in croplands and grasslands and is not recommended for use in forest lands, wetland, settlements or other lands without further development and parameterization, particularly on lands in which coarse woody debris is an important pool of dead organic matter.

Calculate the size of the Active SOC Pool

The size of the active SOC pool is calculated using Equation 2.26C.

EQUATION 2.26C

ACTIVE POOL SOC STOCK FOR THREE-POOL STEADY-STATE C MODEL

$$ACTIVE_y = ACTIVE_{y-1} + \left(ACTIVE_{y^*} - ACTIVE_{y-1}\right) \bullet k_a$$

$$ACTIVE_{y^*} = \frac{\alpha}{k_a}$$

$$k_a = k_{fac_a} \bullet t_{fac} \bullet w_{fac} \bullet \left(0.25 + \left(0.75 \bullet sand\right)\right) \bullet till_{fac}$$

Where:

$ACTIVE_y$ = active pool SOC stock in year y, tonnes C ha^{-1}

$ACTIVE_{y-1}$ = active pool SOC stock in previous year, tonnes C ha^{-1}

$ACTIVE_{y^*}$ = steady-state active pool SOC stock given conditions in year y, tonnes C ha^{-1}

k_a = decay rate for active SOC pool, year^{-1}

α = C input to the active SOC pool, tonnes C ha^{-1} year^{-1} (see Equation 2.26H)

k_{fac_a} = decay rate constant under optimal conditions for decomposition of the active SOC pool, year^{-1} (see Table 2.3C)

t_{fac} = temperature effect on decomposition, dimensionless (see Equation 2.26F)

w_{fac} = water effect on decomposition, dimensionless (see Equation 2.26G)

$till_{fac}$ = tillage disturbance modifier on decay rate for active and slow pools, (see Table 2.3C)

$sand$ = fraction of 0-30 cm soil mass that is sand (0.050 – 2mm particles), proportion

NOTE: If the estimated k_a value is above 1, then set the value of k_a to 1 in the equation for calculating $ACTIVE_y$ in the first equation.

Calculate the size of the Slow SOC Pool

The size of the slow SOC pool is calculated using Equation 2.26D.

EQUATION 2.26D

SLOW POOL SOC STOCK FOR THREE-POOL STEADY-STATE C MODEL

$$SLOW_y = SLOW_{y-1} + \left(SLOW_{y^*} - SLOW_{y-1}\right) \bullet k_s$$

$$SLOW_{y^*} = \frac{[\left(C_{input} \bullet LC\right) \bullet f_3] + \left[\left(ACTIVE_{y^*} \bullet k_a\right) \bullet f_4\right]}{k_s}$$

$$k_s = k_{fac_s} \bullet t_{fac} \bullet w_{fac} \bullet till_{fac}$$

$$f_4 = 1 - f_5 - \left(0.17 + 0.68 \bullet sand\right)$$

Where:

$SLOW_y$ = slow pool SOC stock in y, tonnes C ha^{-1}

$SLOW_{y-1}$ = slow pool SOC stock in previous year, tonnes C ha^{-1}

$SLOW_{y^*}$ = steady-state slow pool SOC stock given conditions in year y, tonnes C ha^{-1}

k_s = decay rate for slow SOC pool, year^{-1}

C_{input} = total carbon input, tonnes C ha^{-1} year^{-1}

LC = lignin content of carbon input, proportion (see Sections 5.2.3.2 and 6.2.3.2 for cropland and grassland default values, respectively, otherwise compile country-specific values)

$ACTIVE_{y^*}$ = steady-state active pool SOC stock given conditions in year y, tonnes C ha^{-1}

k_a = decay rate for active carbon pool in the soil, year^{-1}

k_{fac_s} = decay rate constant under optimal condition for decomposition of the slow carbon pool, year^{-1} (see Table 2.3C)

t_{fac} = temperature effect on decomposition, dimensionless (see Equation 2.26F)

w_{fac} = water effect on decomposition, dimensionless (see Equation 2.26G)

$till_{fac}$ = tillage disturbance modifier on decay rate for active and slow pools, unitless (see Table 2.3C)

f_3 = fraction of structural pool decay products transferred to the slow pool, proportion (see Table 2.3C)

f_4 = fraction of active pool decay products transferred to the slow pool, proportion (see Table 2.3C)

f_5 = fraction of active pool decay products transferred to the passive pool, proportion (see Table 2.3C)

$sand$ = fraction of 0-30 cm soil mass that is sand (0.050 – 2mm particles), proportion

NOTE: If the estimated k_s value is above 1, then set the value of k_s to 1 in the equation for calculating $SLOW_y$ in the first equation.

Calculate the size of the Passive C Pool

The size of the slow SOC pool is calculated using Equation 2.26E.

EQUATION 2.26E

PASSIVE POOL SOC STOCK FOR THREE-POOL STEADY-STATE C MODEL

$$PASSIVE_y = PASSIVE_{y-1} + \left(PASSIVE_{y^*} - PASSIVE_{y-1}\right) \bullet k_p$$

$$PASSIVE_{y^*} = \frac{\left[\left(ACTIVE_{y^*} \bullet k_a\right) \bullet f_5\right] + \left[\left(SLOW_{y^*} \bullet k_s\right) \bullet f_6\right]}{k_p}$$

$$k_P = k_{fac_p} \bullet t_{fac} \bullet w_{fac}$$

Where:

$PASSIVE_y$ = passive pool SOC stock in year y, tonnes C ha^{-1}

$PASSIVE_{y-1}$ = passive pool SOC stock in previous year, tonnes C ha^{-1}

$PASSIVE_{y^*}$ = steady state passive pool SOC given conditions in year y, tonnes C ha^{-1}

k_P = decay rate for passive SOC pool, year^{-1}

$ACTIVE_{y^*}$ = steady-state active pool SOC stock given conditions in year y, tonnes C ha^{-1}

k_a = decay rate for active carbon pool, year^{-1}

$SLOW_{y^*}$ = steady-state slow pool SOC stock given conditions in year y, tonnes C ha^{-1}

k_s = decay rate for slow carbon pool, year^{-1}

k_{fac_p} = decay rate constant under optimal conditions for decomposition of the slow carbon pool, year^{-1} (see Table 2.3C)

t_{fac} = temperature effect on decomposition, dimensionless (see Equation 2.26F)

w_{fac} = water effect on decomposition, dimensionless (see Equation 2.26G)

f_5 = fraction of active pool decay products transferred to the slow pool, proportion (see Table 2.3C)

f_6 = fraction of slow pool decay products transferred to the passive pool, proportion (see Table 2.3C)

NOTE: If the estimated k_p value is above 1, then set the value of k_p to 1 in the equation for calculating $PASSIVE_y$ in the first equation.

Calculate Temperature Effect on Decomposition

Calculate the temperature effect on soil organic matter decomposition using Equation 2.26F.

EQUATION 2.26F

TEMPERATURE IMPACT ON DECOMPOSITION FOR THREE-POOL STEADY-STATE C MODEL

$$t_{fac} = \frac{1}{12}\sum_{i=1}^{12} T_i$$

$$T_i = \left(\frac{t_{max} - temp_i}{t_{max} - t_{opt}}\right)^{0.2} \bullet exp\left\{0.076 \bullet \left[1 - \left(\frac{t_{max} - temp_i}{t_{max} - t_{opt}}\right)^{2.63}\right]\right\}$$

Where:

t_{fac} = annual average temperature effect on decomposition, unitless

T_i = monthly average temperature effect on decomposition, unitless (i = 1, 2, …, 12)

t_{max} = maximum monthly temperature for decomposition, degrees C (see Table 2.3C)

$temp_i$ = monthly average temperature (i = 1, 2, …, 12), degrees C

t_{opt} = optimum temperature for decomposition, degrees C (see Table 2.3C)

NOTE: When the monthly average temperature is greater than 45 °C (i.e., the maximum average temperature) set T_i to 0.

Calculate Water Effect on Decomposition

Estimate the water effect on soil organic matter decomposition using Equation 2.26G

EQUATION 2.26G

WATER EFFECT ON DECOMPOSITION FOR THREE-POOL STEADY-STATE C MODEL

$$w_{fac} = 1.5 \bullet \left(\frac{1}{12}\sum_{i=1}^{12} W_i\right)$$

$$w_i = 0.2129 + \left(w_s \bullet mappet_i\right) - \left(0.2413 \bullet mappet_i^{\,2}\right)$$

$$mappet_i = \min\left(1.25, \frac{precip_i}{PET_i}\right)$$

Where:

w_{fac} = annual water effect on decomposition, dimensionless

W_i = monthly water effect on decomposition, dimensionless

$mappet_i$ = ratio of total precipitation to total potential evapotranspiration (dimensionless) for month i (i = 1, 2, …, 12)

$precip_i$ = total precipitation for month i, mm

PET_i = total potential evapotranspiration for month i, mm

NOTE: If the $mappet_i$ is >1.25, then set the value of $mappet_i$ for the month to 1.25 for non-irrigated system (i.e., $mappet_i$ does not exceed 1.25). Set W_i for months with irrigation to 0.775.

Calculate C Input to the Active Pool

Calculate alpha value using Equation 2.26H, which is the C input to the active SOC pool.

EQUATION 2.26H

C INPUT TO THE ACTIVE SOC POOL FOR THREE-POOL STEADY-STATE C MODEL

$$\alpha = \frac{[\beta \bullet f_1] + \left[\left(C_{input} \bullet (1 - LC) - \beta\right) \bullet f_2\right] + \left[\left(C_{input} \bullet LC\right) \bullet f_3 \bullet (f_7 + f_6 \bullet f_8)\right]}{1 - (f_4 \bullet f_7) - (f_5 \bullet f_8) - (f_4 \bullet f_6 \bullet f_8)}$$

$$\beta = C_{input} \bullet \left[0.85 - 0.018 \bullet \left(\frac{LC}{NC}\right)\right]$$

Where:

α = C input to the active soil carbon pool, tonnes C ha^{-1}

β = C input to the metabolic dead organic matter C pool, tonnes C ha^{-1} year^{-1}

C_{input} = total carbon input, tonnes C ha^{-1}year^{-1}

f_1 = fraction of metabolic dead organic matter decay products transferred to the active pool, proportion (see Table 2.3C)

f_2 = fraction of structural dead organic matter decay products transferred to the active pool, proportion (see Table 2. 3C)

f_3 = fraction of structural dead organic matter decay products transferred to the slow pool, proportion (see Table 2. 3C)

f_4 = fraction of active pool decay products transferred to the slow pool, proportion, See Equation 2.26C

f_5 = fraction of active pool decay products transferred to the passive pool, proportion (see Table 2. 3C)

f_6 = fraction of slow pool decay products transferred to the passive pool, proportion (see Table 2. 3C)

f_7 = fraction of slow pool decay products transferred to the active pool, proportion (see Table 2. 3C)

f_8 = fraction of passive pool decay products transferred to the active pool, proportion (see Table 2. 3C)

LC = lignin content of carbon input, proportion (see Sections 5.2.3.2 and 6.2.3.2 for cropland and grassland default values, respectively, otherwise compile country-specific values)

NC = nitrogen fraction of the carbon input, proportion (see Sections 5.2.3.2 and 6.2.3.2 for cropland and grassland default values, respectively, otherwise compile country-specific values)

Table 2.3C provides the default parameters, minimum and maximum values for parameters, and their associated standard deviation. The probability distribution functions for the parameters should be constructed as truncated normal distributions, in which parameter values lower than the minimum value are constrained the minimum value, and parameter values greater than the maximum values are constrained to the maximum value. Uncorrelated draws from the probability distribution functions of the parameters can be made using the data in this table, but more robust estimates of uncertainty can be made using a truncated joint probability distribution with the parameter covariance matrix found in Annex 2A.3

Step-by-Step procedure for implementing the Three-Pool Steady-State C Model for Mineral Soils

Steps 1 to 8 are conducted for each grid cell or region, depending on the spatial unit of the inventory. Step 9 sums the changes across the entire spatial domain[8].

Step 1. Calculate the Initial Stocks of the Active, Slow and Passive SOC pools

The initial stocks are calculated based on the climatic, soil texture, management and carbon input data for a run-in period[9] of 5 to 20 years (more years may be used if data are available).

Step 1.1 Calculate the average annual values of *tfac* (Equation 2.26F) and *wfac* (Equation 2.26G) for the run-in period.

Step 1.2 Calculate the C input to the active pool (α) for the run-in period (Equation 2.26H) using the following data:

a. the average annual carbon input (CI) for the run-in period
b. the appropriate values for LC and NC for the crop and/or grass in place during the run-in period can be found in the three-pool steady-state model section for cropland and grassland (see Sections 5.2.3.2 and 6.2.3.2 for cropland and grassland default values, respectively, otherwise compile country-specific values)
c. the value of f_2 from Table 2.3C
d. the sand content of the 0-30 cm soil layer.

Step 1.3 Calculate the values of k_a (Equation 2.26C), k_s (Equation 2.26D) and k_p (Equation 2.26E) using:

a. the average values of tfac and wfac calculated in Step 1.1,
b. the values of k_{fac_a}, k_{fac_s}, k_{fac_p} and the appropriate tillage factor ($till_{fac}$) from Table 2.3C, and
c. the sand content of the 0-30 cm soil layer.

Step 1.4 Calculate the values for $ACTIVE_{y^*}$ (Equation 2.26C), $SLOW_{y^*}$ (Equation 2.26D) and $PASSIVE_{y^*}$ (Equation 2.26E) for the run-in period, which become the initial SOC stocks for the ACTIVE, SLOW and PASSIVE SOC pools at the commencement of the inventory period.

[8] An example of the Tier 2 steady-state model is provided in a supplementary file, Chap2_Tier 2_Steady State Model.

[9] Compilers can use longer run-in periods than 20 years to establish the initial soil organic C stocks for the inventory, but 5 years is considered a minimum period of time for this method. Initial values of the active, slow and passive pools can lead to biases in results if the run-in period is not long enough to capture the trajectory of the stocks based on legacy effects associated with historical land use and management.

NEW GUIDANCE: TABLE 2.3C
MODEL PARAMETERS USED TO ESTIMATE STEADY STATE STOCKS OF SOIL ORGANIC CARBON POOLS (ACTIVE, SLOW AND PASSIVE)

Parameter	Practice	Value (min, max)	Standard Deviation	Description
$till_{fac}$	Full-till	3.036 (1.4, 4.0)	0.579	Tillage disturbance modifier for decay rates
	Reduced-till	2.075 (1.0, 3.0)	0.569	
	No-till	1		
w_s	All	1.331 (0.8, 2.0)	0.386	slope parameter for mappet term to estimate w_{fac}
k_{fac_a}	All	7.4	n/a	Decay rate constant under optimal conditions for decomposition of the active pool
k_{fac_s}	All	0.209 (0.058, 0.3)	0.566	Decay rate constant under optimal conditions for decomposition of the slow pool
k_{fac_p}	All	0.00689 (0.005, 0.01)	0.00125	Decay rate constant under optimal conditions for decomposition of the passive pool
f_1	All	0.378 (0.01, 0.8)	0.0719	Fraction of metabolic dead organic matter decay products transferred to the active pool
f_2	Full-till	0.368 (0.007, 0.5)	0.0998	Fraction of structural dead organic matter decay products transferred the active pool
f_3	All	0.455 (0.1, 0.8)	0.201	Fraction of structural dead organic matter decay products transferred to the slow pool
f_5	All	0.0855 (0.037, 0.1)	0.0122	Fraction of active pool decay products transferred to the passive pool
f_6	All	0.0504 (0.02, 0.19)	0.0280	Fraction of slow pool decay products transferred to the passive pool
f_7	All	0.42	n/a	Fraction of slow pool decay products transferred to the active pool
f_8	All	0.45	n/a	Fraction of passive pool decay products transferred to the active pool
t_{opt}	All	33.69 (30.7, 35.34)	0.66	Optimum temperature to estimate temperature modifier on decomposition
t_{max}	All	45	n/a	Maximum monthly average temperature for decomposition.

References for deriving parameters: Campbell et al. 1997; Collins et al. 2000; Dick et al. 1997; Diaz-Zorita et al. 1999; Dimassi et al. 2014; e-RA 2013; Glendining 2013; Gregorich et al. 1996; Halvorson et al. 1997; Huggins and Fuchs 1997; Janzen et al. 1997; Jenkinson 1990; Jenkinson and Johnston 1977; KBS LTER 2017; Küstermann and Hülsbergen 2013; Maillard et al. 2018; Marchado 2013; Marchado et al. 2008; Pierce and Fortin 1997; Rasmussen and Smiley 1997; Schultz 1995; Skjemstad et al. 2004; Vanotti et al. 1997; See Annex 2A.3 for more information.

Step 2. Calculate C Input to the Active Pool for each year of the inventory period

Calculate value of α (the C input to the active SOC pool) for each year in the inventory period using Equation 2.26H.

Step 2.1 Calculate the C input to the metabolic dead organic matter pool (β).

Step 2.2 Calculate the C input to the active soil carbon pool (α).

Step 2.3 Repeat Steps 2.1 to 2.2 for all other years in the inventory period to derive annual values for β and α.

Step 3. Calculate Water Effect on Decomposition

Estimate the water effect on soil organic matter decomposition using Equation 2.26G.

Step 3.1 For each month in a year, calculate the ratio of total precipitation to total potential evapotranspiration.

a. If the ratio is ≤1.25 then set the value of $mappet_i$ for the month to the estimated ratio.
b. If the ratio is >1.25 then set the value of $mappet_i$ for the month to 1.25.
c. Set W_i for months with irrigation to 0.775.

Step 3.2 Calculate water effect on decomposition for each month ($\boldsymbol{W_i}$) in a year. For land area under irrigation management, set the water effect on decomposition for the month ($\boldsymbol{W_i}$) to 0.775.

Step 3.3 Calculate the annual water effect on decomposition (w_{fac}).

Step 3.4 Repeat steps 3.1 to 3.3 to calculate the water effect (w_{fac}) on decomposition for all years in the inventory period.

Step 4. Calculate Temperature Effect on Decomposition

Calculate the temperature effect on soil organic matter decomposition using Equation 2.26F.

Step 4.1 For each month in a year, calculate temperature effect on decomposition (T_i) using the values for maximum monthly temperature for decomposition (t_{max}), optimum temperature for decomposition (t_{opt}) and the monthly average temperature ($temp_i$).

a. If the monthly average temperature is ≤45 °C, use the calculated value of T_i
b. If the monthly average temperature is >45 °C, set T_i equal to 0.

Step 4.2 Calculate annual temperature effect on decomposition ($\boldsymbol{tfac}$).

Step 4.3 Repeat steps 4.1 and 4.2 to calculate the annual temperature effect on decomposition for all years in the inventory.

Step 5. Calculate the size of the Passive C Pool

Calculate the size of the passive pool using Equation 2.26E.

Step 5.1 Calculate decay rate for the PASSIVE SOC pool in the soil ($\boldsymbol{k_P}$).

Step 5.2 Calculate the steady state stock for the PASSIVE pool SOC stock $\left(\boldsymbol{PASSIVE_{y^*}}\right)$.

Step 5.3 Calculate the PASSIVE pool SOC stock by determining the additional increase or decrease in SOC from the previous year in the inventory ($\boldsymbol{PASSIVE_y}$). Note that the initial size of the PASSIVE SOC pool used at the start of the inventory period is calculated as defined in step 1. Note also that if the estimated k_p value is above 1, then set the value of k_p to 1 in the equation for calculating $\boldsymbol{PASSIVE_y}$.

Step 5.4 Repeat steps 5.1 to 5.3 to calculate the PASSIVE SOC stocks for all years in the inventory.

Step 6. Calculate the size of the SLOW SOC Pool

Calculate the size of the slow pool using Equation 2.26D.

Step 6.1 Calculate decay rate for SLOW SOC pool in the soil ($\boldsymbol{k_s}$).

Step 6.2 Calculate the steady-state stock for the SLOW SOC pool $\left(\boldsymbol{SLOW_{y^*}}\right)$.

Step 6.3 Calculate the SLOW SOC stock by determining the additional increase or decrease in SOC from the previous year in the inventory ($\boldsymbol{SLOW_y}$). Note that the initial size of the SLOW SOC pool used at the start of the inventory period is calculated as defined in step 1. Note also that if the estimated k_s value is above 1, then set the value of k_s to 1 in the equation for calculating $\boldsymbol{SLOW_y}$.

Step 6.4: Repeat steps 6.1 to 6.3 to calculate the SLOW SOC pool stocks for all years in the inventory.

Step 7. Calculate the size of the ACTIVE SOC Pool

Calculate the size of the active pool using Equation 2.26C.

Step 7.1 Calculate decay rate for the ACTIVE SOC pool in the soil ($\boldsymbol{k_a}$).

Step 7.2 Calculate the steady-state stock for the ACTIVE SOC pool $\left(\boldsymbol{ACTIVE_{y^*}}\right)$.

Step 7.3 Calculate the ACTIVE SOC stock by determining the additional increase or decrease in SOC from the previous year in the inventory ($\boldsymbol{ACTIVE_y}$). Note that the initial size of the ACTIVE SOC pool used at the start of the inventory period is calculated as defined in step 1. Also note that if the estimated k_a value is above 1, then set the value of k_a to 1 in the equation for calculating $\boldsymbol{ACTIVE_y}$.

Step 7.4: Repeat Steps 7.1 to 7.3 to calculate the ACTIVE SOC pool stocks for all years in the inventory.

Step 8. Calculate the annual SOC stock changes

Step 8.1 Calculate the total SOC stock (SOC_y) by summing the SOC in the ACTIVE, SLOW and PASSIVE pools ($ACTIVE_y$, $SLOW_y$ and, $PASSIVE_y$, respectively).

Step 8.2 Calculate the change in SOC stock ($\Delta C_{Mineral}$) as the difference between the total SOC stock after completing the calculations described in steps 1-7 (SOC_Y) and the stocks present at the end of the previous year (SOC_{Y-1}).

Step 9. Calculate the total SOC stock change for the inventory

Step 9.1 Calculate the total change in SOC stocks over the duration of the inventory by summing all total annual SOC stock changes across all grid cells or regions included in the inventory.

Organic soils

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

Biochar C Amendments to Mineral Soils

Tier 2 methods for biochar C amendments use the same definitions and equations as Tier 1, but with country-specific values obtained for biochar-C allocated to each land use[10], F_{C_p} and/or F_{PERM_p}. Country-specific values for F_{C_p}—the carbon fraction of the biochar (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 type and similar process conditions as the biochar that is applied to soils in the country.

F_{PERM_p} is defined as the fraction of biochar carbon remaining after a defined period of time (1000 years for Tier 1). It is not possible to measure this value directly due to the long-time scales involved, and so F_{PERM_p} is estimated from other data. The elemental composition of biochar, specifically the ratio of hydrogen to organic carbon (H/Corg) or ratio of oxygen to organic carbon (O/Corg), 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/Corg or O/Corg 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. F_{PERM_p} can be derived from the biochar elemental composition using published equations relating this composition to mean residence time or half-life (for example H/Corg, Lehmann et al., 2015; or O/Corg, 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 1000 years is used.

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.

[10] Land use includes croplands, grassland, forestlands, wetlands, and settlements, but requires a scientific understanding of the impacts of biochar-C on dead organic matter and soil C stocks, as well as other greenhouse gas emissions for forestlands, wetlands and settlements.

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; and Tate *et al.*, 2005). 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. Consequently, Tier 3 approaches are capable of providing a more accurate estimation of C stock changes associated with land-use and management activity.

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 2.2D

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. Examples in Box 2.2E provide illustrations of Tier 3 methods for estimating change in mineral soil C stocks,

BOX 2.2E
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 and 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 forestland, cropland, grassland, deforested land, forest land converted to cropland and grassland, grassland converted to forestland, and land with sparse woody vegetation based on national landuse 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 (http://www.environment.gov.au/climate-change/greenhouse-gas-measurement/publications/national-inventory-report-2015). Here a summary of the Tier 3 approach as applied to soil organic carbon stocks under croplands and grasslands is provided.

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 and 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 measureable 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 and 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 and humus form of carbon were calibrated to Australian conditions by optimizing the fit of model outputs to soil carbon stock data collected from a range of field experiments (Chappell and Baldock 2014; Skjemstad *et al.* 2004). The impact of soil temperature and water content on decomposition is modelled through the application of decomposition rate constant modifiers as done in the RothC soil carbon model (Jenkinson 1990). The inert fraction does not decompose.

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

BOX 2.2E
EXAMPLES OF TIER 3 MINERAL SOIL C STOCK CHANGE METHODS (CONTINUED)

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 GHG inventory 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). Model has been extensively tested against independent data on forest lands (Lehtonen *et al.* 2016; Rantakari *et al.* 2012; Tupek *et al.* 2016) and also on croplands (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

Japan

Japan uses a Tier 3 method to estimate soil organic C stock changes in agriculture land (cropland and managed grassland) based on the Rothamsted Carbon Model (RothC). RothC model is a soil carbon dynamic model validated by using long-term field experiments (Coleman and 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 and 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 and 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 and 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 GHG inventory, 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 GHG inventory (statistical data) are not consistent very much and so Japan put its priority using a consistent land area data among every estimates relating to agriculture land in AFOLU sector. This is one of the key challenges of the model application to the GHG inventory and the development of a standard spatially explicit land use data set is needed for the further improvement of estimations.

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BOX 2.2E
EXAMPLES OF TIER 3 MINERAL SOIL C STOCK CHANGE METHODS (CONTINUED)

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 croplands and grasslands (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 and 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.

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.

including information such as type of data required, brief description of the models and methods that are used to apply the models. Sources of soil carbon stock data that may be useful in the development and/or implementation of a Tier 3 approach include: 1) Globalsoilmap.net ((http://www.globalsoilmap.net/), 2) Soil Grid (https://soilgrids.org/#!/?layer=TAXNWRB_250m&vector=1) and 3) FAO Global Soil Organic Carbon Map (http://www.fao.org/global-soil-partnership/pillars-action/4-information-and-data/global-soil-organic-carbon-gsoc-map/en/). 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).

Organic soils

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

Biochar C Amendments to Mineral Soils

Tier 3 methods can be used to account for GHG sources and sinks not captured in Tiers 1 or 2, such as priming, to address changes to N_2O or CH_4 fluxes from soils, and to estimate changes to net primary production (and associated C inputs to soil organic C pools). 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 and Lehmann, 2008; Woolf et al., 2010, Hammond et al. 2011). Tier 3 models may address the long-term impacts of biochar on priming, soil GHG fluxes, net primary production, the mechanisms underlying these interactions, and associated interactions with soil, climate and other environmental variables. It is also important to recognise that the dynamic nature of biochar decomposition is important because its net impact on carbon 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 and 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 and 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).

Soil inorganic C

No Refinement

2.4 NON-CO_2 EMISSIONS

This section has updates to the factors for agricultural residues.

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.

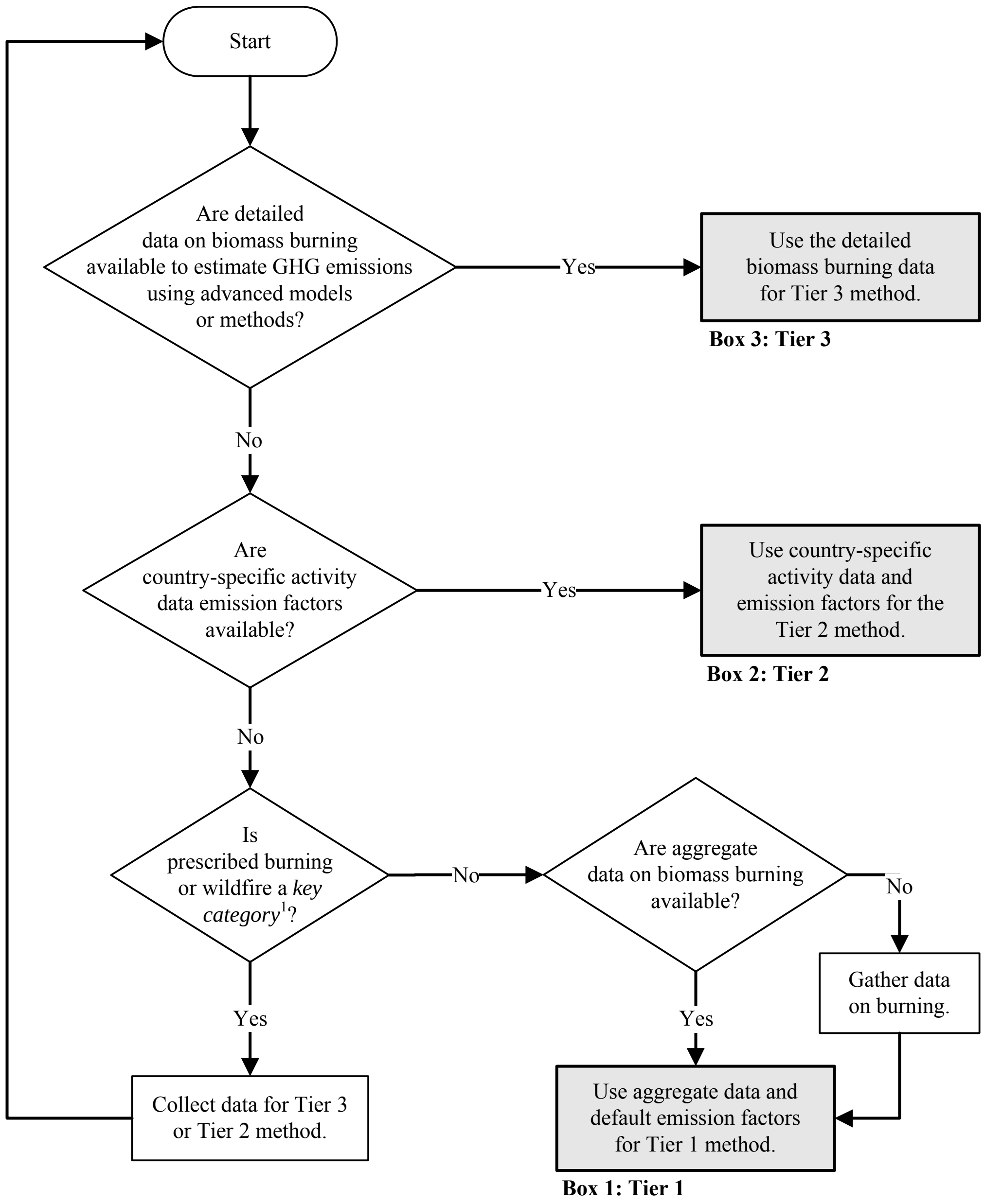
For CO_2 emissions, Equation 2.27 relates to Equation 2.14, which estimates the annual amount of live biomass loss from any type of disturbance.

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.

UPDATED - TABLE 2.4
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**	**100.8**	
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

UPDATED - TABLE 2.4 (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 • C_f ' , i.e., an absolute amount)

Vegetation type	**Subcategory**	**Mean**	**SE**	**References**
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**	
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		**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)	$M_B = AGR_{(T)} \times Frac_{Brunt(T)}$			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.

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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.

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UPDATED - TABLE 2.6
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

UPDATED - TABLE 2.6 (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

This section has an elaboration of methods and updates.

Description of Elaboration: *The 2006 text has been reviewed and refined to expand on guidance on how to parameterize and evaluate Tier 3 models, the integration of data to models, and means to increase transparency. Include case studies demonstrating how parties have developed and worked with Tier 3 methods including models have been included.*

Note: grey highlighted text reflects original 2006 text. Strikethrough text is original text to be deleted. White highlighted text is proposed new elaboration text.

~~The guidelines in this volume focus mainly on Tier 1 methods, along with general guidance to assist with the development of a Tier 2 inventory. Less attention is given to Tier 3 methods, but some general guidance is provided in this section.~~ 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 ~~approaches.~~ 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 ~~approaches~~ 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 ~~specific considerations for implementing issues surrounding~~ Tier 3 ~~approaches~~ methods relevant to all sectors found in Volume 1, Chapter 6, which includes a useful checklist for ensuring good practice in the use of higher tier models in national greenhouse gas inventories. ~~for individual source categories may be provided later in the volume, and supplement the general guidance found in this section.~~

The estimation of emissions and removals always involves both measurements and modelling but can be done using one of two different strategies (or their combination). One tries to obtain representative measurements (directly or together with model-based values such as emission factors or volume functions) as emission or removal estimates. For taking the measurements and upscaling them, appropriate concepts (such as sampling and stratification) are used. The other strategy uses model outputs as emission or removal estimates. In this strategy, upscaling is done by assuming that the model outputs are representative, and measuring is restricted to developing model parameters mainly in appropriate case studies. Both strategies may involve elements of different Tiers. For example, estimating carbon stock changes using tree measurements in a forest inventory (a Tier 3 approach) in combination with expansion and conversion factors that can be Tier 2 (such as wood density) and even Tier 1 (such as carbon fraction). The below guidance focuses on requirements related to Tier 3 methodology.

2.5.1 Measurement-based Tier 3 inventories

Inventories can be based on direct measurements ~~of C stock changes~~ from which emissions and removals of carbon are estimated. Measurement of some non-CO_2 greenhouse gas emissions is possible, but because of the high spatial and temporal variability of non-CO_2 emissions, Tier 3 methods will likely combine ~~process~~ models with measurements to estimate non-CO_2 emissions. Model based Tier 3 methods (e.g., using empirical or process-based growth models) to estimate national emissions will be discussed in Section 2.5.2. Purely measurement-based inventories, e.g., based on repeated measurements using a national forest inventory or similar estimation methods can produce ~~derive~~ carbon stock change estimates ~~without relying on process models, but they do require~~ 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.

Some countries already have an existing inventory system that will provide data to the inventory compiler. For countries that do not have an existing system~~, and for the spatial and temporal scaling of plot measurements to a national inventory. Approaches based on dynamic models(e.g., process-based models) to estimate national emissions will be discussed in Section 2.5.2. In general,~~ the following six steps should be considered when ~~are involved with implementation of~~ implementing ~~a Tier 3~~ measurement-based Tier 3 inventory.

Step 1. *Develop sampling scheme, including sample unit (plot) design and measurements to be collected*. Sampling schemes can be developed using a variety of approaches such as simple random, stratified random, systematic or model-based sampling.~~, but typically involve some level of randomization of sampling sites within strata. (Even inventories based on a regular grid typically select the starting point of the grid at random). Inventory~~

~~compilers will~~ When designing a sampling scheme, countries will typically also consider factors such ~~Determining an appropriate approach given size of their country~~ spatial variability and temporal dynamics of carbon stocks, key environmental variables (e.g., climate) and management systems (e.g., harvested forests, grazed grasslands).~~in their region. The latter two may serve as stratification variablesis not completely random. In addition, it~~It is *good practice* for sampling to ~~provide wide spatial coverage~~ be representative of the range of environmental and management conditions that result in emissions and/or removals for ~~a particular~~ key ~~source category~~ categories.

When ~~The inventory compiler should establish an appropriate time period over which sites will be re-sampled if~~ using a repeated measures design, the timing of re-measurement should ~~will~~ depend on the rate of stock changes or non-CO_2 greenhouse gas emissions. 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. ~~Where fluxes are measured directly, greater temporal and spatial variability will require more frequent or more intensive sampling to capture fluxes which might otherwise be missing from the measurement record.~~ When deciding to implement 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 measurements have been conducted (often more than 10 years in total).

Some approaches do not include re-sampling of the same sites. Such designs ~~are acceptable, but~~ may limit the statistical power of the analysis, and therefore lead to greater uncertainty. It is likely that a repeated measures design with permanent plot locations will provide a better basis for estimating carbon stock changes or emissions in most countries. If plots are permanent, their utility may be greater if they are accurately georeferenced to facilitate the use of remotely sensed auxiliary variables to increase accuracy (GFOI, 2016).

For some carbon pools, in particular soil carbon, it is not 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). Where countries wish to use direct measurement methods for these pools, the sampling design needs to ensure that sufficient samples are taken at each measurement time for estimating stock change.

Plot designs should consider the practicality of implementing these in the field given country circumstances (e.g., terrain, access, safety, vegetation type). Plot designs should also consider the extent remotely sensed data are going to be used to enhance the accuracy of the estimates. It is *good practice* to document the plot design, in particular how plots are to be located and, in the case of repeated measures designs, re-located for future measurements (Vidal et al., 2016).

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.

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 for sampling in case it is not possible to sample some original locations. In a repeated measures 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 data are not available at the national scale, the inventory developer should re-evaluate the design and stratification (if used) in Step 1 and possibly modify the sampling design.

Normally the sampling intensity should be the same within a stratum and if possible between strata e.g. different sampling intensities per land-use category within a stratum would likely lead to inconsistencies after a potential land-use change. The same is valid between strata using a high-resolution stratification where e.g. the stratification is based on land-use (i.e., each strata constitute one land-use category). Both cases will be solved by using a permanent inventory design over a larger area.

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 final set of sites are determined, a sampling team can visit those locations, establish plots and collect initial samples. The initial samples will provide initial carbon stocks~~, or serve as the first~~

~~measure of emissions~~. ~~It is *good practice* to establish field measurement and laboratory protocols before the samples are collected.~~ ~~In addition,~~ It ~~may be~~ is helpful to take geographic coordinates of plot locations or sample points with a global positioning system, and, if repeated measures are planned, to permanently mark (with markings not be visible to the land owner) the location for ease of finding and re-sampling the site in the future.

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 measures designs, sampling sites will be periodically re-sampled ~~in order~~ to estimate changes ~~evaluate trends~~ in carbon stocks or non-CO_2 emissions over an inventory time period. The time between re-measurement will depend 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 biomass 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.~~

Step 5. *Analyze data and determine carbon stock changes/non-CO_2 emissions, and infer national emissions and removal estimates and ~~measures of~~their uncertainty*. It is *good practice* to select an appropriate statistical method for data analysis based on the sampling design. 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. It is *good practice* to also include estimates of uncertainty, which will include sampling errors, measurement errors ~~in the sample collection~~, uncertainties in allometric and other prediction models that relate actual measurements on the ground to carbon stocks and laboratory processing (i.e., the latter may be addressed using standards and through cross-checking results with independent labs)~~, sampling variance associated with monitoring design,~~ and other relevant sources of uncertainty (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 or using additional strata or covariates to explain more of the variance. Model uncertainty may be relatively small – at least in situations with well-developed models (e.g., Breidenbach et al., 2014; Ståhl et al., 2014). The model uncertainty is introduced by using empirical models rather than destructive measurements to assess the carbon on the sample units.

The analysis will include scaling of measurements to a larger spatial or temporal domain, which again will depend on the design of the sampling scheme. Scaling will range from simple averaging or weighted averaging to more detailed interpolation/extrapolation techniques.

To avoid biased estimates, it is *good practice* for the scaling method and the sampling design to be consistent. Based on a standard NFI-inventory design, the precision of estimates of carbon stock changes is quite high in absolute terms but, especially for carbon stock changes of uncommon land-use categories, precision of estimates is low in relative terms. The precision of estimates can be estimated from an estimator of the variance of the estimate.

To obtain national estimates of stock changes or emission of non-CO_2 greenhouse gases, it is often necessary to extrapolate measurements using models that take into consideration environmental conditions, management and other activity data. ~~While the net changes of carbon-based greenhouse gasses can (at least in theory) be estimated purely by repeated measurements of carbon stocks, statistical and other models are often employed to assist in the scaling of plot measures to national estimates. National emission estimates of non-CO_2 greenhouse gases are unlikely to be derived from measurements alone.~~ Such models are usually necessary because of the expense and difficulty in obtaining expansion and/or conversion factors that need to be applied in combination with the sample-based measurement of the activity data. For example, N_2O emissions from forest fires ~~cannot be measured empirically but~~ are typically inferred from samples of activity data on the area burnt, and fuel consumption estimates that are derived from specific case studies. In ~~contrast~~ similar fashion, soil N_2O emissions ~~can~~ could be readily estimated using chambers, but it would 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.

It is *good practice* to analyze 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.

Most countries using a measurement-based Tier 3 method will already have an existing National Forest Inventory or similar system that has been established for many years. Typically, these systems have been established for purposes other than estimating greenhouse gas emissions and removals, in particular timber resource assessment, nonetheless the data can be used for measurement based Tier 3 systems. Where an existing national forest inventory is used it is important to ensure that any changes in methods through time, such as changes in the sampling design and/or data collected, do not affect the consistency of estimates of carbon stocks.

As such when developing/collating documentation for reporting Tier 3 measurement-based methods it is good practice to:

- Describe how the sampling design and/or measurements have changed through time and how these changes are accounted for to ensure changes in carbon stocks are not due to methodological changes;
- Document changes in measurements between inventory cycles, including those measurements that have been added over time to cover additional pools and how these are extrapolated/interpolated to cover the required reporting periods;
- Describe how area estimates derived from the national forest inventory are reported consistently with area estimates for other land-uses;
- Show that where there are significant time periods between measurement cycles, this does not lead to the under reporting of emissions from certain activities, such as non-CO_2 emissions from fire; and,
- If applicable, document 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.

Documentation may include 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, including quality assurance procedures in which peer-reviewers not involved with the analysis evaluate the methodology. 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.

NEW GUIDANCE - TABLE 2.6A

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. Analyze data and determine carbon stock changes and other sources of emissions, and infer national emissions and removal 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 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 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 ~~advanced~~ models.

In all cases models used in Tier 3 methods ensure higher accuracy only when they are correctly applied and capable of representing the population of interest.

Numerous different models have been developed to estimate carbon stocks and changes in carbon stocks and can be used to help separate multiple different effects (e.g., forest growth, soil carbon dynamics, disturbance impacts, climatic variability). In many cases previously developed models need to be adapted, coupled and/or integrated to provide a complete estimate of carbon stock changes in each carbon pool. All models require measured data; both to calibrate and evaluate the model. In all cases this calibration and evaluation should enable modelled processes to be accurately described as far as practicable.

~~It is *good practice* to have independent measurements to confirm that the model is capable of estimating emissions and removals in the source categories of interest (Prisley and Mortimer, 2004).~~

In general, the following ~~seven~~ eight steps are used to implement a Tier 3 model-based inventory (see also Figure 1, Volume 1, Chapter 6, Section 2.4~~, Figure 2.7~~).

Step 1. Select or develop a process for using the models

It is unlikely that one single model will be suitable for estimating emissions and removals for all carbon pools and non-CO_2 gases for all land-uses, land-use changes and management actions. Therefore, inventory compilers will need to select a suite of different models that cover the full range of activities and processes that occur within a country. When selecting each individual model, it is important to consider how the model will be used and how it will interact with other models. This is particularly important when using Tier 3 mass-balance methods and when using Tier 3 models in combination with Tier 1 or 2 emissions factors (e.g., if different soil carbon models are used for different land-uses, how will the carbon pools be transferred between them in the case of land-use change).

The selected models may be run individually for different land-uses and carbon pools and the results combined, or they may be integrated into a single framework. Individual model simulations are typically used where multiple agencies are responsible for developing different parts of the inventory (e.g., the forest agency does forestry, the agriculture agency does croplands and grasslands).

Models can be brought together using coupling and integration techniques. 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). Additionally, integration frameworks can help organize data and estimation methods at any level of methodological complexity and facilitate the systematic progression from simpler to more complex methods (GFOI, 2106). Both Australia (Commonwealth of Australia, 2017) and Canada (Kurz & Apps, 2006, Kurz et al., 2009, Kurz et al., 2013) apply model integration in their enumeration of land-use and land-use change emissions and removals. It is *good practice* to ensure that the selected model corresponds to the proposed activity data and can report results by relevant land-use category (or activity). 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. Evaluation results are an important component of the reporting documentation, justifying the use of a particular model for quantifying GHG emissions and removals.

Where the models are to be run individually, it is *good practice* to document:

- how land areas and carbon stocks are transferred between models, in particular following land-use change;
- how activity data is used consistently across all models over time;
- how input variables are provided to the individual models and the processes for ensuring all models use a consistent set of inputs;
- how results from the individual model runs are combined;
- how uncertainties are combined;
- how results of any sensitivity analysis conducted, i.e. how the variability (i.e., uncertainty) in the output of a model can be apportioned, qualitatively or quantitatively, to different sources of variation in the input of the model.

When selecting or developing an integrating framework, it is *good practice* to document how the framework:

- links the models and how they operate together for different land-uses and changes in land-use;
- links the models to activity data;
- completes internal checks to ensure consistent representation of lands and allocation of emissions and removals to each land-use;
- conducts uncertainty analysis.

~~**Figure 2.7 Steps to develop a Tier 3 model-based inventory estimation system**~~

Step 2. Model selection or development ~~*Select/develop a model for calculating the stock changes and/or greenhouse gas emissions.*~~

A model should be selected or developed ~~that~~ based on how ~~more~~ accurately it represents stock changes or non-CO_2 greenhouse gas emissions than is possible with Tier 1 and 2 methods. ~~approaches.~~ As part of this decision, it is *good practice* to consider the availability of input data (Steps 3) and the computing resources needed to implement the model (Step 5).

Models should be developed or selected based on their suitability for the country circumstances to which they are being applied. Suitability refers to the applicability of a model/s for estimating GHG emissions and removal in the country, including the scope, boundaries and structure. When developing or selecting a model the following issues can be considered when determining model suitability:

- Can the model produce the required outputs for estimating and reporting emissions and removals?
- Can the model be calibrated for the required land-uses and/or activities?
- Can the model represent or be modified to represent the required activity data and management actions?
- Can the model work consistently with other models in the inventory?
- Are all the required input variables (e.g., climate data, site indices) available at the required spatial and/or temporal resolution?
- Do they cover the entire period of the inventory and will they continue to be available in the future?
- Is the model sufficiently accurate for the purposes of the inventory?
- Can the accuracy and uncertainty of the model be evaluated?
- Can the model be run in an operational context with available time and resources?

When a model is selected, it is *good practice* to consider and document responses to the following questions:

- Is the model designed for the specific purpose of the GHG inventory or was the model developed for another purpose?
- Are underlying processes and drivers required to use the model correlated with changes in carbon pools?
- What limitations and constraints may apply in case the model does not fit exactly for GHG inventory purposes?
- Is the model designed, or portable to, the current national circumstances (e.g., types and number of strata)?
- Are the conditions for which the model is applied different from those for which the model originally was developed (e.g., ecological or management)?
- How sensitive is the model to extrapolation or interpolation?
- Are model specifications logical (tested by partial-studies e.g., when fixing all parameters except for X, how does Y respond to changing X?)

Although it is true that simple models cannot account for the complexity of the system being analysed, it is also true that very complex models can be over specified, and difficult to understand, construct and use.

It is *good practice* for inventory compilers to evaluate national circumstances (e.g. data availability, system maintenance costs) and the desired/possible level of accuracy to find a balance between simplicity and complexity for the purposes of running an operational system.

~~As part of this decision, i~~It is *good practice* when selecting or developing models to consider and document the model scope, spatial and temporal scale, representation of land-use/land-use change types, possibility of stand level modelling, spatial resolution, coupling/integration capabilities (Step 1), availability of input data (Steps 3) and the computing resources needed to implement the model (Step 5).

Step 3. Model Calibration

Model calibration (i.e., parameterization) is the process of adjusting model parameters to obtain results that best represent the processes of interest. The model calibration procedure basically readies a model for its further use in simulation. It is good practice to calibrate the model with independent data prior to its implementation (i.e., data used to calibrate the model is not used to validate the model results). Calibration data should where possible match the quality and scale of data sets used in the model runs.

Two common methods of model calibration are:

- Manual – where the parameters are determined by people, typically using statistical analysis packages.
    - These techniques are suitable for simple, empirical models, such as empirical forest growth models based on forest age or site indices.
- Automated – automated systems where the parameter sets are estimated using computer simulations to best match known results by varying the model parameters within known ranges.
    - These techniques are well suited to more complex modelling systems with multiple, often interacting parameters.

In all cases it is *good practice* to provide summaries of the calibration results that include:

- an analysis of the bias-variance tradeoff (i.e. tradeoff in trying to simultaneously minimize these two sources of error that prevent supervised learning algorithms from generalizing beyond their training data set)
- demonstration that the model is not applied outside the range of data that was used to calibrate it or, if so, that the model outputs are reasonable in this range, too (i.e., does the model move past the data it was calibrated against, e.g., is the maximum biomass predicted by the model in a country greater than the highest biomass measurement in the calibration set).
- demonstration that the domain of the model/s calibration is applicable to all circumstances (e.g., across multiple forest or soil types).

NEW - BOX 2.2F

MODEL CALIBRATION THROUGH DATA ASSIMILATION

This information in this box is for the purpose of presenting an example of model calibration through data assimilation.

Analyses of the ability of the CBM-CFS3 to predict ecosystem C stocks in independent plots established as part of Canada's national forest inventory (NFI) demonstrated both close agreement in the predictions of total ecosystem C stocks (within 1%) and compensating errors (bias) in specific pools, ecozones, and plots with different leading tree species (Shaw et al. 2014, see also Box 2.11).

In an effort 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 C stocks of six deadwood and soil C 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 C stocks in small and fine woody debris, reducing RMSE by 54.3%, followed by the snag stems (RMSE reduced by 23.2%), and coarse woody debris (13%). Twenty of the 45 parameters were well constrained by the available data. The calibrated parameters resulted in increased rates of C cycling in fine and coarse woody debris and the soil organic layer, distinct C dynamics in hardwood and softwood dominated stands, and increased temperature sensitivity of the C 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.

Lack of substantial improvements in the calibrated model performance indicates the need for the inclusion of additional processes in C 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 2.2I) in the CBM-CFS3. Further data assimilation analyses are ongoing.

Step 4. Model Evaluation ~~*with calibration data.*~~

This is a critical step for inventory development in which model results are compared directly with measurements independent to those used for model calibration/parameterization ~~(e.g., Falloon and Smith, 2002)~~. Comparisons can be made using statistical tests and/or graphically, with the goal of demonstrating that the model effectively simulates measured trends for all conditions in the source category of interest for which the model is simulating.

It is *good practice* to ensure that the model responds appropriately to variations in activity data and that the model is able to report results by land-use category as per the conventions laid out in Chapter 3. 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, justifying the use of a particular model for quantifying emissions in a source category.

~~**Step 3.**~~**Step 5. Collate data inputs**

~~*Gather spatio-temporal data on activities and relevant environmental conditions that are needed as inputs to a model.*~~ Models, even those used in Tiers 1 and 2 methods ~~approaches~~, require specific input information ~~in order~~ to estimate greenhouse gas emissions and removals associated with a source category. The inputs required to run the model are identified and located in Step 1. These inputs may range from weather and soils data to livestock number, forest types, natural disturbances or cropping management practices. Where these data are not yet available, but are to be developed as part of model development, it is *good practice* for the input data to be consistent with spatio-temporal scale of the model (i.e., algorithms). For example, if a model operates on a daily time step then the input data should provide information about daily variation in the environmental characteristic or activity data. In some cases, input data may be a limiting factor in model selection, requiring some models to be discarded as inappropriate given the available activity and/or environmental data.

Step 6. Implement the model

The major consideration for this step is ~~that there are~~to obtain enough computing resources and personnel time to prepare the input data, conduct the model simulations, and analyze 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 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 2). It may be possible to increase the efficiency of this process using ~~This will depend on the efficiency of the~~ programming scripts, re-coding parts of the ~~model complexity of the model, as well as~~ the model and adjusting the spatial and temporal extent and resolution of the simulations.

Step 7. Evaluation of model results with independent data

~~It is important to realise the difference between Steps 2 and 6.~~ Model evaluation during the selection process Step 2- involves testing model output with field data that were used as a basis for calibration (i.e., parameterization), in contrast, evaluation with independent data is done with a completely independent set of data from model calibration (i.e., parameterization), providing a more rigorous assessment of model components and results. It is *good practice* to have independent measurements for the evaluation.

Optimally, independent evaluation should be based on measurements from a monitoring network or from research sites that were not used to calibrate model parameters. The network would be similar in principle to a series of sites that are used for a measurement-based inventory. However, the inference (i.e., uncertainty) of the estimates (output) from a model-based approach does not depend directly on the sample size and therefore the sampling ~~does not~~ need not ~~to~~ be as dense. ~~because the network is not forming the basis for estimating carbon stock changes or non-CO_2 greenhouse gas fluxes, as in a purely measurement-based inventory, but is used to check model results.~~ In some cases, independent evaluation may demonstrate that the model-based estimation system is inappropriate due to large and unpredictable 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 two cases, it is *good practice* for the inventory developer to return to either Steps 3 or 6 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 2) or to further refine the existing model.

During Step 3~~2~~ ~~that follows the selection/development step,~~ it is *good practice* to avoid using the independent evaluation data to re-calibrate or refine algorithms. If this occurs, these data would no longer be suitable for independent evaluation, and therefore not serve the purpose for Step 6 in this inventory approach.

Tier 3 model-based spatially explicit systems typically use large volumes of input data and produce even greater volumes of potential outputs. Spatially explicit Tier 3 systems typically create a very large number of individual model simulations using data from remote sensing, sampling and other spatial and non-spatial auxiliary data. Checks should be conducted for each simulation to identify errors in input data or model constructs that could lead to unrealistic results.

It is *good practice*, at a minimum, to ensure that systems can complete the following checks and provide reports confirming that:

- Mass-balance has been maintained through all simulations
- Estimates of carbon stocks in all pools do not exceed pre-defined expected limits (i.e., the limits need to be provided in the inventory report)
- Total land area is correctly predicted and land-use areas can be compared to other sources (e.g., sample bases or other statistical analyses)
- Changes between land-use types are logical in terms of the type, frequency and time periods between changes, defined by the country
- All failed simulations are reported, including individual pixels or stands, and justified.

The process of evaluating Tier 3 models should accompany the development of the method and should therefore be an iterative process. Examples of iterative model evaluation include: 1) an evaluation of the performance of Yasso07 and ROMULv models against forest soil carbon stock measurements undertaken by Lehtonen et al. (2016) and 2) an evaluation of the ability of CBM-CFS3 to predict ecosystem C stock estimates derived from an entirely independent data set from the initial establishment of Canada's new National Forest Inventory (Gillis et al., 2005; Stinson et al., 2016).

It is *good practice* to consider the suitability for a given purpose; the use of current knowledge and data; and the degree of complexity of system abstraction.

Step 8. Quantify uncertainties. Uncertainties are often due to imperfect knowledge about the activities or processes leading to greenhouse gas fluxes, and are typically manifested in the model structure and inputs and the measurements used to calibrate and evaluate the model. Consequently, uncertainty analyses are intended to provide a rigorous measure of the confidence attributed to a model estimate based on uncertainties in the model structure, calibration and input data, generating a measure of variability in the carbon stock changes or non-CO_2 greenhouse gas fluxes[11].

It is important to estimate the uncertainty of the emissions and removals for each land-use and any other country specific sub-categories. Countries may also choose to estimate uncertainty for each pool and gas. 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, however it may not be feasible or sensible to apply full Monte Carlo simulations to, for example, every pixel.

As such it is *good practice* to select a subset of model simulations to estimate uncertainty that are sufficiently representative of the range of land-uses, management activities and environmental conditions. Outputs from the systems could include:

- Uncertainty estimates for each carbon pool by land-use, with further stratification as per country circumstance;
- Sensitivity of the results to key parameters and input variables;
- Estimates of carbon stocks, carbon stock changes and emissions and removals for all locations where calibration and validation data have been collected to allow assessment of accuracy;
- Estimates of carbon stocks, carbon stock changes and emissions and removals from a statistical sample of locations for which model outputs have been produced.

Uncertainty analysis should not be confused with sensitivity analysis. Uncertainty analysis attempts to describe the entire set of possible outcomes of a model together with their associated probabilities of occurrence and derive uncertainty estimates that can be propagated through the inventory to arrive at robust 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.

It is *good practice* to conduct uncertainty and sensitivity analysis as part of model evaluation and report:

- the error distribution of key parameters (i.e., model parameter covariance matrix);
- results of either Error Propagation (Approach 1) or Monte-Carlo analysis (Approach 2) (see Volume 1 Chapter 3);
- results of an evaluation of uncertainties with regard to uncertainties in input data and model structure and assumptions;
- results of a sensitivity analysis or identification of key parameters/inputs to which the model outputs are more sensitive.

[11] Volume 1, Chapter 3 provides general guidance on appropriate methods for conducting these analyses.

NEW - BOX 2.2G

MODEL EVALUATION AND IMPROVEMENT

The purpose of this box is to present examples 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). The majority of countries apply soil carbon models to estimate carbon stock changes. Individual soil carbon models are commonly evaluated against repeated soil inventories with findings indicating that models are able to estimate soil carbon stock change in the same magnitude as was measured, however, uncertainties of both measurements and model estimates are often higher than actual measurements (Ortiz et al., 2009; Rantakari et al., 2012) making the evaluation of outputs challenging.

An evaluation of the performance of Yasso07 and ROMULv models against forest soil carbon stock measurements was undertaken by Lehtonen et al. (2016). Litter input of trees was estimated from stem volume maps provided by the National Forest Inventory, while understorey vegetation was estimated using new biomass models. The litter production rates of trees were based on earlier research, while for understorey biomass they were estimated from measured data. The Yasso07 and ROMULv models were applied across Finland and ran run until models achieved steady state; thereafter, measured soil carbon stocks were compared with model estimates. Findings from the model evaluation showed that the role of understorey litter input was underestimated when the Yasso07 model was parameterised, 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 to the decomposition of organic layers. The model evaluation results imply improving understorey litter estimation in the northern latitudes would be an area for improvement in greenhouse gas inventories (Lehtonen et al., 2016).

Canada

An evaluation of the ability of CBM-CFS3 to predict ecosystem C stock estimates derived from an entirely independent data set from the initial establishment of Canada's new National Forest Inventory (Gillis et al., 2005; Stinson et al., 2016) was undertaken. Estimates of aboveground biomass, dead organic matter and soil C 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 national inventory report in 2010 and 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% 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%) and deadwood (30.8%) pools compared favourably to the IPCC-2003 GPG standards of 8% and 30%, respectively. Further details are provided in (Shaw et al., 2014).

Subsequent analyses assessed the reasons for the consistent under prediction of organic C stocks in low productivity boreal sites, in which mosses can contribute 30% or f more of total ecosystem Net Primary Production (Bona et al., 2013). Although mosses are not a C stock that is included in the IPCC pools, it is increasingly evident that omitting them will result in significant under prediction of both C 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% 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 C stocks and inputs will reduce bias in organic C stock estimates (Bona et al., 2016). Efforts are now under way to evaluate the performance of the revised model with the integrated moss module as part of inventory continuous improvement priorities

NEW - BOX 2.2H

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.

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 was varied during Monte-Carlo simulations using the entire national system. These factors include the processes used to initialize dead organic matter and soil C pools (DOM), biomass increment data (a multiplier with a range of ±50% was applied to net biomass increment), activity data (wildfire (±10%), insects (±25%), and harvest (range varies by jurisdiction)), selection of stands during the allocation of natural disturbances to affected stands, and parameters defining litter input and DOM pool dynamics. Parameter ranges for 32 biomass turnover and DOM C 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 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% confidence interval (CI) was defined from the 2.5th and 97.5th percentiles of these national estimates.

Under the assumptions of this analysis, 95% confidence interval widths averaged 16.2 Pg C (+8.3 and –7.9 Pg C, or ±15%) for total ecosystem C stocks and 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 C 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).

Step 9~~7~~. Reporting and Documentation

It is *good practice* to assemble inventory results in a systematic and transparent manner for reporting purposes. Documentation in support of transparency of results from model-based Tier 3 inventories may include those items listed in Table 2.6B, taking into consideration the elaborations at each step above.

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.

NEW GUIDANCE - TABLE 2.6B

EXAMPLES OF DOCUMENTATION TO ASSEMBLE IN SUPPORT OF TRANSPARENT REPORTING OF TIER 3 MODEL-BASED INVENTORIES

Step 1. Select or develop a process for using the models	List of modelled processes
Step 2 – Model selection or development	A description of the model/s Reason for choosing or designing the model demonstrating applicability Discussion of any likely consequences if the model is used outside the parameter space for which it was originally developed.
Step 3 - Model calibration and parameterisation	Description of data sources used and the process undertaken.
Step 4 - Model evaluation	Model evaluation results including sources of experiments and/or measurement data from monitoring network
Step 5 - Collate data inputs	Summary of model input data sources
Step 6 - Implement the model	Explanation of any differences in local conditions compared to those for which the model was constructed were treated (e.g., ecological or management) including any possible effects these differences might have on the accuracy of model estimates.
Step 7 - Evaluation of model results with independent data	Results of the evaluation of the model results 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
Step 8 - Quantify uncertainties	Description of the approach taken to estimate uncertainty of the model outputs.
Step 9 – Reporting and Documentation	Information on how QA/QC was done

2.6 INTER-ANNUAL VARIABILITY

In the AFOLU sector, 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). The Managed Land Proxy (MLP) is currently recognised as the only universally applicable approach to estimating anthropogenic emissions and removals in the AFOLU sector (IPCC 2010). However, it is also recognised that the reported emissions and removals on managed lands represent a combination of both anthropogenic (direct and indirect) and natural effects (Vol. 4 Chapter 1 p1.5; IPCC 2010).

Emissions and removals from land may be 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. As described in the IPCC KP Supplement 2013, "the two largest causes of actual inter-annual variability in GHG emissions and removals in the LULUCF sector are natural disturbances (such as fire, insects, wind throw, and ice storms) and climate variability (e.g. temperature, precipitation, drought, and extreme events). "The third cause of interannual variability in GHG emissions and removals is the variation in the rate of human activities, including forest harvesting, land use, and land-use change."

This refinement, together with the 2006 IPCC Guidelines, is designed to assist in estimating and reporting national inventories of anthropogenic greenhouse gas emissions and removals. However, when the MLP is used and there is high interannual variability, it can be difficult to gain a clear understanding of the role of human activities compared to the impacts of natural effects. In such situations disaggregating[12] MLP emissions and removals into human and natural effects may increase transparency, and provide refined estimates of the emissions and removals that are due to human activities such as harvesting, land use and land-use change. Disaggregating the reported emissions and removals by their predominant causes can increase the understanding and transparency of annual anthropogenic emissions and removals estimates. Furthermore, disaggregation can contribute to improved

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

quantification of the trends in emissions due to human activities and the impact of mitigation actions aimed at reducing anthropogenic emissions, and preserving and enhancing carbon stocks.

Disaggregating emissions and removals according to anthropogenic and natural effects has long been recognised as a major scientific challenge (Canadell et al. 2007; Vetter et al. 2008; IPCC 2010; Kurz 2010; Smith 2010; Brando et al. 2014; Henttonen et al. 2017). The last IPCC Expert Report (IPCC 2010) on this topic has encouraged further development of scientific methods. Examples of the application of such methods in national GHG inventories are briefly outlined here.

The guidance in this section is provided as an option that may be used to disaggregate MLP emissions and removals into those that are considered to result from human effects and those that are considered to result from natural effects. These approaches may be of interest to countries with AFOLU sector emissions that have high IAV due to natural effects. 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 interannual variability of emissions and removals. A generic methodology to estimate, disaggregate and report the contribution of natural disturbances to the emissions and removals on managed lands is then provided, along with country-specific examples of approaches to disaggregating anthropogenic and natural effects on managed lands. The purpose of this guidance is to support countries that wish to increase the transparency of anthropogenic GHG flux estimates on managed lands.

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 2.7A summarizes the main factors that cause these effects and their occurrences in managed and unmanaged lands. The specific effects included in land sector annual estimates reported in GHG inventories 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 GHG inventory, and its understanding by the scientific and policy communities (Grassi et al. submitted).

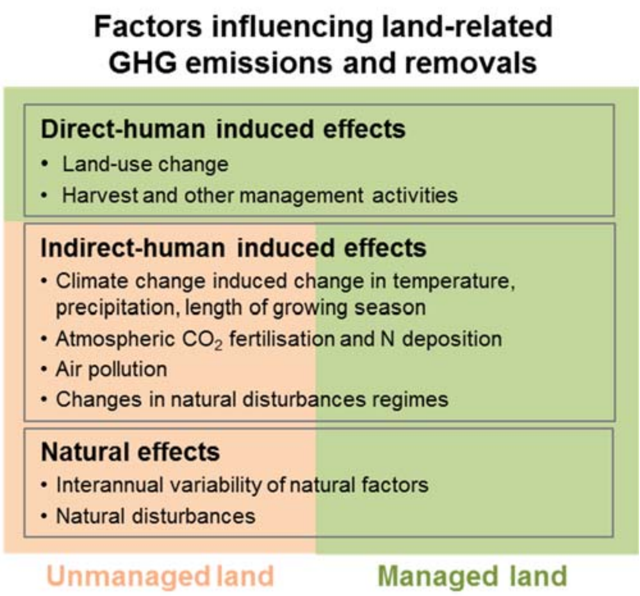

Figure 2.7A: Conceptual illustration of how various anthropogenic (direct and indirect) and natural factors simultaneously affect land-related GHG emissions and removals (Source: Grassi et al. submitted). In rare cases, natural or indirect-human induced effects can also lead to land cover changes, e.g. repeated wildfires can lead to forest regeneration failure and conversion to non-forest (with grass or lichen ground cover).

Direct human-induced effects (i.e., the direct impact of any management activity on emissions or removals) only occur on managed lands. Indirect human-induced effects (i.e., the second order impacts of human activities on emissions or removals) and natural effects 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). Although the natural effects (i.e. the natural 'background' of GHG emissions and removals) "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) their interannual variability in emissions and removals is of relevance to annual GHG inventories. Depending on the estimation method and data used, GHG estimates for managed land may capture all or only some of this IAV.

Land sector GHG emissions and removals are typically affected simultaneously and to varying degrees by both human and natural factors. These factors determine the cause, the magnitude and the duration of the GHG fluxes associated with disturbances (de Miranda et al. (2014), Morton et al. (2013), Schimel et al. (2015)).

The IPCC describes the MLP as a method to approximate estimates of anthropogenic emissions and removals, but this proxy also contains emissions and removals resulting from natural disturbances. To refine the approximation of the anthropogenic component of emissions and removals, this section introduces a second order approximation that builds on the first order approximation of the MLP. The second order approximation is obtained by subtracting the emissions and removals due to natural disturbances (ND E/R) from MLP totals. This second order approximation is a refined estimate of emissions and removals from anthropogenic causes.

2.6.1.2 NATURAL DISTURBANCES

Natural disturbances, in particular wildfire, can contribute to large IAV in emissions. The frequency and intensity of fire events is strongly controlled by climate: high temperatures and persistent drought events are key drivers of forest fires, for instance in the Amazon region (Morton et al. 2013) or in Indonesia (Schimel et al. 2015). Frequent fires can affect ecosystem structure and carbon stocks across time; for instance, savannahs are frequently affected by fire events that reduce average tree basal area across time (Lehmann et al. 2014). In the Brazilian Cerrado, severe drought events explain the loss of almost 30% 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). Unlike fires, 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, these long-term trends can also make it difficult to identify trends in emissions and removals that result from human activities.

IAV in emissions from natural disturbances can be larger than the IAV of emissions caused by e.g. 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 2.7C). The National GHGIs for Portugal (Figure 6-32 of Portugal's NIR 2017) and Australia (Table 6.20 of Australia's NIR 2015 Volume 2) 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 (van der Werf et al. 2010; Stinson et al. 2011). Such IAV is far greater than the impacts of variation in human activities (in AFOLU and even in all other sectors) and, therefore, a time-series that includes annual emissions and removals from natural disturbances may mask changes in emissions and removals from human activities.

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 interannual variability 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 in different temporal and disaggregation resolutions (annual to periodic, averaged or disaggregated by drivers). To increase transparency and comparability of reported estimates of emissions and removals, Table 2.6C summarises how the choice of estimation method affects whether or not factors contributing to IAV of reported emissions and removals are captured in GHG inventories

NEW GUIDANCE - TABLE 2.6C

DOES THE ESTIMATION METHOD DISTINGUISH BETWEEN THE IMPACT OF THE DRIVERS BELOW ON THE INTER-ANNUAL VARIABILITY OF REPORTED ANNUAL EMISSION AND REMOVAL ESTIMATES?

Method			Drivers			
			Direct Human	**Indirect Human**	**Natural climate variability**	**Natural Disturbances**
Stock Difference (SD)[13] **Periodic measurements (multi-year)**			No	No	No	No
Stock Difference (SD)[14] **Annual measurements**			Yes	Yes	Yes	Yes
Gain Loss (G/L)[2]	Live AGB & BGB pools	Growth defined by EF or Empirical Yield Tables	Yes	No	No	Yes
		Growth defined by process (or hybrid) model	Yes	Yes	Yes	Yes
	DOM & SOM pools	DOM/SOM dynamics based on EF	Yes	No	No	No
		DOM/SOM dynamics with constant climate	Yes	No	No	Yes
		DOM/SOM 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 on a land between 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 therefore do not allow the quantification of the IAV of emissions and removals and its relation to the various drivers. Periodic inventories can show variation in net emissions by period.

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 (panels) of inventories can by themselves not detect interannual variability 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, auxiliary data may be required when the stock change method is used.

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

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

[14] Forest inventories with annual remeasurements for the same plots can detect interannual variability, but are rarely implemented.

The Gain/Loss method requires annual data on forest management, land-use change and natural disturbances and it can therefore 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 factors such as natural climate variability and indirect human impacts 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 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 Methodological approach to estimate the contribution of ND to the emissions and removals reported for managed lands

It is *good practice* for countries to apply the Managed Land Proxy (MLP). For countries that choose to refine the estimates of anthropogenic emissions and removals, this section describes a generic methodological approach that may be applied to disaggregate emissions and subsequent removals from natural disturbances from the total emissions and removals estimated using the MLP. As discussed above, disturbances - i.e. events and circumstances not associated with management practices – may have a natural and an anthropogenic component, the methodological approach aims to separate the contribution of the natural and the anthropogenic components in the total emissions and subsequent removals associated with disturbances.

The elements of a generic methodological 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 (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 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. Country-specific definition of natural disturbances

Recalling the generic definition of natural disturbances provided in section 2.6.1.2, countries describe and apply their definition of natural disturbances consistently over time. The description includes the types of disturbances for which the disaggregation of emissions and subsequent removals is implemented, as well as the methods and criteria to identify the areas affected by such disturbances. The description also explains how the country-specific definition of natural disturbances excludes the impacts of human activities, e.g., salvage logging, prescribed burning, and deforestation.

3. Quantification E/R due to natural disturbances

The quantification of the natural component in emissions and subsequent removals from disturbances is done by applying the ND definition to either the disturbed areas or the total emissions from disturbances. Both approaches provide for the:

a. Identification of the lands affected by natural disturbances.

b. For those lands, estimation of the emissions and subsequent removals associated with natural disturbances only, e.g. salvage logging emissions are not included.

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

4. Disaggregation of the MLP

The natural disturbance component is subtracted from the total MLP flux, yielding a refined estimate of the anthropogenic emissions and removals from managed lands. This is the “refined MLP flux”, i.e. the second order approximation of the anthropogenic component of E/R from managed land. The refined MLP flux has a lower interannual variability than the total MLP flux because the variability resulting from natural disturbances has been removed. For instance, in Australia’s NGHGI the coefficient of variation in the time series of fires including natural disturbances on forest lands is 3.74, after separation of non-anthropogenic emissions and removals the coefficient of variation is reduced to 0.58 (Government of Australia, 2017).

Balance of emissions and subsequent removals:

The CO_2 emissions from areas affected by natural disturbance are expected to be balanced by subsequent removals at some future point, consistent with the assumption under the MLP that carbon emissions and removals associated with natural effects will average out over time (see also Volume 4, Chapter 1). This expectation remains valid for the methodological approach applied to derive a second order approximation. This expectation has no established time limit because the time to balance depends on the types of forest vegetation affected by disturbances and their rates of regrowth. Note that this balance is expected at the scale of areas affected by ND and not at the country scale, where the total area affected by ND may increase over time.

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, making it more difficult to achieve the balance. If environmental changes contribute to increased growth rates or reduced mortality rates, then the balance will be achieved faster.

The expectation that CO_2 removals subsequent to the natural disturbance balance the CO_2 emissions caused by the disturbance may not be valid if land-use change occurs. Consequently, emissions associated with land-use changes (deforestation) after natural disturbances along with the emissions from the natural disturbance are reported as human-caused emissions.

Given the above expectation of the balance, 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 in the time series removals contributed by lands affected by natural disturbances that occurred prior to the start of the time series and to report these removals as part of the natural disturbance component and not to attribute them to the managed component. In many countries 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.

Depending on the time required to regrow forests after natural disturbances, the removals on lands affected by disturbances prior to 1990 can be large. In the case of Canada, 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. in review). During times when fire and insect disturbance emissions increase (Kurz et al. 2008, Kurz et al. in review) the cumulative net balance of the disaggregated emissions and removals is a source that can be balanced some time in the future.

Legacy effects of disturbances that occurred prior to 1990, e.g. a large cohort of stands of similar ages that result from an extreme disturbance event (large fire or hurricane) can also affect trends in emissions and removals but these are not expected to have impacts on IAV and are therefore not further addressed. Legacy effects that result from human activities prior to 1990, such as a period of high afforestation rates, can affect emissions and removals after 1990 and any IAV is reported in the anthropogenic component.

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 their emissions will be balanced by removals. However, such emissions do not accumulate permanently in the atmosphere since biochemical and physical processes contribute to their degradation.

NEW - BOX 2.2I: LIST OF EXAMPLES OF NATURAL DISTURBANCES (FROM THE IPCC 2013 KP SUPPLEMENT)

• Wildfires: Wildfires occur in many forests and interact with the functioning of the forest ecosystems in which they occur. Wildfires can be important to the functioning of forest ecosystems, but they can also have undesirable environmental, social and economic impacts. Fire regimes (fire intensity, frequency and season of the occurrence (Gill 1975)) can have significant impacts on forest carbon stocks across considerable spatial and temporal scales (King et al. 2011). Recent studies on wildfires and forests include: Hirsch and Fuglem (2006); Williams and Bradstock (2008); Swetnam and Anderson (2008) and Girardin et al. (2010).

• Insect pests and disease infestations: Diseases (pathogens such as fungi, phytoplasma, or virus, cf. page 4.74 in Chapter 4, Volume 4 of the 2006 IPCC Guidelines) and insect pests can influence ecological processes and substantially affect large-scale regional GHG balances (Kurz et al. 2008) (Hicke et al. 2012). Outbreaks of forest diseases and pest insects can also have significant negative economic, social and environmental impacts on forested lands. Recent studies on insect and disease infestations in forests include: Canadian Council of Forest Ministers (2012a, 2012b and 2012c); Raffa et al. (2008) and Bentz et al. (2010).

• Extreme weather events: Extreme weather events can involve droughts, floods, heavy and wet snowfall, avalanches, ice, and damaging winds, occurring either as a single event or in combinations such as ice storms (Chambers et al. ; Fujimori et al. 1987 ; Yamashita et al. 2002; Kato 2008; Kramer 2008; Bebi et al. 2009; Phillips et al. 2009; Allen et al. 2010; Lindner et al. 2010). Besides causing emissions e.g. through the decay of dead organic matter (DOM) following storm damage or stem breakage due to high snow loads, extreme weather events can negatively affect forests, making them more susceptible to other natural disturbances. For example, there is a higher incidence of wildfires after drought periods.

• Geological disturbances: Geological disturbances may include volcanic eruptions, landslides, tsunamis, and earthquakes (Kamijo & Hashiba 2003; Viña et al. 2011).

Examples of methodological approaches that have been developed are presented for Australia (Box 2.2J), Canada (Box 2.2K) and for a European country that applied variations of the method approved for the Kyoto Protocol's second commitment period (Box 2.2L).

NEW - BOX 2.2J: AUSTRALIAN APPROACH TO MANAGING INTERANNUAL VARIABILITY DUE TO NATURAL DISTURBANCES

In Australia, all lands are considered managed lands. All areas and carbon stock changes on managed land from anthropogenic and 'natural disturbances'[15] 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 organisations 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. Most Australian wildfires are not stand-replacing and carbon stocks typically recover after 11 years (Roxburgh *et al.* 2015)[16]. 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 95% probability level) in the series of annual carbon stock losses due to fire at the national level and, spatially, as fires in those regions (States) experiencing abnormal fire activity in that year.

'Natural disturbance' of 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 2.7B).

The approach ensures that Australia's modelled implementation of the MLP is comparable to 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).

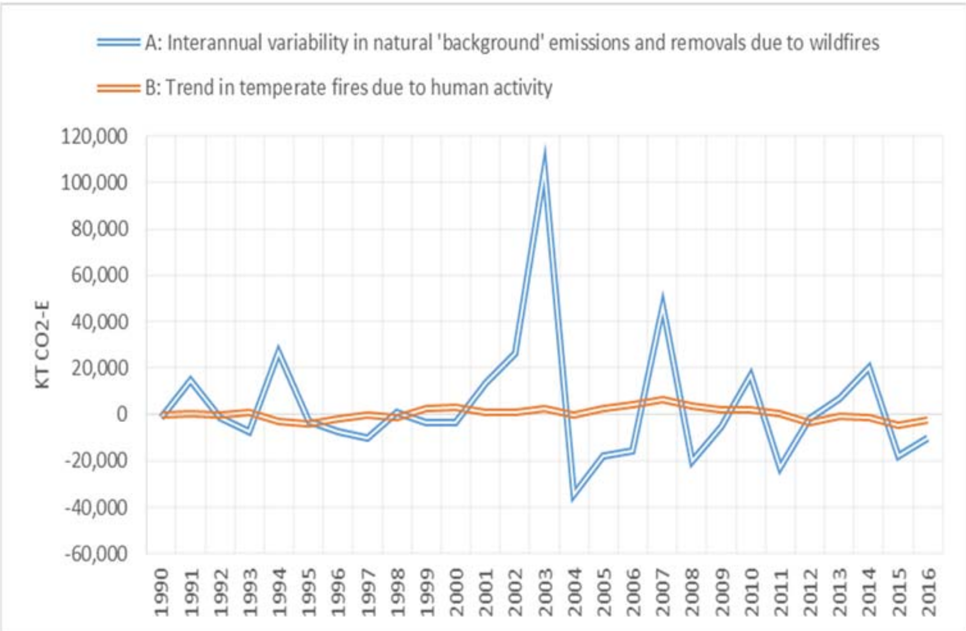

Figure 2.7B: Example of the disaggregation of fire emissions in Australia into 'natural disturbance' emissions and removals and the emissions and removals from fires due to human activity.

[15] References to 'natural disturbances' in this box refer to the *natural 'background' of greenhouse gas emissions and removals by sinks* described in IPCC 2006 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."

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[16] Roxburgh, S., Volkova, L., Surawski, N., Meyer, M. and Weston, C., 2015. *Review of fuel loads, burn efficiencies, emissions factors, and recovery functions used to estimate greenhouse gas emissions and removals associated with wildfire on temperate forested lands*. Commonwealth Scientific and Industrial Research Organisation (CSIRO), Canberra. Report for prepared for the Department of the Environment (*https://publications.csiro.au/rpr/download?pid=csiro:EP178326&dsid=DS3*)

[17] IPCC 2006 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. This leaves the greenhouse gas emission and removals from managed lands as the dominant result of human activity."

NEW - BOX 2.2K: CANADA'S APPROACH TO MANAGING INTERANNUAL VARIABILITY FROM NATURAL DISTURBANCES

In the 2017 National GHG Inventory Report[18] Canada first revised its reporting approach in an effort 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 lands affected by natural disturbances from emissions and subsequent removals on lands subject to forest management. The concept of the Managed Land Proxy (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. (in review) and are summarized here.

For the purpose of disaggregating the total fluxes into those considered dominated by natural disturbances and those from the remaining managed forest lands, 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% tree mortality (biomass) in affected stands. The threshold of 20% was selected because large areas of forests are affected by insects that cause low levels of mortality and/or growth reductions. This is considered part of the background level of natural disturbances.

For all areas affected by stand-replacing fire disturbances, CO_2 and non-CO_2 GHG emissions and subsequent CO_2 removals were reported in the natural disturbance land category for several decades following the fire event. The time at which stands affected by natural disturbances re-enter 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% biomass mortality, E/R were reported in the natural disturbance category until the pre-disturbance biomass values were reached. For the 1990 to 2016 time series,

stands regenerating following wildfire that are younger than the re-entry age are reported 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 that occurred since 1990. This approach contributes to balanced reporting as otherwise only removals from stands affected by natural disturbances after 1990 would appear in the natural disturbance category.

The new approach had the intended outcome: reported emissions and removals without natural disturbances showed clear temporal trends that were correlated with changes in the rates of human activities such as rates of clear cut harvesting (Box 2.2L, Figure 2.7C). In areas strongly affected by the Mountain Pine Beetle outbreak (Kurz *et al.* 2008) the trend in reported emissions is still influenced by the impacts of the beetle (Kurz et al. in review). The high inter-annual variability resulting primarily from fires has been reduced and is reported separately (Table 6.5 in 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. in review).

[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

NEW - BOX 2.2K: CANADA'S APPROACH TO MANAGING INTERANNUAL VARIABILITY FROM NATURAL DISTURBANCES (CONTINUED)

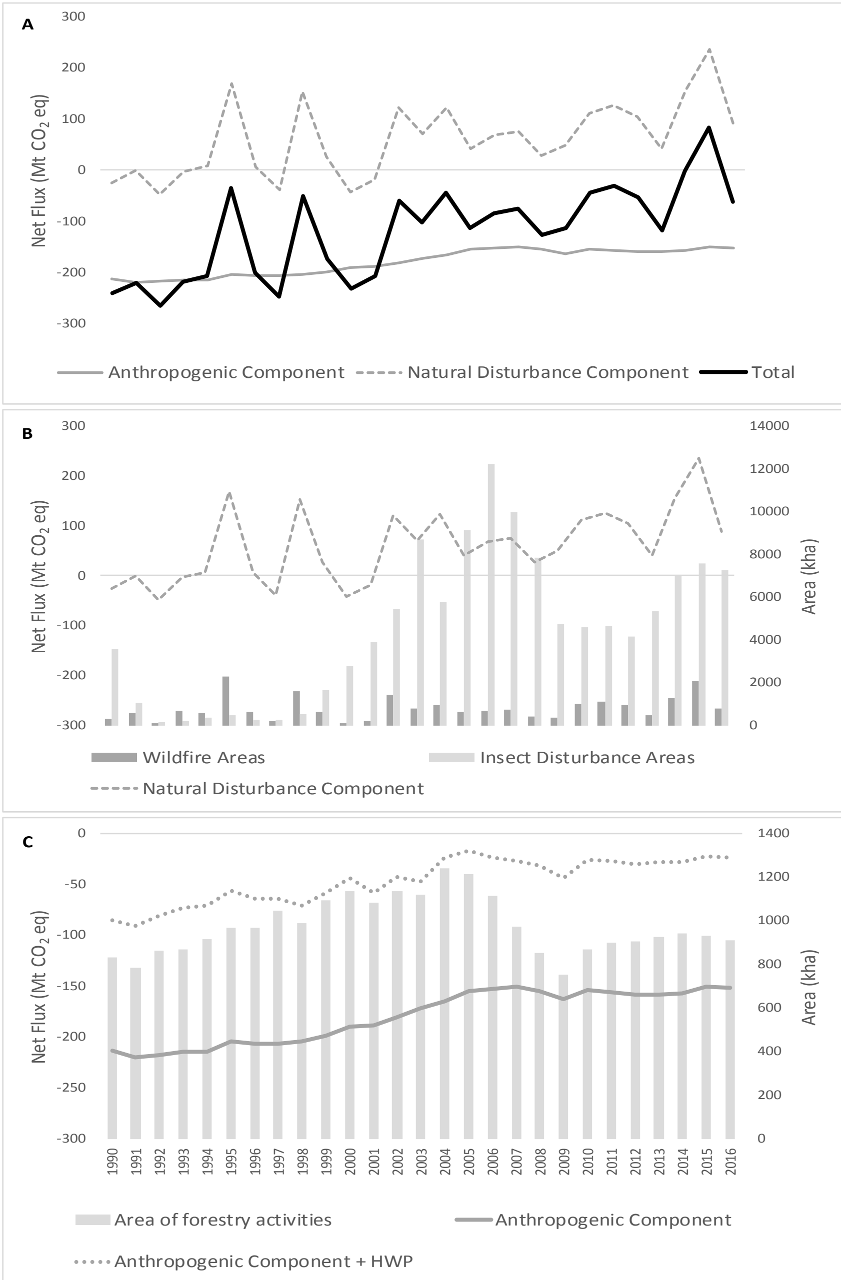


Figure 2.7C: Example of the separation of Canada's FL-FL emissions and removals into those occurring on lands dominated by natural disturbance impacts and those occurring in the remaining managed forest (A). Note the high IAV in the natural disturbance fluxes (up to 250 Mt CO_2e/yr) (B) that are related to the area affected by natural disturbances (wildfires and insects) and the low IAV in the anthropogenic fluxes (C) that are related to the areas of forestry activities (e.g. clearcutting, partial cutting). Fluxes in C are shown with (solid line) and without (dashed line) the emissions from harvested wood products. Data from Canada's 2018 National Inventory Report (NIR 2018) and figure from Kurz et al. in review).

New - BOX 2.2L: Methodology based on the 2013 IPCC KP Supplement[20]

Forests of country Z are prone to wildfires that in years with extreme weather conditions, i.e. drought, especially if combined with strong winds, may cause large emissions from biomass burning and cause high IAV in the net CO_2 balance. 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. Consequently, emissions from wildfires have both an anthropogenic and a natural component.

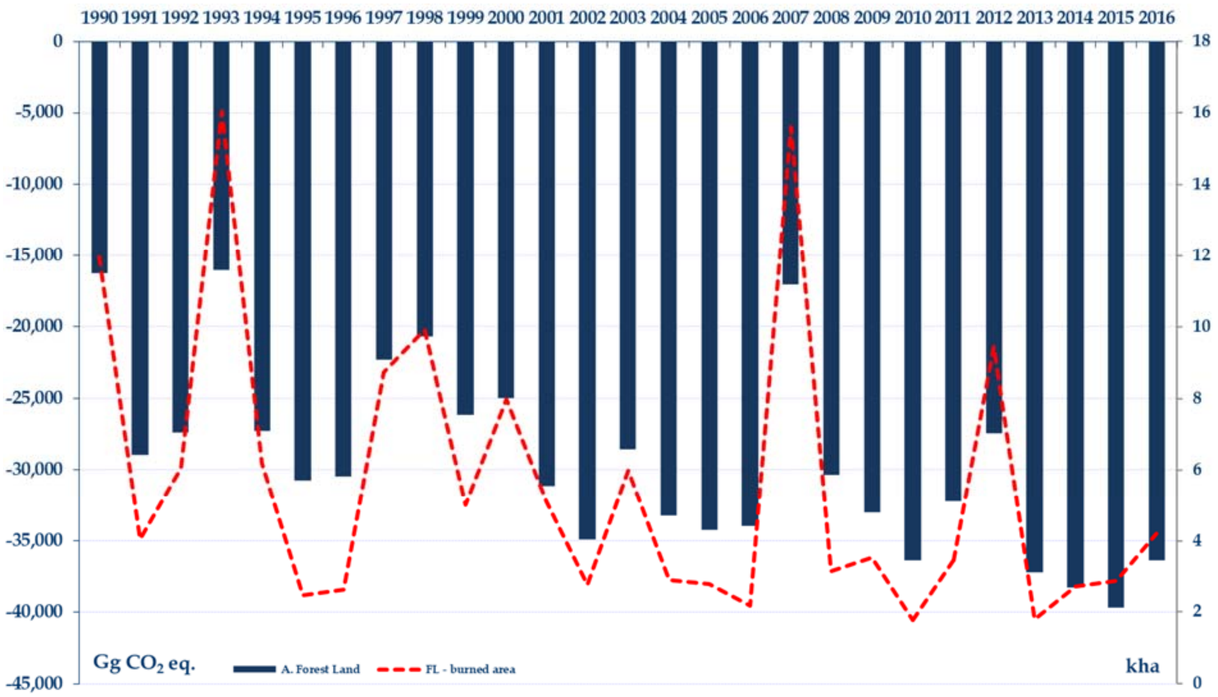


Figure 2.7D: Time series of managed forest land total GHG net emission (anthropogenic + natural disturbance (ND) and area burnt. Bars (left Y-axis) represent annual total net GHG emission (CO_2e) from managed forest land. The coefficient of variation of the time series is 0.224. The dashed red line (right Y-axis) represents the area burnt.

To disaggregate the natural component of emissions and removals from wildfires, the country builds its national definition of natural disturbances from that contained in the 2013 IPCC KP Supplement: *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 forests 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.

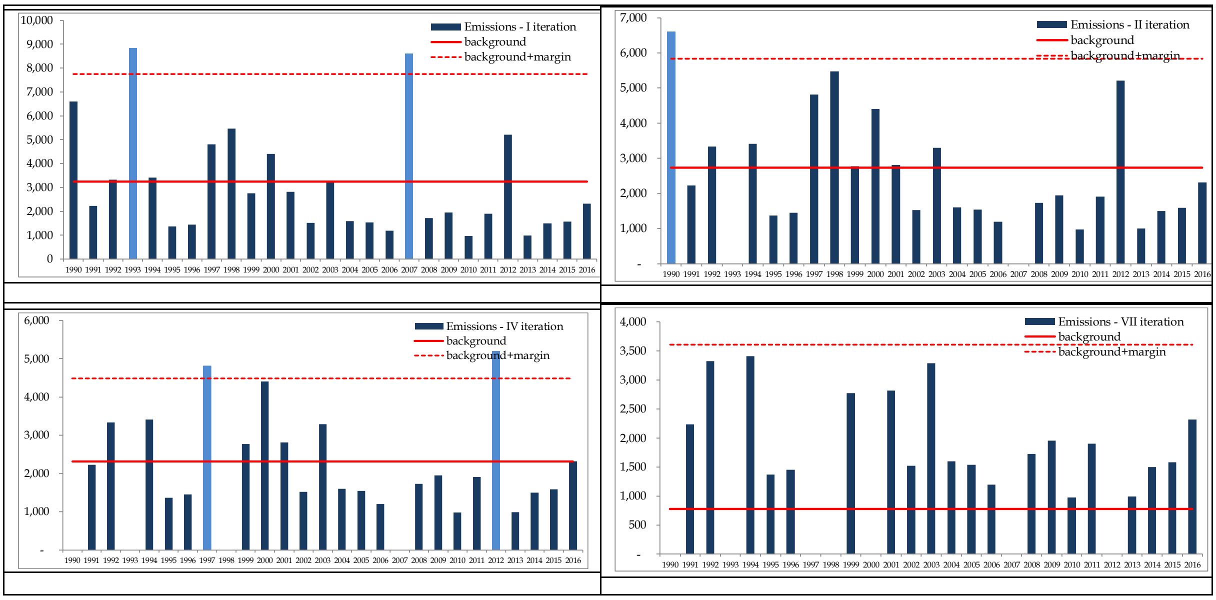
To identify wildfires that cause significant emissions and are beyond the control of the country's fire management system and are therefore considered natural disturbances, the country looks for statistical outliers that fall outside the 95% confidence interval of the variability of historical time series of the annual GHG emissions from wildfires[21], the distribution of which is assumed to be normal. An outlier value in this approach is considered as the signal of a disturbance event that is too unlikely to have been generated by anthropogenic causes alone and includes therefore a natural component.

[20] The presented methodology is based on that in Chapter 2.3.9 of the 2013 IPCC KP Supplement, although it addresses in the reporting the legacy of emissions and subsequent removals from pre-1990 natural disturbances, while the KP method addresses it in the accounting.

[21] 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.

In practice, first a historical time series of annual emissions[22] from wildfires is constructed starting from 1971, i.e., the base year (1990) of the national GHG inventory of the country minus 20 years. Then, using an iterative process, outliers (if any) that are larger than the mean plus two times[23] the standard deviation are removed from the time series in successive iterations.

Figure 2.7E: Iterative process to calculate the background level and margin (i.e. 95% CI) used to identify years in which area burned exceeded the mean plus two standard deviations. The time series extends back to 1971 and only iterations that affect 1990 or later years are shown.



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) exclude all the outliers found. Based on these statistics, natural disturbances are those that occur in years when the total direct 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 direct CO_2 emissions (F) and total subsequent CO_2 removals[24] (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[25] 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 fact that conversion of burnt forests to other land uses does not occur because law forbids it and that post-fire management activities are aimed at rehabilitating the same 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[26] 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).

[22] 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

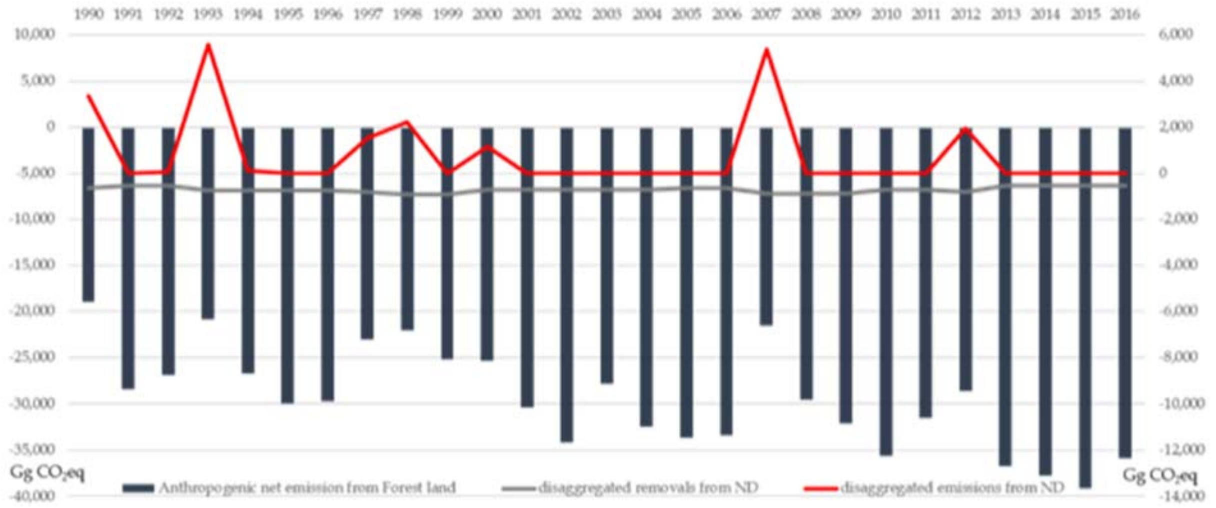
[23] This is an approximation of Student's t value for data series with number of data>=30.

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

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

[26] This means that in any year Y of the GHG inventory 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 achieved yet their pre-disturbance level of C stocks.)

Figure 2.7F: Time series of managed forest land GHG net emissions. Bars (left Y-axis) represent annual anthropogenic GHG net emissions (CO_2e) from managed forest land. The coefficient of variation of the time series is 0.184. The two lines (right Y-axis) represent the disaggregated emissions and removals from natural disturbances.



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

Transparency of reported fluxes can be increased through the optional disaggregation of emissions and removals into those that are due to anthropogenic impacts and those due to natural impacts, as well as their totals. 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 and papers therein), but separating the emissions and removals on managed lands that are attributable to natural disturbances and subsequent removals is a helpful first step.

Box 2.2M describes a possible approach to reporting three categories of emissions and removals:

1. From natural disturbances,
2. From anthropogenic activities, and
3. The total of the previous two categories.

The first category includes direct emissions from natural disturbances, delayed emissions from dead organic matter that was added by the disturbance to the already existing DOM pools and subsequent net removals that are the balance of removals associated with biomass growth following the natural disturbance. It is methodologically challenging to separate emissions from dead organic matter that was created by the disturbance from emissions resulting from the decay of DOM that was present prior to the disturbance, or has been added after the disturbance. However, it is possible to estimate the amount of biomass carbon that was transferred from live to dead organic matter pools, from where it will subsequently decay.

The second category includes emissions and removals that are from human activities calculated as the difference between total emissions and removals minus those from natural disturbances. The third category represents the emissions and removals that are the aggregated fluxes from the first two categories and is reported under the current MLP assumption.

Providing optional estimates of the emissions and removals associated with natural disturbances greatly reduces the inter-annual variability of the anthropogenic emissions and removals (see country examples in Boxes above) as demonstrated in recent national GHG reports (Government of Australia, 2017, Environment and Climate Change Canada 2018).

Example of a reporting table that shows the first and second order approximations of the anthropogenic emissions and removals on managed lands. The second order approximation is derived by subtracting from the first order approximation of the net emissions (the MLP) those emissions and removals that are attributed to natural disturbances.

NEW - BOX 2.2M

EXAMPLE OF THE TABLE FORMAT THAT COULD BE USED FOR VOLUNTARY DISAGGREGATION OF REPORTED FLUXES ON MANAGED LANDS DUE TO ANTHROPOGENIC AND NATURAL DISTURBANCES, AND THEIR TOTALS.

Land-use category	**e.g. Forest land remaining forest land**					
Years		**Start year**	**…**	**…**	**…**	**Inventory year**
Annual area of natural disturbances (kha)[27]						
Area subject to natural disturbances (kha)[28]						
Carbon stock change	Gains					
	Losses					
	Net					
non-CO_2 fluxes	Emissions					
CO_2-e	Total					
Remaining area of managed land (kha)						
Carbon stock change	Gains					
	Losses					
	Net					
non-CO2 fluxes	Emissions					
CO_2-e	Total #					
Total area (kha)						
Carbon stock change	Gains					
	Losses					
	Net					
non-CO_2 fluxes	Emissions					
CO_2-e	Total *					

This is the "refined MLP flux", i.e. the second order approximation of the anthropogenic emissions and removals

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

<u>Transparency:</u>

For those countries that choose to refine MLP flux estimates by disaggregation, it is *good practice* to provide information that describes the approaches and methods that are implemented to identify, quantify and disaggregate natural disturbance emissions and subsequent removals.

27 Report here the area of natural disturbance in the year it first occurs

28 Report here the cumulative area the has been subject to natural disturbances up to and including the current inventory year, minus the area of natural disturbances on which past emissions are considered to be balanced by subsequent removals.

It is *good practice* to include the following information:

- The **types** of natural disturbances for which emissions and subsequent removals are identified, quantified and disaggregated within MLP reporting (see Box 2.2I).
- 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 may be demonstrated by providing information to show that the disturbances were **"**not materially influenced by, and beyond the control of, a country".

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

- Reducing the likelihood of the disturbance occurring, by preventive measures or modifying factors related to the occurrence or propagation of the disturbance. Examples include public information campaigns or fire bans during high-risk fire seasons. Some of the actions taken in this regard may themselves cause emissions, which need to be estimated as part of the management practice. For example, thinning to increase stand stability against storm damage, prescribed burning to reduce the amount of combustible material, or introduction of firebreaks to make the spread of fire less likely.
- Managing or controlling the disturbance during its occurrence. This may be facilitated through the implementation of monitoring programs and early warning systems, firefighting operations, integrated coordination with fire squads, etc.

Depending on national circumstances, particularly the organizational, administrational and governance responsibilities, examples of transparent and verifiable information demonstrating these efforts could include, but are not necessarily limited to:

- A national or sub-national (regional, provincial, community) level strategy, a forest policy, forest management plan or fire management policy or plan that is valid and enforced for the region where the disturbance occurred, and that defines a national or sub-national strategy for managing the types of natural disturbance that led the country to apply the provision for natural disturbance;
- Information showing that the country took practicable efforts to manage or control the individual disturbances (for example, expenditures on the fire suppression effort and/or the incident management plans for the disturbance, and their relationship to total budget for forest management).
- A description of 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 (see above).
- The methods by which fluxes are disaggregated from total MLP fluxes.
- For lands subject to ND, documentation on how subsequent land-use change (e.g., deforestation, cropland conversion), if any, is identified and how GHG fluxes previously disaggregated as associated with natural disturbances are re-assigned following land-use change?
- Documentation on the manner in which emissions, and subsequent removals, associated with human activities (which do not cause a land-use change, such as salvage logging and site rehabilitation) that occur after the natural disturbance event, are estimated and reported.

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ANNEX 2A.1 Default Mineral Soil Reference C Stocks

This is a new section.

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 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 guidelines.

The following equation was used to compute SOC stocks:

$$T_d = \sum_{i=1}^{k} \rho_i P_i D_i \left(1 - S_i\right) \qquad [1]$$

where T_d is the total amount of organic carbon over depth, d, (in kg m^{-2}), ρ_i is the bulk density of layer i (Mg m^{-3}), P_i is the proportion of organic carbon in layer i (g C Kg^{-1}), D_i is the thickness of the layer (m), and S_i is the volume of the fraction of fragments >2 mm. Gaps in bulk density and coarse fragment >2mm content data were filled using taxo-tranfer 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 Supporting Material for the Estimation of Soil Carbon Stock Change from Biochar Amendments to Mineral Soils

This is new guidance.

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 300 °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 300°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 above 300°C (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 20% after pre-drying; in comparison, wet slurries typically have liquid water contents above 80%.

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Priming of native soil organic carbon by biochar amendments

Mineralisation of native soil organic carbon is on average reduced by 4% (95% CI = -8.1–0.8%) 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.

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Nitrous oxide emissions from soil after biochar amendments

Meta-analyses have found that nitrous oxide emissions are on average reduced between 54% (Cayuela *et al.*, 2014) to 0% (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.*, 2009).

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.

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Calculation of default values for F_{perm_p}

The default values for F_{PERM_p} were calculated from field and laboratory studies for biochars made under different conversion conditions after a comprehensive survey of the literature (See data sources below). The amount of biochar carbon remaining after 1000 years was conservatively estimated by fitting a two-pool double-exponential model to only those datasets that exceeded one year and allowed a two-pool model to be fitted following the rationale outlined by Lehmann *et al.*, (2015). The F_{PERM_p} estimate was also adjusted for CH_4 and N_2O emissions occurring during the pyrolysis and gasification processes.

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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 are 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 carbon 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 carbon 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 carbon into the soil column as dissolved or colloidal organic carbon (Lehmann and 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 carbon in organic soils.

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ANNEX 2A.3 Parameterisation of Three-Pool Steady-State C Model for Mineral Soils: Tier 2 Method

The Tier 2 steady-state mineral soil C model was parameterised using Bayesian methods after evaluating the sensitivity of the model parameters. The studies that were used to evaluate model sensitivities and parameterise the model are given in Table 2A.3-1.

TABLE 2A.3-1.
STUDIES THAT WERE USED TO EVALUATE THE MODEL SENSITIVITIES AND PARAMETERISE THE THREE-POOL STEADY STATE MODEL MINERAL SOILS

References	Site Location	Length of Study (years)	Treatments
Halvorson et al. 1997	Akron, CO, USA	25	Till
Vanotti et al. 1997	Arlington, WI, USA	34	MN
Dimassi et al. 2013	Boigneville, France	41	Till
Juma et al. 1997	Breton, AB, Canada	62	MN, ON
e-RA 2013; Glendining 2013; Jenkinson 1990	Broadbalk, Rothamsted, UK	153	MN, ON
Pierce and Fortin 1997	East Lansing, MI, USA	12	Till, CC
e-RA 2013; Glendining 2013; Jenkinson and Johnston 1977	Hoosefield, Rothamsted, UK	146	MN, ON
Dick et al. 1997	Hoytville, OH, USA	42	CR, Till
Campbell et al. 1997	Indianhead, SK, Canada	35	MN, CR
KBS LTER 2017; Collins et al. 2000	Hickory Corners, MI, USA	7	Till
Díaz-Zorita et al. 2004	General Villegas, Argentina	25	Till
Huggins and Fuchs 1997	Lamberton, MN, USA	32	MN
Janzen et al. 1997	Lethbridge, AB, Canada	41	MN, CR
Janzen et al. 1997	Lethbridge, AB, Canada	80	CR
Marchado 2003; Rasmussen and Smiley 1997	Pendleton, OR, USA	64	MN, ON
Machado et al. 2008; Marchado 2003; Rasmussen and Smiley 1997	Pendleton, OR, USA	55	MN, Till
Dick et al. 1997	South Charleston, OH, USA	29	Till
Küstermann et al. 2013	Scheyern, Germany	12	Till
Maillard et al. 2018	Swift Current, SK, Canada	30	Till, CR
Skjemstad et al. 2004; Schultz 1995	Tarlee, Australia	20	CR
Gregorich et al. 1996	Woodslee, ON, Canada	36	MN
Dick et al. 1997	Wooster, OH, USA	31	CR, Till

MN = Mineral nitrogen additions; ON = organic nitrogen additions; Till = Tillage change; CR = Crop Rotations; CC = Cover Crops

The sensitivity analysis was based on a method developed by Sobol (2001). We evaluated all parameters except for the temperate effect on decomposition (Equation 2.26F) and moisture effects on decomposition (Equation 2.26G). The parameters in these functions were highly correlated so we only evaluated one parameter from each function (t_{opt} for Equation 2.26F and w_1 for Equation 2.26G). A bootstrap sampling method was used to evaluate the total global sensitivity index of the parameters given the log-likelihood value of the mismatch between the model output and the observed data. This information was used to determine if the sample size was sufficient for ranking the sensitivity of the parameters (i.e., minimising the variance enough on the index values to avoid Type

1 error). The sensitivity analysis was conducted in R using the Sensitivity Package (Pujol, Iooss, & Janon, 2017). The results are given in the Table 2A.3-2.

TABLE 2A.3-2
SENSITIVITY OF MODEL PARAMETERS, PARAMETER VALUES AND MINIMUM AND MAXIMUM VALUES FOR THE THREE-POOL STEADY STATE MODEL FOR MINERAL SOILS

Parameter	Practice	Sensitivity	Value (min, max)
$till_{fac}$	Full-till	0.001	3.036 (1.4, 4.0)
	Reduced-till	<0.001	2.075 (1.0, 3.0)
	No-till	n/a[1]	1
w_s	All	0.003	1.331 (0.8, 2.0)
k_{fac_a}	All	<0.001	7.4
k_{fac_s}	All	0.005	0.209 (0.058, 0.3)
k_{fac_p}	All	0.015	0.00689 (0.005, 0.01)
f_1	All	0.032	0.378 (0.01, 0.8)
f_2	All	0.016	0.368 (0.007, 0.5)
f_3	All	0.003	0.455 (0.1, 0.8)
f_5	All	0.020	0.0855 (0.037, 0.1)
f_6	All	0.040	0.0504 (0.02, 0.19)
f_7	All	<0.001	0.42
f_8	All	<0.001	0.45
t_{opt}	All	0.960	33.69 (30.7, 35.34)
t_{max}	All	n/a[2]	45

[1] No-till cultivation factor is fixed at a value of 1 based on the model formulation.
[2] The maximum temperature for decomposition was not evaluated because it was highly correlated with the temperature optimum for decomposition.

Bayesian parameterisation techniques were used to determine the probability distributions of the most sensitive parameters, which included parameters with a sensitivity greater than 0.001 (Table 2A.3-2). However, the $till_{fac}$ parameter for reduced-till is included because the parameter for full-till was included. Sampling-importance resampling was used to generate a joint posterior distribution (Rubin, 1998). This approach includes two steps, a) drawing independent random samples from a known prior distribution, and b) resampling the initial draws from step (a) based on importance sampling weights for individual parameter sets. Samples are more likely to be maintained in the posterior distribution with higher likelihoods (Smith & Gelfand, 1992). Uniform priors were selected with an initial sample size $n = 1{,}000{,}00$ and a re-sample size $m = \sqrt{n}$, i.e., 1000, which allows for distributional convergence in the posterior distribution (Givens & Hoeting, 2005). The final posterior distribution was estimated as a truncated multivariate distribution under the assumption that parameter values should not exceed the minimum and maximum values in the posterior distribution. The resulting parameters are given in Table 2A.3-2 and the covariance matrix is given Table 2A.3-3.

TABLE 2A.4-3
COVARIANCE MATRIX FOR THE THREE-POOL STEADY STATE MODEL FOR MINERAL SOILS

	$till_{fac}$ - CT	$till_{fac}$ - RT	w_{par}	k_{fac_s}	k_{fac_p}	f_1	f_2	f_3	f_5	f_6	t_{opt}
$till_{fac} - CT$	0.3353436	-0.0007128	0.0124072	0.0077939	0.0000277	0.0007889	-0.0010958	-0.0024497	0.0001000	0.0015558	0.0387919
$till_{fac} - RT$	-0.0007128	0.3239992	-0.0167975	0.0008191	-0.0000013	0.0041484	0.0020256	0.0068887	0.0000775	-0.0017836	0.0047429
w_{par}	0.0124072	-0.0167975	0.1486482	-0.0005654	-0.0001156	0.0084023	0.0055629	-0.0033270	0.0004484	0.0011228	-0.0389749
k_{fac_s}	0.0077939	0.0008191	-0.0005654	0.0032024	0.0000244	0.0022843	0.0015645	0.0008130	-0.0001062	-0.0002235	0.0051276
k_{fac_p}	0.0000277	-0.0000013	-0.0001156	0.0000244	0.0000016	0.0000217	0.0000186	0.0000116	0.0000033	0.0000077	0.0002567
f_1	0.0007889	0.0041484	0.0084023	0.0022843	0.0000217	0.0051767	0.0021790	0.0023559	-0.0001210	-0.0004680	-0.0086628
f_2	-0.0010958	0.0020256	0.0055629	0.0015645	0.0000186	0.0021790	0.0099681	-0.0049865	0.0000755	-0.0005823	-0.0139913
f_3	-0.0024497	0.0068887	-0.0033270	0.0008130	0.0000116	0.0023559	-0.0049865	0.0405470	-0.0001415	0.0001638	-0.0274010
f_5	0.0001000	0.0000775	0.0004484	-0.0001062	0.0000033	-0.0001210	0.0000755	-0.0001415	0.0001479	-0.0000365	-0.0009000
f_6	0.0015558	-0.0017836	0.0011228	-0.0002235	0.0000077	-0.0004680	-0.0005823	0.0001638	-0.0000365	0.0007861	-0.0057748
t_{opt}	0.0387919	0.0047429	-0.0389749	0.0051276	0.0002567	-0.0086628	-0.0139913	-0.0274010	-0.0009000	-0.0057748	0.4347643

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