Good Practice Guidance for Assessing UN Sustainable Development Goal Indicator 15.3.1: Proportion of land that is degraded over total land area

Annex 3: Carbon stocks, above and below ground

DRAFT

Contents

1 Definition and Concepts

Land degradation is the reduction or loss of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes arising from human activities.

Land cover has been defined by the UN Food and Agriculture Organisation (FAO) as the "*observed (bio) physical cover of the earth's surface"* (Latham et al. 2014). To some extent land cover is one of the most easily detectable properties of the earth's surface and has been used as an important indicator of change, both human induced and natural. However, at the fine scale, land cover can be a complex arrangement of different vegetation and abiotic components. For example a given land unit may include vegetation with a soil substrate. The vegetation may include a community of woody and non-woody species arranged in a complex structure both horizontally and vertically. Land cover is the description of these components in a way that has meaning at the spatial unit of interest and in the thematic context being considered. Thus, land cover is categorised in different ways depending on the application.

Land productivity is the biological productive capacity of the land, the source of all the food, fibre and fuel that sustains humans. Land productivity points to long-term changes in the health and productive capacity of the land and reflects the net effects of changes in ecosystem functioning on plant and biomass growth (UNSTATS 2016).

Carbon stock is the quantity of carbon in a pool (i.e. a system which has the capacity to accumulate or release carbon). Ecosystem carbon pools, as defined in IPCC (2003, Table 3.1.2), are biomass (aboveground biomass and belowground biomass), dead organic matter (dead wood and litter, above and below ground), and soil (soil organic matter).

Total carbon stock is the quantity of carbon in all of the ecosystem carbon pools i.e. aboveground biomass, belowground biomass, dead wood, litter and soil.

Aboveground biomass is all biomass of living vegetation, both woody and herbaceous, above the soil including stems, stumps, branches, bark, seeds, and foliage.

Belowground biomass is all biomass of live roots. Fine roots of less than (suggested) 2 mm diameter are often excluded because these often cannot be distinguished empirically from soil organic matter or litter.

Litter is all non-living biomass with a size greater than the limit for soil organic matter (suggested 2 mm) and less than the minimum diameter chosen for dead wood (e.g. 10 cm), lying dead, in various states of decomposition above or within the mineral or organic soil. This includes the litter layer as usually defined in soil typologies. Live fine roots above the mineral or organic soil (of less than the minimum diameter limit chosen for below-ground biomass) are included in litter where they cannot be distinguished from it empirically.

Dead wood is all non-living woody biomass not contained in the litter, either standing, lying on the ground, or in the soil. Dead wood includes wood lying on the surface, dead roots, and stumps, larger than or equal to 10 cm in diameter (or the diameter specified by the country).

Soil organic matter includes organic carbon in mineral and organic soils (including peat) to a specified depth chosen by the country and applied consistently through the time series. Live fine roots (of less than the suggested diameter limit for below-ground biomass) are included with soil organic matter where they cannot be distinguished from it empirically (IPCC 2003).

Soil organic carbon (SOC) is the amount of carbon stored in soil and is a component of soil organic matter.

Soil organic carbon stock is the mass of soil organic carbon per unit area for a reference depth. The reporting standard is SOC stock in tonnes of organic C per hectare to a depth of 0-30 cm (IPCC, 1997). Determination of soil organic C stock requires measurements of soil organic C concentration, soil bulk density and gravel content:

$$SOC\ stock = SOC_m \times \rho \times \left(1 - \frac{g}{100}\right) \times d \tag{1}$$

Where: SOC_m is the mass of organic carbon in the soil (%), ρ is the soil bulk density (g cm^{-3}), g is the gravel content (g g^{-1}), and d is the thickness of the layer (cm).

Note: Quantifying SOC stock at fixed depths as the product of soil bulk density, depth and organic carbon concentration, provides a simple approach for reporting change in SOC stock. However, in the context of land use/management change, this method can systematically overestimate SOC stocks where bulk densities have increased (e.g. under changes from full to minimum tillage in croplands). Where bulk densities differ between managements or over time periods, more accurate estimates of SOC stock can be derived based on quantification in equivalent soil masses (ESMs; see Wendt and Hauser, 2013). This ESM approach is gaining uptake; for example, the approach is being recommended and used in the Australian soil carbon method under the Emissions Reduction Fund (DotE 2014a, Australian Government 2014).

Indicators are variables that reflect a process of interest.

Metrics are measures that are used to quantify or assess indicators/sub-indicators.

Monitoring will be based on evaluating the significant changes in the sub-indicator via the associated metric.

Baseline (SOC_{t0}) carbon stocks are required to enable an assessment of the initial status of the sub-indicator in *absolute* terms. January 2016 is considered the nominal start date for setting the baseline for the 15.3 target. Specifically, this means that it is good practice to determine the baseline for carbon stocks in the SOC pool prior to the 1st of January 2016. This start date is referred to as t_0 and future reporting is referred to as $t_1,\ldots,t_n$. The baseline should be quantified over an extended period prior to t_0, rather than using the values of a single year to take account of climatic variation. We recommend the baseline period should be 10-15 years. This agrees with recommendations for monitoring progress towards the Land Degradation Neutrality target (Orr et al. 2017) and is comparable to the historical periods used for REDD+ Forest Reference Emission Levels.

Monitoring Period (t_n) is the time period over which the metric is measured (yr). The 15.3 target date (specified as 2030) is referred to as t_1. The metric should be quantified for the monitoring period using the same methods employed for the baseline period. Potential intermediate monitoring points have been suggested on an interval of 4 years for land degradation neutrality (Orr et al 2017), noting that for land cover, available data sets cover epochs of five years. In the context of SOC change, this frequency is likely to be too short to detect change where an on-ground monitoring approach is used. Even in landscapes where soil carbon is changing, the minimum period for reliable detection will rarely be less than 10 years (e.g. Smith 2004); the obvious case being when land clearing occurs. Thus although methods may allow for calculation of SOC stock change at shorter intervals, the results are unlikely to be meaningful in the context of assessing degradation.

Change in carbon stocks, is defined as the change in C stocks between the monitoring period (t_n) and the baseline (t_0), in the units of t C ha^{-1}.

False positive refers to a case where carbon stocks have increased for a land use transition that is actually considered land degradation, such as woody encroachment (i.e., land cover change from grassland to shrubland). Assessment of this type of exception (i.e., “false positive”) requires knowledge and interpretation at the local level (see Section 4.4).

Spatial feature refers to the spatial unit (e.g. watershed, polygon) at which degradation is reported on and may be a uniform land cover class or a mix of land cover classes.

2 Introduction

Carbon stocks reflect the integration of multiple processes affecting plant growth and the gains and losses from terrestrial organic matter pools. They are elementary to a wide range of ecosystem services and their levels and dynamics are reflective of land use and management practices. The aim of this Annex is to provide good practice guidance on methods for estimating the sub-indicator *change in carbon stocks above and below ground* in the context of assessing SDG indicator 15.3.1 "*the proportion of land that is degraded over the total land area*". As outlined in Decision 22/COP.11[1], *soil organic carbon stock* is the metric that will be used to assess carbon stocks above and below ground, and once operational, this metric will be replaced by *total terrestrial system carbon stock*. Therefore the main focus of this document is to provide approaches for estimating change in SOC stocks. Some guidance on approaches for estimating change in carbon stocks in other pools, particularly aboveground biomass, is also provided.

The methods outlined draw on global and regional datasets, whilst encouraging the use of national and sub-national information to estimate SOC stock change. The methods describe how to:

1. Set the baseline to determine the initial status of SOC stocks;
2. Detect change in SOC stocks, including validation/evaluation of results in the context of national circumstances; and
3. Derive the status of the carbon stocks sub-indicator by determining if there has been an increase, decrease or no change in SOC over the monitored period.

The choice of method used by a country to make these estimates will largely depend on the availability of data and analytical capability. Guidance is provided on global default approaches and national approaches, including on-ground monitoring.

Many of the processes affecting soil organic matter over the past century have been dominated by human management of vegetation (ITPS 2015). Changes in vegetation cover, including those in response to climate and to land use or management, influence SOC stocks by altering the rates, quality and location of plant litter inputs to soils. The default approach described here for estimating SOC stock is therefore strongly reliant on activity data from sub-indicator 1 – Land cover change (Annex 1). However, although change in SOC stocks is estimated based on known changes associated with changed land use and/or management, it is possible to obtain a different status of change (positive, negative, no change) to that of sub-indicator 1. This is because the status of a particular land cover change is a national decision for sub-indicator 1, with countries generating a land cover class transition matrix that identifies the processes (flows) that cause transition between land cover classes (Annex 1), but is derived from established relationships with SOC stocks for this sub-indicator.

3 Method of computation

In this section we outline the steps required in estimating the metric, change in SOC stocks, and computation of the final sub-indicator. Broadly, the following steps are required:

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[1] http://www.unccd.int/en/programmes/Science/Monitoring-Assessment/Documents/Decision22-COP11.pdf

1. Estimation of an average SOC stock (and 95% confidence interval) for each identified spatial feature for the baseline period.
2. Estimation of an average SOC stock (and 95% confidence interval) for each identified spatial feature for the monitoring period.
3. Comparison of SOC in the monitoring period with the average baseline SOC for the same spatial feature.
4. Assessment of whether there has been an increase, decrease or no change in SOC for each identified spatial feature, and assignment of whether the area is degraded or not degraded.
5. Identification and justification of potential “false positives” and explainable anomalies.

The rationale and interpretation behind the methods, and a discussion of data sources are outlined in subsequent sections.

3.1 Choice of Method

The three-tiered structure outlined by the IPCC (2006) for data and methods is a useful model to consider here. This includes three tiers of data from least to most detail. In the case of the SOC stocks metric, these tiers might include:

1. Globally-available land cover classes and global defaults for reference SOC stocks, change factors and emission factors.
2. Nationally-derived land cover classes and defaults for reference SOC stocks, change factors and emission factors specific to local conditions.
3. National data based on the integration of ongoing ground-measurement programs, earth observation data and models.

Factors such as the significance of the source/sink (proportional contribution to national inventory), available data, and analytical capability will determine selection of the tier. The IPCC recommends that it is good practice to use higher tiers for the measurement of significant sources/sinks.

Progressing from Tier 1 to Tier 3 generally represents a reduction in the uncertainty of GHG estimates, though at a cost of an increase in the complexity of measurement processes and analyses. Lower Tier methods may be combined with higher Tiers for pools which are less significant. There is no need to progress through each Tier to reach Tier 3. In many circumstances it may be simpler and more cost-effective to transition from Tier 1 to 3 directly than produce a Tier 2 system that then needs to be replaced. Data collected for developing a Tier 3 system may be used to develop interim Tier 2 estimates.

The default methodologies described below draw on the significant body of work of the Intergovernmental Panel on Climate Change (IPCC) which has published the methodological guidance that countries have agreed to use in estimating greenhouse gas inventories for reporting to the United Nations Framework Convention on Climate Change (UNFCCC). Of most relevance to the carbon stocks sub-indicator is the 2003 Good Practice Guidance for Land Use, Land-use Change and Forestry (IPCC 2003), the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006), which consolidates and updates previous guidance, and the 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands (IPCC 2014), which fills gaps and extends the 2006 Guidelines and updates emission/removal factors including on wetlands and drained soils. The IPCC will produce a Methodology Report by 2019 as a supplement (not full revision) to be used in conjunction with the 2006 IPCC Guidelines[2].

The maximum equilibrium carbon content for a soil at a given location is determined by environmental factors such as rainfall, evaporation, solar radiation and temperature. A lack of nutrients and a limited capacity to store and supply water in a soil can reduce this potential maximum, as can other constraints to plant growth (e.g. toxicities). Within these constraints, the actual amount of organic carbon contained in a soil will be determined by the balance between carbon inputs and losses, which are strongly influenced by land management and soil type. Agricultural practices that alter rates of carbon input (e.g. plant residues, compost, mulch) or loss (e.g. removal of crops, cultivation) change the stock of soil organic carbon.

The IPCC defaults for SOC stocks use 'strata' based on factors such as land use and land management. While 'land use' refers essentially to the six IPCC categories (i.e. Forest Land, Cropland, Grassland, Wetlands, Settlements, Other Land), land management refers to stratification of the main land uses. For mineral soils, land management is a required level of stratification for consistency with IPCC factors for SOC stock change, while the defaults for reference stock, i.e. under native vegetation, are based on default climate regions and soil types (Note: default IPCC soil classes are defined in Volume 4 of the IPCC 2006 Guidelines, Annex 3A.5; IPCC default soil classes derived from the Harmonized World Soil Data Base are available at http://www.isric.org/data/ipcc-default-soil-classes-derived-harmonized-world-soil-data-base-ver-11; see Section 5.1). However, it should be noted that for 'higher tier' methods, soil type may not be a useful stratification. For organic soils (with high organic content, see Section 3.4 for definition), IPCC default coefficients stratify the areas by climatic region. Here we use the term 'homogeneous land cover unit' instead of the IPCC term 'stratum' to avoid confusion with land cover terminology. All land in a homogeneous land cover unit should have common biophysical conditions and management history over the time period to be treated together for analytical purposes. In the context of the calculations described below, a 'spatial feature' is the spatial unit (e.g. watershed, polygon) at which degradation is reported on and is likely to be a mix of land cover classes, while a homogeneous land cover unit is a uniform land cover class (IPCC 'stratum') within a spatial feature.

3.2 Estimating baseline SOC stocks

Estimation of SOC in the baseline period (SOC_{t_0}) for a given spatial feature is based on a national-level assessment of carbon stocks for the 10-15 year period preceding 1st of January 2016. For land cover, global data sets are now available annually (e.g. European Space Agency's Climate Change Initiative Land Cover (CCI-LC) dataset (see Annex 1). A historical averaging approach to minimise the effects of seasonal and inter-annual climate variability is the simplest option for estimating the baseline. The absolute numerical value of the metric for each spatial feature is quantified by averaging across an extended (10–15 year) period prior to t_0, at annual or less frequent periods

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[2] IPCC (2016). Report of IPCC Scoping Meeting for a Methodology Report(s) to refine the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Eds: Ngarize, S., Kranjc, A., Baasansuren, J., Shermanau, P. Report of the IPCC Scoping Meeting, Pub. IGES, Japan. Available at: http://www.ipcc-nggip.iges.or.jp/public/mtdocs/pdfiles/1608_Minsk_Scoping_Meeting_Report.pdf

depending on data availability and resources. The issue of spatial disaggregation is discussed in Section 4.2.

The availability of annual land cover products also allow extrapolation of a trend fitted to historical data. This approach requires confidence that the past trend is likely to be representative of the future, otherwise frequent updating is needed, and is appropriate if there is a clear trend in historical data (GFOI 2016). However, Orr et al. (2017) state that comparing trends is not useful or appropriate in the context of assessing land degradation neutrality. They argue that only comparing trends with trends (rather than an absolute numerical value vs. an absolute numerical value) could lead to an unintended outcome where, for example, the metric could have increased from a low start point in 2000–2010, increased significantly from 2010-2015, but then declined a little from 2015–2030. The unintended outcome is that this would be labelled as declining when the magnitude of the change suggests otherwise. Thus only using the trend over the time period to assess degradation is not recommended. In section 3.8, we propose a hybrid approach of using the trend (or the direction of change) in the metric over the reporting period AND the magnitude of the relative change in carbon stocks between the baseline and the current estimate to assess degradation.

Rather than relying than on spatial analysis alone, most assessments of soil organic carbon change involve the integration of multiple lines of evidence from diverse sources such as field experiments, paired sites, monitoring sites, scientific studies, and land management surveys (e.g. ITPS 2015; SoE 2011). When deriving baseline estimates from ground-based measurements, the sampling design used must provide unbiased estimates of the mean SOC stock and the standard error of the mean (de Gruitjer et al. 2006; Chappell et al. 2013). Some examples of the types of data for SOC stock that could be used to inform a baseline are provided in Table 1.

Table 1. Types of data that could be used to derive a SOC stocks baseline.

Data type	Typical scale
Default values[1]	Global/regional/national
Soil maps	All scales
Historical point data	National/sub-national
Spatial monitoring data[2]	National/sub-national
Intensive monitoring data[3]	Sub-national
Experimental data[3]	Sub-national
Models[4]	Sub-national

[1] for reference stocks and stock change factors for land use, management and climate units;

[2] e.g. national grid;

[3] from ground-based sampling using conventional or sensing methods;

[4] calibrated/validated using ground measurements.

The choice of method (as described for the three IPCC tiers above) for estimating change in SOC stocks by a country will largely depend on the current, and likely future, data availability and will have implications for determining the SOC baseline. Baselines could be derived in two main ways:

1. As estimates of total SOC stocks for the particular land use/management stratification; or
2. As spatially-explicit baselines.

For 1, estimates could be derived from the global default method or using a national approach. The global default approach, where either default values are applied to the land stratification data from Earth Observation to derive the baseline stocks (or reference stocks, IPCC 2006) as described in the calculations in Section 3.4, or a global product such as SoilGrids250m (Hengl et al. 2017) is used to derive the baseline stocks (see Section 5.1). However, it is likely that these estimates will be subject to large uncertainty. Alternatively, a national approach where countries either: i) use the same linear equations as the global default method in conjunction with country-specific factors to improve the accuracy of the relative change factors, reference SOC stocks, climate regions, soil types, and/or land management classification systems, or ii) use high-resolution maps to improve the accuracy of the reference SOC stocks (e.g. in Australia, the 90 m grid SOC stock baseline (Viscarra Rossel et al. 2014) could be used). This is likely to reduce uncertainty in the estimates, but the variability of SOC stock needs to be accurately quantified (see Section 5.2).

For 2, when deriving a spatially-explicit baseline, the appropriate resolution would need to be defined. A spatiotemporal data-model assimilation approach that uses easily accessible Earth Observation data for the updating, but is underpinned by on-ground monitoring could be used (see Section 5.2).

3.3 Estimating SOC stocks in the monitoring year

Where a default approach is used, it is good practice to apply the same methods (equations) used for the estimation of baseline SOC stocks to estimate SOC stocks in the monitoring year. Where a national monitoring approach is used, it is good practice to use standardised spatial and temporal sampling for the estimation of both baseline SOC stocks and SOC stocks in the monitoring year (e.g. see de Gruitjer et al. 2006; Brus et al. 2014). This will enable consistent comparisons and assessment of whether SOC stocks are increasing, decreasing or remaining stable (i.e. no change). Application of the same equations for the monitoring time period (rather than the baseline period) will lead to estimates of SOC stock at the end of the monitoring period (SOC_{t_n}).

3.4 Default approach

Where country-specific data/capability are currently lacking, a default (‘Tier 1’) approach should be used. IPCC Tier 1 methods generally assume that the changes occur over 20 years and that land ceases to be in a conversion category 20 years after the conversion occurred. The influence of land use and management on SOC is very different in mineral versus organic soil types (for discussion, see Section 2.3.3, IPCC 2006). Therefore, separate guidance is provided for estimating carbon stock change in mineral soils and organic soils based on the IPCC good practice guidance and guidelines. Here we follow the definition of organic soils (Histosols) as provided in Annex 3A.5, Volume 4 of the IPCC 2006 Guidelines, which follows that in the World Reference Base for Soil Resources (FAO 1998). Using the three tier terminology of the IPCC, carbon stocks in organic soils are not explicitly computed using Tier 1 or Tier 2 methods (which estimate only annual C flux from organic soils, see below), but C stocks in organic soils can be estimated in a Tier 3 method (see IPCC 2006).

Where both mineral and organic soil types are present, the equation for estimating the change in SOC stocks (Eqn. 2) in a spatial feature is modified from Equation 2.24 in Chapter 2, Volume 4 of the 2006 IPCC Guidelines to exclude inorganic carbon stocks:

$$\Delta SOC = \Delta SOC_{mineral} - L_{organic} \tag{2}$$

Where:

ΔSOC = change in carbon stocks in soils in the spatial feature, t C ha^{-1};

$\Delta SOC_{mineral}$ = change in organic carbon stocks in mineral soils in the spatial feature, t C ha^{-1} (Note: to convert from the units of t yr^{-1} derived from Eqn. 3a to t ha^{-1} here, multiply by the number of years in the monitoring period and divide by the area of the spatial feature);

$L_{organic}$ = loss of carbon from drained organic soils in the spatial feature, t C ha^{-1}, (see Eqn. 4 below) (Note: to convert from the units of t yr^{-1} derived from Eqn. 4 to t ha^{-1} here divide by the area of the spatial feature and multiply by the number of years in the monitoring period);

Note: Most spatial features will not include organic soils.

3.4.1 Mineral Soils

The IPCC provides default (Tier 1) methods for estimating SOC stock changes on mineral soils which can be applied for this sub-indicator. Calculations use reference stocks and stock change factors for SOC. The reference SOC stocks, i.e. under native vegetation, are based on land areas that are stratified by climate regions and default soil types. The stock change factors are very broadly defined and include:

- a land-use factor (*FLU*) that reflects C stock changes associated with type of land use,
- a management factor (*FMG*) representing the main management practice specific to the land-use sector (e.g., different tillage practices in croplands), and
- an input factor (*FI*) representing different levels of C input to soil.

Each of these factors represents the change over a specified number of years, which can vary across sectors, but is typically invariant within sectors (e.g., 20 years for the cropland systems).

All land in a homogeneous land cover unit should have common biophysical conditions (i.e. climate and soil type) and management history over the time period to be treated together for analytical purposes. It will also be necessary to ensure that these units can be aggregated to default land cover classes. Many spatial features will have more than one homogeneous land cover class (particularly for soil type and management system). In such cases, spatially-weighted averaging is required.

Change in organic carbon stocks in mineral soils is estimated using Equation 2.25 in Chapter 2, Volume 4 of the 2006 IPCC Guidelines:

$$\Delta SOC_{mineral} = \frac{(SOC_0 - SOC_{(0-T)})}{D} \tag{3a}$$

and

$$SOC = \sum_{c,s,i}\left(SOC_{REF_{c,s,i}} \times F_{LU_{c,s,i}} \times F_{MG_{c,s,i}} \times F_{I_{c,s,i}} \times A_{c,s,i}\right) \tag{3b}$$

Where:

$\Delta SOC_{mineral}$ = change in carbon stocks in mineral soils in the spatial feature, t C yr^{-1} yr^{-1};

SOC_0 = soil organic carbon stock in the last year of a reporting time period, t C;

$SOC_{(0-T)}$ = soil organic carbon stock at the beginning of the reporting time period, t C;

SOC_0 and $SOC_{(0-T)}$ are calculated using Equation 3b, where the reference carbon stocks and stock change factors are assigned according to the land-use and management activities and corresponding areas at each of the points in time (time = 0 and time = 0-*T*);

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

D = time dependence of stock change factors which is the default time period for transition between equilibrium SOC values, yr. Commonly 20 years, but depends on assumptions made in computing the factors $F_{LU_{c,s,i}}$, $F_{MG_{c,s,i}}$ and $F_{I_{c,s,i}}$. If *T* exceeds *D*, use the value for *T* to obtain an annual rate of change over the reporting time period (0-*T* years);

c represents the climate zones that are present in a spatial feature;

s represents the soil types that are present in a spatial feature;

i = the set of management systems that are present in a spatial feature;

$SOC_{REF_{c,s,i}}$ = the reference carbon stock, t C ha^{-1};

$F_{LU_{c,s,i}}$ = stock change factor for land-use systems or sub-system for a particular land-use, dimensionless [Note: FND is substituted for FLU in forest soil C calculation to estimate the influence of natural disturbance regimes];

$F_{MG_{c,s,i}}$ = stock change factor for management regime, dimensionless;

$F_{I_{c,s,i}}$ = stock change factor for input of organic matter, dimensionless;

$A_{c,s,i}$ = land area of the homogeneous land cover unit being estimated, ha.

3.4.2 Organic soils

The basic methodology for estimating C emissions from organic (e.g., peat-derived) soils is to assign an annual emission factor that estimates the losses of C following drainage and/or fire (IPCC 2013 Wetlands Supplement). Specifically, the area of drained and managed organic soils under each climate type is multiplied by the associated emission factor to derive an estimate of annual CO_2 emissions. Losses from organic soils are estimated using an adaptation of Equation 2.2 in Chapter 2 of the IPCC 2013 Wetlands Supplement:

$$L_{organic} = L_{drainage} + L_{fire} \tag{4}$$

Where:

$L_{organic}$ = total emissions from organic soils for the spatial feature, t C yr^{-1};

$L_{drainage}$ = emissions from drained organic soils for the spatial feature, t C yr^{-1};

L_{fire}= emissions from burning of organic soils for the spatial feature, t C yr^{-1} Note: to convert from the units of t derived from Eqn. 6 to t yr^{-1} here divide by the number of years in the monitoring period.

Emissions from the drainage of peat soils are estimated as follows:

$$L_{drainage} = \sum_{c,n,d} \left(A_{drainage_{c,n,d}} \times EF_{drainage_{c,n,d}}\right) \tag{5}$$

Where:

$L_{drainage}$= annual on-site emissions/removals from drained organic soils in a land-use category, t C yr^{-1};

$A_{drainage}$ = land area of drained organic soils in a land-use category in climate domain *c*, nutrient status *n* and drainage class *d*, ha;

$EF_{drainage}$ = emission factors for drained organic soils, by climate domain c, nutrient status *n* and drainage class *d*, t C ha^{-1} yr^{-1}.

Default values for carbon dioxide, methane and nitrous oxide emissions should be taken from Tables 2.1, 2.3 and 2.5, respectively, in Chapter 2 of the 2013 IPCC Wetlands Supplement.

Emissions from peat burning are estimated in accordance with Equation 2.8, Chapter 2 of the IPCC 2013 Wetlands Supplement as follows:

$$L_{fire} = \sum_{f=1}^{F} \sum_{g=1}^{G} \left(\left(A_{burnt} \times P_{c,f} \times C \times G_{c,g}\right) \times 10^{-3}\right) \tag{6}$$

Where:

L_{fire} = Amount of CO_2 or non-CO_2 emissions from fire in the spatial feature, tonnes;

A_{burnt} = Area of peat burnt annually in the spatial feature, ha;

P = Average mass of peat burnt in the spatial feature for climate domain *c* and fire type *f* (t d.m. ha^{-1});

f 1, 2 …*F* fire types

C = combustion factor, dimensionless; For all organic soil fires, the default combustion factor is 1.0, since the assumption is that all fuel is combusted (Yokelson et al. 1997);

c represents the climate zones that are present in a spatial feature;

G_g = Emission factor in climate domain *c* for gas *g* (kg t^{-1} d.m. burnt);

g 1, 2, 3 ... *G* greenhouse gases including carbon dioxide, methane and nitrous oxide (unitless);

The value 10^{-3} converts L_{fire} to tonnes.

The amount of fuel that can be burnt is given by the area burnt annually and the mass of fuel available in that area. Default values are provided in Tables 2.6 and 2.7 of the IPCC 2013 Wetlands Supplement, Chapter 2. Due to limited data available in the scientific literature, organic soils have been very broadly stratified according to climate domain (boreal/temperate and tropical) and fire type (wild vs. prescribed).

3.5 National approach

Where possible, it is good practice for countries to use a national approach to reduce uncertainty, even if they are only able to better specify certain components of the default approach.

For mineral soils, under the simplest national approach (Tier 2), countries may choose to use the same linear equations as the default (Tier 1) method in conjunction with country-specific factors to improve the accuracy of the relative change factors, reference SOC stocks, climate regions, soil types, and/or land management classification systems. Country-specific values may be for all of these components, or any subset which would then be combined with default values. Reference soil C stocks can be determined from measurements, for example, as part of national soil survey and mapping activities. This will provide more representative values for an individual country and the ability to better estimate probability distribution functions that can be used in a formal uncertainty analysis (IPCC, 2003).

Reference stocks should be consistent across the land uses (i.e., Forest Land, Cropland, Grassland, Settlements, and Other Land). Accepted standards for sampling and analysis of SOC and bulk density should be used and documented (see further discussion in Section 5.2). Stock change factors can be estimated from long-term experiments or other field measurements (e.g. chronosequence studies) for a particular country or region. The depth of measurement and time frame over which the management difference has been expressed should be provided (IPCC 2006). For organic soils, Tier 2 approach for CO_2 emissions associated with drainage of organic soils incorporates country-specific information into the inventory to estimate the emissions using the same calculations as provided for Tier 1. Potential improvements may include: deriving country-specific emission factors, specifying climate regions considered more suitable for the country, or using a finer, more detailed classification of management systems attributed to a land-use category.

More advanced national methods which better capture annual variability in fluxes (Tier 3) may also be used. Such methods may include using calibrated and validated models, and/or developing a measurement-based inventory with a monitoring network to capture SOC stock changes. Tier 3 approaches for SOC 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 (IPCC 2006). Such approaches can address the non-linearity in transitions by using more advanced models, 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. Further detail is provided in Section 5.2.

3.6 Estimating relative change in SOC stock between two points in time

Once the baseline SOC stocks and the SOC stocks at the end of the monitoring period have been consistently estimated, the relative percentage change in SOC stocks (i.e. whether carbon stocks are increasing, decreasing or remaining the same) is calculated as:

$$r_{SOC} = \frac{(SOC_{t_n} - SOC_{t_0})}{SOC_{t_0}} \times 100 \qquad (8)$$

Where:

r_{SOC} = relative change in soil organic carbon for spatial feature (%);

SOC_{t_0} = baseline soil organic carbon stock for spatial feature (t C ha^{-1});

SOC_{t_n} = soil organic carbon stock at the end of the monitoring period for spatial feature (t C ha^{-1}).

3.7 Estimating uncertainty

It is good practice to report uncertainties in estimates and to minimise uncertainty as far as practical, even if these uncertainties are not used in a formal sense (i.e. in statistical tests; see Section 3.8). Here we briefly describe the IPCC guidance on how uncertainty is expressed in the default approach and methods for combining uncertainties to generate an overall uncertainty estimate. Guidance on how the individual uncertainties (in the areal estimates, change factors, emissions factors, etc.) are calculated is not provided here, but approaches to this are covered in detail elsewhere.

The IPCC Guidelines recommend the use of a 95% confidence interval, which is the interval that has a 95% probability of containing the unknown true value. Therefore it is good practice to report the 95% confidence interval with estimates of baseline SOC stocks and SOC stocks at the end of the monitoring period. This may also be expressed as a percentage uncertainty, defined as half the confidence interval width divided by the estimated value of the quantity multiplied by 100; Note that this uncertainty is twice the relative standard error (in %), a commonly used statistical estimate of relative uncertainty. Percentage uncertainty' is the main way that uncertainty is provided in the relevant IPCC default tables (see Section 6).

The default method for combining uncertainties is based on error propagation.

Where uncertain quantities are to be combined by multiplication, a simple equation (based on Equation 3.1, IPCC 2006) for the uncertainty of the product, expressed in percentage terms is:

$$U_{total} = \sqrt{{U_1}^2 + {U_2}^2 + \ldots + {U_n}^2} \qquad (9)$$

Where:

U_{total} = percentage uncertainty in the product of the quantities (half the 95% confidence interval divided by the total and expressed as a percentage);

U_i = percentage uncertainties associated with each of the quantities, $i = 1, \ldots, n$

Where uncertain quantities are to be combined by addition or subtraction, a simple equation (based on Equation 3.2, IPCC 2006) for the uncertainty of the sum, expressed in percentage terms is:

$$U_{total} = \sqrt{\frac{(U_1.x_1)^2+(U_2.x_2)^2+\cdots+(U_n.x_n)^2}{|x1+x2+\cdots xn|}} \qquad (10)$$

Where:

U_{total} = the percentage uncertainty in the sum of the quantities (half the 95 percent confidence interval divided by the total (i.e., mean) and expressed as a percentage). This term 'uncertainty' is thus based upon the 95 percent confidence interval;

x_i and U_i = the uncertain quantities and the percentage uncertainties associated with them, respectively.

3.8 Assessing the status of change in SOC stock

A one-out-all-out (1OAO) approach is used to combine the results for the three sub-indicators, to assess degradation status for each monitoring period, for the overall Indicator 15.3.1. Degradation is considered to have occurred if significant negative change in any one of the three sub-indicators is detected, subject to national/local verification including the capacity to report and explain false positives/negatives. This requires assessment of whether there has been a significant decrease in SOC stocks.

One approach to assessing change is to compare the average monitored SOC stock with the upper and lower bounds of the average baseline SOC for the same minimum unit of land. If the average for the same unit of land falls:

i. outside the lower bounds of the 95% confidence interval measured as twice the standard deviation, the area would be considered degraded (significant decline in SOC);
ii. outside the upper bounds of the 95% confidence interval measured as twice the standard deviation, the area would be considered improved (significant increase in SOC);
iii. within the 95% confidence interval, the area would be considered in a stable state (no transition);

An alternative statistical approach would be to assess the 95% confidence interval of the difference in SOC stocks between the baseline and the monitoring period for each land cover class/unit by combining uncertainties as described above. If the 95% confidence interval of the difference does not cover zero, then the change is significant, with the direction of change determined from Eqn. 6.

Given the highly variable nature of the data for SOC stocks, it is likely that the confidence intervals will be large, and thus the two statistical approaches described above may not detect significant change even if degradation is occurring (i.e., result in a Type II error, or “false negative”, where a false null hypothesis is incorrectly retained). This is particularly likely if using the default approach, where, for example, reference stock estimates (IPCC 2003; 2006) have associated uncertainty of up to ± 90%. Based on this limitation, we conclude that statistical significance is likely to be a poor criterion for assessing degradation associated with decreased SOC stock for the default approach.

An alternative approach may be to assess both the direction of change and magnitude of the relative percentage change (Eqn. 8) in SOC stocks, relative to some defined threshold, between the baseline and monitoring period. Then, for SOC stocks, the method of determining the status of change will be defined as:

- Degradation: Spatial features with more than 10% average net reduction in SOC stocks between baseline and current observations.
- Not degraded: Spatial features with less than 10% change or more than 10% average net increase in SOC stocks between baseline and current observations.

Here we have suggested an arbitrary >10% change threshold, however, further refinement and justification of these threshold values is needed. This is likely to be a country decision based on available information, practicalities, etc. The examples provided in Box 1 and Box 2 give some indication of the magnitude of change that might be estimated using the default method. Two contrasting scenarios under the default approach give both a 10% increase based on changed management (reduced tillage) of 80% of the area of a spatial feature that was annual cropland (no degradation), and a 25% decrease based on conversion of 70% of the area of a spatial feature from native forest to annual cropland (degradation).

Others have suggested that interim procedures are required so that assessments of change can be made based on risk, probability and expert opinion (Vaughan et al. 2001). There are several options for this, including:

- Simulation modelling to determine whether suspected trends in SOC stocks are likely to become clear.
- Assembling panels of experts to undertake critical reviews and judge whether a perceived problem is significant – these panels would draw on all lines of evidence (e.g. process understanding, published literature, anecdotal evidence, initial monitoring results, simulation modelling).
- Engaging panels of experts in creative scenario writing to thoroughly consider a range of future states. These scenarios can be used to devise programs of investigation that lead to early detection (Munn 1988).

3.9 Providing national/sub-national context

In the absence of, or as a complement to, national data, it is good practice to contextualize global and regional data sets with information at the national and, where possible, sub-national level. For example, in some cases, carbon stocks may be increasing for land use transitions that are actually considered land degradation, such as woody encroachment in grassland. Another example relates to identifying potential “hotspots” of degradation. An average computed for a country may hide hotspots of intense degradation that may be very significant (e.g. they may be the most fertile soils in the country). Assessment of “false positives” or degradation “hotspots” requires knowledge and interpretation at the local level. The most common approach involves the use of site-based data or a combination of quantitative and qualitative data. It is good practice to incorporate the capacity to generate an "explainable anomalies" or "false positive" map and a “hotspots” map when deriving the sub-indicator, maintaining original data with anomalies identified and explained. Further discussion is provided in Section 4.4.

3.10 Summary of computation steps

1. Where a default approach is used:
    a. Reference soil carbon stocks will be determined and documented for all major soil types, stratified by climate regions.
    b. Stock change factors and emission factors will be determined and documented for all land uses/management systems, and where needed, any additional sub-types.
2. An assessment of SOC stocks within each homogeneous land cover unit of the defined disaggregation scheme will be made for the baseline.
3. An average SOC stock will be generated for each identified stratum for the baseline period. The 95% confidence interval around the average will also be reported.

4. During the reporting period, the monitored SOC will be compared with the average baseline SOC for the same minimum unit of land by calculation the relative percentage change (Eqn. 8).
5. The most appropriate method to assess whether change results in a significant decrease in SOC (degradation) or an increase or no change in SOC (no degradation) will be applied. Where estimated overall uncertainties are relatively low, a statistical approach is the most robust way to estimate whether change is significant. However, in most cases, uncertainty is likely to be high and a thus statistical assessment is not recommended. As an alternative, assessment of both the direction of change and magnitude of the relative percentage change in SOC stocks, relative to some defined threshold, is suggested.
6. Increases in SOC stocks may not always be representative of a positive change. Potential false positives and explainable anomalies should be defined, justified and maintained in the original dataset.

3.11 Worked examples using the default calculations

Example 1: Spatial feature with uniform climate, soil type and broad land cover class but differing cropland management systems

The following example (modified from IPCC 2003) shows calculations for aggregating areas of cropland SOC stock change within a spatial feature over a 5-year reporting period. The spatial feature in a warm temperate moist climate on Mollisol soils (a type of high activity clay mineral soil) is made up of 10,000 ha of permanent annual cropland. Using the IPCC defaults in Table 2.3, IPCC 2006, the native reference carbon stock (SOC_{REF}) for the region is 88 t C ha^{-1}.

At the beginning of the calculation period, the distribution of cropland systems were 4,000 ha of annual cropland with low carbon input levels and full tillage and 6,000 ha of annual cropland with medium input levels and full tillage. Default stock change factors for croplands are provided in Table 5.5, Vol. 4 in the IPCC 2006 Guidelines. Using Eqn 3a & b[1], initial soil carbon stocks (SOC_0) for the area were:

4,000 ha × (88 t C ha^{-1} × 0.69 × 1 × 0.92) + 6,000 ha × (88 t C ha^{-1} × 0.69 × 1 × 1) = 587,770 t C.

In the (current) measurement year, there are: 2,000 ha of annual cropping with full tillage and low C input, 7,000 ha of annual cropping with reduced tillage and medium C input, and 1,000 ha of annual cropping with no-till and medium C input. Thus total soil carbon stocks in the monitoring year (SOC_{0-T}) are:

2,000 ha × (88 t C ha^{-1} × 0.69 × 1 × 0.92) + 7,000 ha × (88 t C ha^{-1} × 0.69 × 1.08 × 1) + 1,000 ha × (88 t C ha^{-1} × 0.69 × 1.15 × 1) = 671,968 t C.

The average annual stock change over the period for the entire area is: (671,968 – 587,770) t C / 20 yr = 84,198 t C/ 20 yr = 4,210 t C yr^{-1} increase.

Using Eqn 2, over our spatial feature area of 10,000 ha and monitoring period of 5 years this is equivalent to 4,210 / 10,000 ha = 0.421 t ha^{-1} yr^{-1} = 0.421 × 5 = 2.1 t ha^{-1} increase. There are no organic soils in this spatial feature.

Calculation of 95% confidence intervals uses the following IPCC default error values:

SOC_{REF}: 88±90% (no estimate available, assumed error)

F_{LU}: long-term cultivated 0.69±12%

F_{MG}: full tillage 1.0±50% (no estimate available, assumed error); reduced tillage 1.08±5%; no-till 1.15±4%;

F_I: low input 0.92±14%; medium input 1.0±50% (no estimate available, assumed error)

Using Eqn. 8, the percentage uncertainty in the product of the quantities (half the 95% confidence interval divided by the total and expressed as a percentage) for t_0 is:

$= (0.4 \times \sqrt{90^2 + 12^2 + 50^2 + 14^2}\ ) + (0.6 \times \sqrt{90^2 + 12^2 + 5^2 + 50^2}\ ) = 104\%$

And for t_n is:

$= (0.2 \times \sqrt{90^2 + 12^2 + 50^2 + 14^2}\ ) + (0.7 \times \sqrt{90^2 + 12^2 + 5^2 + 50^2} + (0.1 \times \sqrt{90^2 + 12^2 + 4^2 + 50^2}\ ) = 104\%$

To calculate relative change (r_{SOC}) from Eqn 8 for this spatial feature, where SOC_{t0} is 587,770 t C / 10,000 ha = 58.8 t ha^{-1} and SOC_{tn} is 671,968 t C / 10,000 ha = 67.2 t ha^{-1}:

$r_{SOC} = (67.2-58.8) / 58.8 \times 100 = 14.3\%$

Based on an increase in carbon stocks of 14%, this spatial feature has not degraded over the reporting period.

[1] Formulation B of the Eqn. is used here (see Box 2.1, Vol 4, IPCC 2006) which assumes activity data with transition matrices where land use changes are known explicitly rather than aggregate statistics.

Example 2; Spatial feature with uniform climate, two soil types and conversion between land cover classes from Forest land to Cropland

The following example shows calculations for SOC stock change within a spatial feature over a 10-year reporting period. The spatial feature in a warm temperate dry climate is made up of 10,000 ha of native forest land; 3,000 ha on low activity clay (LAC) soils and 7,000 ha on high activity clay (HAC) soils.

At the beginning of the calculation period, using the IPCC defaults in Table 2.3, IPCC (2006), the native reference carbon stock (SOC_{REF}) is 24 t C ha^{-1} for the LAC soils and 38 t C ha^{-1} for the HAC soils. Note: If an average baseline was being calculated, this would be the average of the estimates over the period (e.g. two estimates over 10 years), but for simplicity, only one estimate is presented here.

In the (current) measurement year:

2,000 ha of native forest on LAC soils has been replaced by annual cropping with full tillage and low C input and 1,000 ha of native forest on LAC soils remains unchanged.

5,000 ha of native forest on HAC soils has been replaced by annual cropping with full tillage and low C input and 2,000 ha of native forest on HAC soils remains unchanged.

Degradation is assessed separately for each homogeneous land cover unit (in this case soil type) within the spatial feature:

LAC soils

t0 3,000 ha × 24 t C ha^{-1} = 72,000 t C

tn 2,000 ha × (24 t C ha^{-1} × 0.69 × 1 × 0.92) + 1,000 ha × 24 t C ha^{-1} = 54,470 t C

Calculation of 95% confidence intervals uses the following IPCC default error values:

SOC_{REF}: 24±90% (no estimate available, assumed error)

F_{LU}: long-term cultivated 0.69±12%

F_{MG}: full tillage 1.0±50% (no estimate available, assumed error);

F_I: low input 0.92±14%.

Using Eqn. 8, the percentage uncertainty in the product of the quantities (half the 95% confidence interval divided by the total and expressed as a percentage) for t_0 is 90%, and for t_n is:

$= (0.67 \times \sqrt{90^2 + 12^2 + 50^2 + 14^2}) + (0.33 \times 90) = 100\%$

To calculate relative change (r_{SOC}) from Eqn 8 for this homogeneous land cover unit:

SOC_{t0} is 72,000 t C / 3,000 ha = 24 t C ha^{-1} and SOC_{tn} is 54,470 t C / 3,000 ha = 18.16 t C ha^{-1}:

r_{SOC} = (18.16-24) / 24 × 100 = -24.3%

Area LAC soils degraded = 2,000 ha

HAC soils

t0 7,000 ha × 38 t C ha^{-1} = 266,000 t C

tn 5,000 ha × (38 t C ha^{-1} × 0.69 × 1 × 0.92) + 2,000 ha × 38 t C ha^{-1} = 196,612 t C

Calculation of 95% confidence intervals uses the following IPCC default error values:

SOC_{REF}: 38±90% (no estimate available, assumed error)

F_{LU}: long-term cultivated 0.69±12%

F_{MG}: full tillage 1.0±50% (no estimate available, assumed error);

F_I: low input 0.92±14%.

$= (0.71 \times \sqrt{90^2 + 12^2 + 50^2 + 14^2}) + (0.29 \times 90) = 100\%$

To calculate relative change (r_{SOC}) from Eqn 8 for this homogeneous land cover unit:

SOC_{t0} is 266,000 t C / 3,000 ha = 38 t C ha^{-1} and SOC_{tn} is 196,612 t C / 7,000 ha = 28.1 t C ha^{-1}:

r_{SOC} = (28.1-38) / 38 × 100 = -26.1%

Area LAC degraded = 5,000 ha

The total area degraded in the spatial feature is 2,000 ha + 5,000 ha = 7,000 ha

4 Rationale and Interpretation

4.1 Carbon stocks metric

As outlined in Decision 22/COP.11[3], *soil organic carbon stock* is the metric that will be used to assess trends in carbon stocks above and below ground, and once operational, this metric will be replaced by *total terrestrial system carbon stock*. Soil organic carbon is only one part of the system and is not a proxy of overall ecosystem health, but rather, a proxy of soil health. Soil organic carbon is an indicator of overall soil quality associated with soil nutrient cycling, soil aggregate stability and soil structure, with direct implications for water infiltration, vulnerability to erosion and ultimately the productivity of vegetation, and in agricultural contexts, yields. The management of soil organic carbon is central to maintaining soil health and ensuring global food security (Lal, 2004). Consequently, one of the greatest priorities for action concluded by The Intergovernmental Technical Panel on Soils (ITPS) in their Technical Summary[4] of the Status of the World's Soil Resources (Action 2, page ix) is that "*The global stores of soil organic matter (e.g. SOC and soil organisms) should be stabilized or increased. Each nation should identify locally appropriate SOC-improving management practices and facilitate their implementation. They should also work towards a national-level goal of achieving a stable or positive net SOC balance*".

Although carbon stocks in non-forested ecosystems are typically largest in the soil pool, where woody perennial vegetation is present, the largest pool tends to be in the biomass, except where growing on organic soils (GFOI 2016). Further, in forested systems, changes in SOC stocks may not always capture degradation, for example, conversion of native forest to pasture may not result in a change in SOC stock (e.g. see review by Guo and Gifford 2002), but it will substantially reduce biomass carbon stock. Thus inclusion of total carbon stocks in the metric once operational will provide a more comprehensive indicator of degradation, particularly in cases of conversion of forested systems to other land uses.

4.2 Land cover change

Annex 1 outlines the methodological approaches that can be used to derive the activity data required for the default carbon stocks method. These activity data are: 1) baseline areas of land cover classes, stratified as necessary/where possible by management regime etc.; 2) conversion of land cover classes to other land cover classes, and 3) transfer between land cover sub-classes. Land cover classes should be able to be aggregated to the six IPCC classes (see Annex 1).

Although SDG 15.3.1 target will be reported as a single figure, quantifying the area of land degraded as a proportion of land area, spatial disaggregation to the smallest possible unit has been highlighted as a preferable way to present SDG indicators (UNHQ 2015). SDG 15.3 can be mapped and disaggregated by land cover type or other policy-relevant units, such as agro-ecological, bio-cultural or administrative. These spatial feature boundaries can also provide a basis for spatial disaggregation for the land productivity and carbon stocks sub-indicators. It is good practice to

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[3] http://www.unccd.int/en/programmes/Science/Monitoring-Assessment/Documents/Decision22-COP11.pdf

[4] http://www.fao.org/3/a-i5126e.pdf

ensure that feature boundaries are kept constant over the reporting period (nominally 2016-2030), since flows should be calculated from two epochs of land cover within the same geographic area.

Different countries may choose to use different spatial unit approaches. The choice of the spatial unit for land cover and land cover change (i.e. pixel, polygon, natural boundary or administrative boundary) will affect the calculation of changes in SOC stocks, including whether weighting is required. For example, if the spatial unit used is a natural feature (e.g. watershed), it is likely that there will be a mix of land cover classes, given as proportions, and degradation will be reported on this broad spatial unit.

Computation of the carbon stocks sub-indicator requires that the area of land in that spatial unit at times t_0 and t_n is identical and that exactly the same pools of carbon (including reference depths for SOC) are included in all time steps. Land use categories/ carbon stocks may change with improved knowledge. There may therefore be a need to retrospectively correct earlier categorizations/ estimates.

4.3 Uncertainty

The concept of good practice underpins IPCC (2003) and IPCC (2006). Good practice is defined by IPCC (2003, Section 1.3; 2006, Vol. 1, Overview, Section 3) as applying to inventories that contain neither over- nor under-estimates so far as can be judged, and in which uncertainties are reduced as far as is practicable. Although there is no predefined level of precision, this definition aims to maximize precision without introducing bias, given the level of resources reasonably available for greenhouse gas inventory development.

4.3.1 With choice of method

The main consideration in the selection of the default or nationally-specific method by a country is the current and likely future availability of data. Data sources are described in Section 5. The choice of method will have implications for the level of uncertainty in the estimate of changes in the SOC metric.

The default method draws on area data (i.e. activity data) generated from the assessment of land cover change in combination with reference and emission factors obtained from the IPCC default tables corresponding to broad continental land cover types and management regimes. As such, derived estimates provide limited resolution of how carbon stocks vary sub-nationally and have large uncertainty.

The inclusion of national data (and/or use of higher order methods) is a more rigorous approach to generating estimates of changes in the SOC metric, however, this requires the highest level of effort and resources. Reducing uncertainty in estimates requires improving stratifications and/or increasing the number of soil samples to use for the estimation. The capacity to do this will require improvements in analytical capabilities and sensing (see Section 5.2). Requirements include ground measurements, such as national inventories repeated through time, and intensive monitoring sites. Data from national inventories can provide information for default estimation methods, and for developing modelling approaches. Detailed information (at fine scale) generated at intensive monitoring sites can help address the difficulty of estimating stocks and stock changes by supporting development of model parameters, including emissions and removals factors. Derived estimates using such higher order methods provide information sub-national scale and have lower uncertainty.

4.3.2 In estimates

Both land cover areas and carbon densities have uncertainties which need to be combined when estimating changes in carbon stocks. Similarly, uncertainties for estimates of non-CO_2 greenhouse gas emissions are calculated by combining component emission/removal factors and activity data uncertainties.

Each of the IPCC default values has an error estimate provided, as should any nationally-derived data. There will also be different uncertainties associated with estimates for different carbon pools, and where multiple pools are considered and combined (i.e. if biomass carbon was included), this would need to be considered in an overall estimate of uncertainty. Approaches for determining an uncertainty for each C stock estimate for each time period include error propagation and uncertainty analysis (Monte Carlo simulation) (see IPCC 2003 guidance).

4.4 Assessment of false positives

In general, areas with long-term declining carbon stocks may be considered degraded while areas with increasing carbon stocks may be considered improving. However, estimated changes in carbon stocks also requires contextualization with information at national and sub-national levels. For example, in some cases, carbon stocks may be increasing for land use transitions that are actually considered land degradation, such as woody encroachment (i.e., land cover change from grassland to shrubland). Assessment of this type of exception (i.e., “false positive”) requires knowledge and interpretation at the local level.

Identification of false positives could be assessed by using site-based data, and/or qualitative information and stakeholder perspectives from surveys, workshops, in-depth interviews, and the establishment of expert panels. Once the false positive areas have been identified, these transitions would need to be designated as a “negative change”. The relevant land area associated with this change would need to be included with other areas of negative change in the calculation of the overall indicator.

5 Data Sources and Collection

The type and availability of data will vary by country. Existing (and soon to be available) datasets are reviewed below in the context of spatial and temporal resolution, accuracy and validation, consistency and historic and ongoing temporal availability. Reviewed data are sourced from freely-available global datasets, IPCC Good Practice Guidance (2003 GPG), IPCC guidelines (2006 GL) and other documents (e.g. Wetlands Supplement, 2013 WS) and nationally-contributed datasets. Further discussion is provided on monitoring methods for estimating SOC change.

5.1 Global datasets

Where country-specific data are not available, it is good practice to apply the best available defaults for SOC stocks to national land cover maps obtained by Earth observation data (see Annex 1). The minimum would be the six land cover categories of the IPCC (Forest land, Grassland, Cropland, Wetlands, Settlements, Other land) and relevant stratifications based on soil type and land management combined with default values for reference SOC stocks sourced from IPCC default tables (or global soil maps) and default values for relative stock change factors associated with land use, management and inputs (also from IPCC default tables).

In some cases it may be difficult to report on degradation using IPCC defaults because these do not cover all transitions. An alternative default approach, perhaps extending the existing IPCC defaults to include IPCC defaults for stratification by climate, ecological, disturbance or management and national proxy (or 'auxiliary' data, GFOI 2016) data, may be used. There is already a precedent for this by countries reporting on degradation for REDD+ using national data.

5.1.1 Land cover and land cover change

Global default methods for estimating changes in carbon stocks are strongly reliant on land cover change data (see Annex 1), which include:

1. Baseline areas of, as a minimum, the six IPCC land cover classes, sub-stratified as necessary/where possible by type and management regime;
2. Conversion of land cover classes to other land cover classes; and
3. Transfer between land cover sub-classes.

Global or regional land cover products are based on earth observation data. Available global datasets are summarized in Annex 1.

5.1.2 SOC stocks

At the broadest level, the IPCC provides a systematic approach for estimating carbon stock changes in soils (IPCC 2003, 2006, 2013). IPCC defaults exist for the minimum six land cover types and are stratified further into combinations based on soil type, climate and management. Spatial stratification based on these defaults would further improve the quality of the results at the National level.

The IPCC default values for reference SOC stocks and stock change factors reflect the most recent review of changes in soil carbon with conversion of native soils. Some limitations of using the IPCC defaults include the lack of relative change factors for some climates, as well as a paucity of change factors for specific management scenarios. The available defaults are summarised for mineral (see Eqn. 3) and organic soils (see Eqns. 4-6) in Tables 2 and 3, respectively. They are also provided in the IPCC Emission Factor Data Base (http://www.ipcc-nggip.iges.or.jp/EFDB/main.php) which is regularly updated.

Table 2. Source of defaults in IPCC guidance documents for factors associated with change in SOC stocks in mineral soils.

Default parameter	IPCC 2003 GPG	IPCC 2006 GL	IPCC 2013 WS
Reference (under native vegetation) SOC stocks (t C ha^{-1})	Table 3.2.4 Table 3.3.3 Table 3.4.4	Table 2.3	Table 5.2
Relative stock change factors	Table 3.3.4 Table 3.4.5	Table 5.5 Table 5.10 Table 6.2	Table 5.3

As an alternative to using IPCC defaults for reference SOC stocks in mineral soils, where available and considered robust and representative, reference SOC stocks could be derived from global spatial soil datasets and then the IPCC stock change factors be applied (in Eqn. 3 above). For example, in the absence of a national SOC database, use of the SOC 0-30 cm product derived from SoilGrids250m (see details below) as a stand-in for baseline SOC stock has been recommended for Land Degradation Neutrality target setting[5], noting this first requires derivation of stock SOC concentration and bulk density.

Table 3. Source of defaults in IPCC guidance documents for emission factors associated with change in SOC stocks in organic soils.

Default parameter	IPCC Document	Chapter reference	Table reference
Annual CO_2-C emission factor for drained organic soils in managed forests	IPCC 2003 GPG	Ch. 3	Table 3.2.3
Annual CO_2-C emission factor for cultivated organic soils	IPCC 2003 GPG	Ch. 3	Table 3.3.5
Annual CO_2-C emission factor for managed grassland organic soils	IPCC 2003 GPG	Ch. 3	Table 3.4.6
Annual CO_2-C and N2O-N emission/removal factors for drained organic soils in managed forests	IPCC 2006 GL	Ch. 4	Table 4.6
Annual CO_2-C emission factor for cultivated organic soils	IPCC 2006 GL	Ch. 5	Table 5.6
Annual CO_2-C emission/removal factors for drained grassland organic soils	IPCC 2006 GL	Ch. 6	Table 6.3
Annual CO_2-C on-site emissions/removals factor and CO_2-C off-site emission factor for drained organic soils in all land-use categories	IPCC 2013 WS	Ch. 2	Tables 2.1, 2.2
Annual N_2O-N emissions factor for drained organic soils	IPCC 2013 WS	Ch. 2	Tables 2.3, 2.4
CO_2-C and CH_4 emissions/removals factors for peat fires in all land-use categories	IPCC 2013 WS	Ch. 2	Tables 2.7

International organizations such as FAO, International Soil Reference and Information Center (ISRIC) World Soil Information, and others have compiled and harmonized national soil information in several global datasets. These have different spatial resolutions and are at different stages of development, but have potential for estimating reference SOC stocks. Existing freely-available sources include:

- **Harmonized World Soil Database (HWSD)**: This is the current de facto standard soil grid for the world despite its acknowledged shortcomings (GSP 2014). Version 1.2 is the latest

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[5] *Methodological note to set national voluntary Land Degradation Neutrality (LDN) targets using the UNCCD indicator framework , December 2016*

update (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/). Spatial resolution is 30 arc seconds (about 1 km). ISRIC has updated the HWSD (Batjes, 2016) resulting in a database (**WISE30sec**) with more depth intervals and more parameters quantified, and an estimate of uncertainty (SD). There is no assessment of accuracy.

- **SoilGrids1km** (Hengl et al. 2014; http://www.isric.org/content/faq-soilgrids) is a global 3D soil information system at 1 km resolution containing spatial predictions for a selection of soil properties (at six standard depths) including SOC stock (t ha^{-1}). Prediction accuracies assessed using 5–fold cross-validation were only 23% for SOC (Hengl et al. 2014).

Two other datasets with higher spatial resolution are currently under development:

- **GlobalSoilMap** (Arrouays et al. 2014a,b; http://www.globalsoilmap.net/) is a digital soil map project that aims to provide a fine-resolution (100 m) global grid of soil functional properties, including SOC stock, with estimates of their associated uncertainties. A gridded date-map will be made to indicate the date (in years) that the soil property value most closely reflects. To date, several countries have produced grids of soil properties, including SOC and bulk density (e.g. Viscarra Rossel et al. 2015). However, progress on this has been very slow.
- **SoilGrids250m** (Hengl et al. 2017; http://www.isric.org/content/faq-soilgrids) is a global 3D soil information system at 250 m spatial resolution. Products of SOC percentage, bulk density, gravel fraction and depth to bedrock can be used to calculate a predicted SOC stock for 0-30 cm. Accuracy was assessed using 10-fold, repeated cross-validation. Relative to SoilGrids1km, the amount of explained variation for SOC was improved from about 23% to about 69%. The June 2016 version of SoilGrids250m is known to over predict SOC stocks for soils with > 8% SOC (approx. 4% of soil profiles) due to issues with the bulk density layer not decreasing at a sufficiently fast rate with increasing %SOC (see https://github.com/ISRICWorldSoil/SoilGrids250m/issues/27). An updated version is currently under development. For now, SOC stocks should be considered as an overestimate[6].

It should be noted that, as for the IPCC defaults, the predictions derived from soil maps at a specified location will have very wide confidence intervals. In general, the use of datasets with the highest spatial resolution is recommended.

There are several issues and limitations with currently-available data for SOC stocks. For example, for SoilGrids250m, several limitations to the current maps used to construct SOC stock have been identified[6]. These relate primarily to predictions being based on soil legacy data and include:

- There is a paucity of data on bulk density and gravel content. Misuse of these data in calculation of SOC stocks can lead to systematic overestimation (e.g. see Poeplau et al. 2017);
- Measurements for SOC (%), bulk density, gravel content and soil depth have been collected with different measurement methods;

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[6] *Methodological note to set national voluntary Land Degradation Neutrality (LDN) targets using the UNCCD indicator framework, December 2016.*

- Soil data were collected over a large period of time (approximately the past 60 years for SOC, with the bulk centred on ~1995) and predictions were not made for the year 2000 (but assumed so in the absence of other, more suitable global data);
- Soil data were collected for various purposes, so there may be sampling bias (e.g. an over-representation of agricultural areas is common);
- The collection of legacy data (WOSIS) is nowhere near exhaustive, with much existing legacy data yet to be accessed.

Many of these issues identified for SoilGrids250m are also relevant to the other global maps that exist or are under development. Further, many map soil organic carbon content and bulk density but not soil carbon stocks which requires multiplying the maps and average the depths to derive the 0-30 cm SOC stocks.

Not all of the currently available global map products are likely to provide a better alternative to the IPCC defaults. However, SoilGrids 250m is likely to be a better alternative for deriving reference SOC stocks, although as might be expected, it may provide estimates that are biased. Where available, regional and country-specific, for example (but not exclusively) produced to GlobalSoilMap specifications, are likely to provide the best alternative (see Section 5.2.2).

The global spatial products described above for estimating SOC reference stocks are currently not dynamic. However, even if planned improvements in the accuracy of predictions are made, the global grid (even time-stamped releases over several decades) would not necessarily be the most effective way of detecting SOC stock change. Other strategies are more sensitive (e.g. a well-designed monitoring network such as Land Use/Cover Area Frame Statistical Survey (LUCAS); see Section 5.2.2.2) and can provide policy-relevant information faster (e.g. through the use of expert elicitation). Ideally, country-specific baseline maps would be used to design future monitoring programs for evaluating the impacts of land cover and land management on SOC stock for Tier 3 methodologies.

5.2 National datasets

The *Framework and Guiding Principles for a Land Degradation Indicator*[7] recommends that countries: "*Use National Data, to the greatest extent possible, to derive the sub-indicators and other relevant indicators and information at the country level covering bio-physical, governance and socio-economic conditions as well as the status of land resources*".

5.2.1 Land cover and land cover change

Guidance for land cover change is provided in Annex 1. National land cover products are based on earth observation data at finer resolutions than for global products. Landsat satellites provide a time series of remotely sensed digital images spanning 40 years and are being used widely in monitoring activities. Available datasets are summarized in Annex 1. Broadly, national datasets for land cover change can include:

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[7] *Framework and Guiding Principles for a Land Degradation Indicator (Draft for Consultation)*, available at: http://www.unccd.int/Lists/SiteDocumentLibrary/Rio+20/LDN%202016/Framework%20and%20Guiding%20Principles%20for%20a%20Land%20Degradation%20Indicator.pdf

1. Nationally-derived land cover products based on earth observation data, with specifically designed legends and calibration for local conditions; and
2. National land cover products based on the integration of earth observation data and ongoing field survey programs.

Countries can use various methods to obtain land use data, including annual census, periodic surveys and remote sensing. Each of these methods of data collection will yield different types of information (e.g., maps or tabulations), at different reporting frequencies, and with different attributes (IPCC 2006). As outlined in IPCC (2006), it is good practice for all national data to be:

- Adequate, i.e. capable of representing land-use categories, and conversions between land-use categories;
- Consistent, i.e. capable of representing land-use categories consistently over time, without being unduly affected by artificial discontinuities in time-series data;
- Complete, which means that all land within a country should be included, with increases in some areas balanced by decreases in others, recognizing the bio-physical stratification of land if needed (and as can be supported by data); and
- Transparent, i.e. data sources, definitions, methodologies and assumptions should be clearly described.

For countries already reporting to REDD+, some consistency with REDD+ methods in defining forest sub-classes is recommended. For example, a logical extension for countries already reporting to REDD+ would be to stratify forest land into sub-classes of primary forest, modified natural forest and planted forest (as per the minimum number of national sub-categories identified in GFOI 2016 and similarly, in FAO 2015).

5.2.2 SOC stocks

A summary of existing regional (continent) and country baseline maps for SOC stocks is provided in Table 4. Recent information on surveyed SOC stock estimates from 20 regions in the world is also provided in Minasny et al. (2017).

Table 4. Examples of continents/countries that have estimated spatially-explicit baselines of SOC stocks for the 0–30 cm layer.

Country/continent	Reference
Australia	Viscarra Rossel et al. (2014)
New Zealand	New Zealand Agricultural Greenhouse Gas Research Centre (2016)
South Korea	Hong et al. (2010)
USA	Odgers et al. (2012)
Mexico	Vargas et al. (2017)
Chile	Pandarian et al. (2016)
Nigeria	Akpa et al. (2016)
Europe	de Brogniez et al. (2015)
Denmark	Adhikari et al. (2014)
France	Mulder et al. (2016)
Scotland	Poggio and Gimona (2014)

Turkey	Madenoglu et al. (2017)

As concluded by the Intergovernmental Technical Panel on Soils (ITPS) in their Technical Summary[8] of the Status of the World's Soil Resources (Action 4, page ix), regional assessments frequently base their evaluations on studies from the 1990s based on observations made in the 1980s or earlier. Thus there is a strong a need to improve our knowledge about the current state and trend in the condition of soil, and an initial emphasis should be on improving observation systems, including for soil organic carbon.

Of particular relevance to national capability in estimating SOC stocks is Pillar Four of the Global Soil Partnership (GSP). The aim of Pillar 4 is to enhance the quantity and quality of soil data and information: data collection (generation), analysis, validation, reporting, monitoring and integration with other disciplines. 'The Plan of Action for Pillar Four' (GSP 2014), officially endorsed by all countries, has four recommendations:

- **Recommendation 1**: An enduring and authoritative system for monitoring and forecasting the condition of the Earth's soil resources should be established under the auspices of the Global Soil Partnership to meet international and regional needs.
- **Recommendation 2**: The global soil information system should use soil data primarily from national and within-country systems through a collaborative network and the distributed design should include facilities for incorporating inputs from the new sources of soil data and information that are evolving rapidly.
- **Recommendation 3:** The global soil information system should be integrated into the much larger effort to build and maintain the Global Earth Observing System of Systems (overseen by the Group on Earth Observations) and close attention should be given to issues relating to the protection of privacy, intellectual property rights and terms of use.
- **Recommendation 4:** Implementation of the global soil information system should include a training program to develop a new generation of specialists in mapping, monitoring and forecasting of soil condition, with an emphasis on countries where improved soil knowledge is essential for food security and restoration and maintenance of ecosystem services.

The subsequent Pillar 4 Implementation Plan[9] provides the guidance to build the global soil information system based on soil data sets provided by national and other institutional soil information institutions according to product specifications, and recognizes governance as an important element of the plan.

Under the **Global Soil Partnership (GSP)**, FAO member countries and all GSP partners have been invited to support and contribute to the development of the **Global Soil Organic Carbon map (GSOC map)** that will be released by the end of 2017[10]. Initial guidelines for sharing national data/information to compile the GSOC map have recently been released[11].

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[8] http://www.fao.org/3/a-i5126e.pdf

[9] http://www.fao.org/3/a-bl102e.pdf

[10] http://www.fao.org/global-soil-partnership/resources/highlights/detail/en/c/435193/

[11] http://www.fao.org/3/a-bp164e.pdf

5.2.2.1 Country-specific defaults

At the broadest level, use of national datasets might include national stratification of land cover categories/subcategories and country-specific defaults for SOC stocks and stock change factors for these units. Where countries have their own information on reference SOC stocks and/or change factors they should use these in accordance with Tier 2 methodologies for preparing National Greenhouse Gas Inventories in IPCC (2006). Ground-based data can be used to estimate SOC values and to derive stock change factors for mineral soils, as well as to estimate emissions and removals factors for organic soils. For nationally-derived default data on SOC stocks, it is good practice to:

1. Use standardised measurement units, i.e. tonnes SOC per ha for 0–30 cm depth.
2. Where available and robust, use national spatial datasets for SOC reference stocks (e.g. see Table 4).
3. Where countries have their own information on the effect of management within land cover classes (i.e. change factors for land use change, management within land uses and/or inputs on SOC stocks), use these.

For the latter, existing agricultural field trials provide one immediately available resource for the study of management impacts on soil carbon sequestration. These data sets have both informed soil carbon modelling (e.g. Parton et al 1987; Skjemstad et al 2004) and formed the basis for the stock change factors used in current IPCC inventory guidelines (IPCC 2006; Ogle et al 2005). A recent review (Sanderman and Baldock 2010) highlighted some of the difficulties in using field trial data in a predictive capacity to account for changes in SOC stocks, and presented a critical evaluation of current IPCC Guidelines (IPCC 2006) for accounting for emissions or removals resulting from SOC stock changes. They found that results from most agricultural field trials indicate a relative increase in soil carbon stocks with the adoption of various improved management practices. However, the few available studies with time series data suggest that this relative gain is often due to a reduction or cessation of soil carbon losses rather than an actual increase in stocks. Thus they argued that stock change data from agricultural field trials may have limited predictive power when the state of the soil carbon system is unknown and that current IPCC accounting methodologies developed from the trial results may not properly credit these management activities. We suggest that there is a real need for a large technical program to more comprehensively establish relationships between land management and SOC stocks and stock change for a wider range of land uses and managements, across all regions.

5.2.2.2 Integration of ground-based data

More advanced approaches would include integration of ground-based data from national monitoring systems with earth observation and modelling. Because estimates from default values and maps have wide associated uncertainties, more sensitive methods are recommended to detect soil change. Where possible, it is good practice to use ground-based monitoring of SOC stocks to: i) calibrate and validate models for spatial and temporal estimation of SOC stocks, and ii) detect and interpret any changes detected, assess their causes, and identify management interventions that address land degradation. As discussed earlier, Pillar 4 of the GSP aims to provide national capability in this area.

In the context of SOC stock change, examples of relevant ground-based observations include:

- Inventories (national, subnational) based on plot (or transect) measurements;

- Intensive monitoring studies, where the focus is on ecosystem functioning and processes;
- Auxiliary spatial data on land use, management, disturbance history, soil type which can be used to guide the selection and application of emissions and removals factors;
- Research data that can be used to estimate emissions and removals.

Determination of soil organic C stock requires measurements of soil organic C concentration, soil bulk density and gravel content, as described in Eqn. 1. Monitoring is challenging because SOC stocks can change slowly (often over decades) and early detection can be difficult; short-range spatial variation is typically large and can be easily confused with temporal variation; and measurement is often time consuming and relatively expensive (McKenzie et al. 2002). Sampling, i.e. the selection of locations and times on which observations are taken, is an important part in mapping and monitoring of soil carbon stocks. Indeed, appropriate sampling design is essential for the success of monitoring programs for detecting change in SOC stocks. It is good practice to use appropriate sampling designs for ground-based measurements to enable robust and reliable estimation of SOC stocks and stock change. Some considerations in measurement and monitoring of SOC stocks include:

- Spatial sampling strategies (site selection, sampling locations, number of samples, bulking etc.)
- Temporal sampling strategies (timing, frequency)
- Measurement (accuracy, cost, etc.)
- Scaling of point measurements to areal estimates.

Specific guidance on these aspects is context-specific, and is not provided here, but is covered in a number of references (e.g. Arrouays et al. 2014c; Chappell et al. 2013; DotE 2014b; de Gruijter et al. 2006; 2016; McKenzie et al. 2002). Few countries currently have national systems in place for statistically-based sampling of SOC, with most examples in Europe (e.g. France, UK). One example is provided in Box 3.

Box 3: Example of statistically-based sampling of soil: LUCAS

The European project LUCAS (Land Use/Cover Area Frame Statistical Survey[12]) may provide some guidance for monitoring, although some modifications are recommended in the context of SOC stocks. In 2009, the European Commission extended the periodic LUCAS to sample and analyse the main properties of topsoil in 23 Member States of the European Union (EU)[13]. This topsoil survey represents the first attempt to build a consistent spatial database of the soil cover across the EU based on standard sampling and analytical procedures, with the analysis of all soil samples being carried out in a single laboratory. Approximately 20,000 points were selected out of the main LUCAS grid for the collection of soil samples. A second round of sampling is being processed. The topsoil survey was designed to monitor a number of soil properties. In the context of monitoring SOC stocks, two modifications would be recommended. First, sampling to depths that meet IPCC standards (i.e., to 30 cm) rather than the 20 cm currently used in LUCAS. Second, measuring bulk density in addition to SOC concentration to derive SOC stocks. The first rounds of sampling derived bulk density from spatial data on topsoil packing density available from the European Soil database, however, methods have now been adapted for the planned 2018 sampling to collect samples for the assessment of new properties including bulk density and thickness of the organic horizon in peat soils[14].

5.2.2.3 Use of proximal sensing

The development of new analytical methods based on sensing can help with the acquisition of data for SOC stocks, including estimating baselines (see Box 4). Sensors can provide rapid, accurate, non-destructive and inexpensive measurements of soil properties. For carbon accounting, they need to be accurate, sensitive to detecting small changes in SOC stocks, and enable timely feedback to account for the change. There are current reviews on the use of soil sensing for measuring SOC concentration which highlight the usefulness of visible-near infrared (vis–NIR) and mid-infrared (mid-IR) spectroscopy (e.g. Stenberg et al., 2010; Bellon-Maurel and McBratney, 2011; Viscarra Rossel et al., 2011; Reeves et al., 2012; Izaurralde et al., 2013). Although there are fewer articles that address the sensing of soil bulk density, there have been some recent advances that use gamma-ray attenuation to accurately measure soil bulk density (e.g. Lobsey & Viscarra Rossel 2016). Calculation of SOC stock requires measures of bulk density and gravel content, and new systems that integrate different soil sensors (e.g. vis–NIR; gamma-ray attenuation, digital cameras) with robust statistical analytics and modelling are being developed to address the lack of such data for monitoring SOC stocks (e.g. Viscarra Rossel et al. 2017). Further, there is recent work demonstrating the use of soil sensors for SOC stock baselining (e.g. Viscarra Rossel et al. 2016).

Viscarra Rossel and Bouma (2016) provide discussion on the use of proximal soil sensors and their role in the development of sustainable agricultural productions systems and innovative environmental and regional policies. They suggested that proximal soil sensing can be also used to effectively monitor SOC stock for accounting purposes and be central to the adoption of best

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[12] http://esdac.jrc.ec.europa.eu/projects/lucas

[13] http://esdac.jrc.ec.europa.eu/ESDB_Archive/eusoils_docs/other/EUR26102EN.pdf

[14] http://publications.jrc.ec.europa.eu/repository/bitstream/JRC105923/jrc105923_lucas2018_jrctechnicalreport.pdf

agronomic practices that also reduce greenhouse gas emissions and allow significant carbon sequestration to reach the ‘4 per 1000’ proposal made by the French authorities ahead of the 21st Conference of Parties to the United Nations Framework Convention on Climate Change (COP21).

Box 4: Example of deriving a baseline using current and historical point data and archived soil samples combined with spectroscopic sensors

Viscarra Rossel et al (2014) derived a baseline for SOC stocks in Australia for the period 2000–2013. They utilised data from a national Soil Carbon Research Program that produced current data on SOC stocks for agricultural regions of Australia. However, with this dataset alone, it would have been impossible to map the whole of the country because there was no data for the large majority of areas in the north, northwest and centre of Australia. Therefore they used historical archives of soil samples and measured their carbon and bulk density with spectroscopic sensors to enhance the dataset so that it had good spatial coverage over the entire country. Without the new analytical capability from the spectroscopic sensors, it would have been too expensive to analyse the archived soil for organic C and not possible to analyse them for bulk density. This same approach is now being used elsewhere in the United States of America and in China.

6 Total carbon stocks

Based on Decision 22/COP.11, once operational, the metric for the carbon stocks sub-indicator will be broadened from SOC stock to total carbon stocks in all pools (i.e. aboveground biomass, belowground biomass, litter, dead wood and soil). In this section we briefly describe approaches that could be used to estimate total carbon stocks.

6.1 Default approach

Where country-specific data/capability are currently lacking, a default (‘Tier 1’) approach should be used to estimate the other carbon pools. The IPCC provides a systematic approach for estimating carbon stock changes biomass and debris (IPCC 2003, 2006, 2013). The equation for estimating the change in total carbon stocks (Eqn. 11) in a spatial feature is modified from Equation 2.3 in Chapter 2, Volume 4 of the 2006 IPCC Guidelines to exclude harvested wood products:

$$\Delta C = \Delta C_{AG} + \Delta C_{BB} + \Delta C_{DW} + \Delta C_{LI} + \Delta SOC \tag{11}$$

Where:

ΔC = total carbon stocks in the spatial feature;

ΔC_{AB} = carbon stocks in aboveground biomass in the spatial feature;

ΔC_{BB} = carbon stocks in belowground biomass in the spatial feature;

ΔC_{DW} = carbon stocks in dead wood in the spatial feature;

ΔC_{LI} = carbon stocks in litter in the spatial feature;

ΔSOC = organic carbon stocks in soil in the spatial feature.

As outlined in IPCC (2006), depending on country circumstances, stock changes may not be estimated for all pools shown in Equation 11. There are simplifying assumptions about some carbon pools under Tier 1 methods: change in below-ground biomass C stocks are assumed to be zero; dead wood and litter pools may be combined as 'dead organic matter' and dead organic matter stocks are assumed to be steady for non-forest land use categories; though, for Forest Land converted to another land use, default values for estimating dead organic matter carbon stocks are provided. Relevant default (Tier 1) equations for estimating changes in biomass and debris pools are provided in Chapter 2, Volume 4 of the 2006 IPCC Guidelines.

IPCC defaults exist for the minimum six land cover types and are stratified further into combinations based on climate, ecological, disturbance or management. Spatial stratification based on these defaults would further improve the quality of the results at the National level. The available IPCC defaults are provided in the 2003 Good Practice Guide, 2006 Guidelines and 2013 Wetlands Supplement for aboveground biomass stocks, root to shoot ratios (for estimating belowground biomass from aboveground biomass) and debris stocks, and are summarised in Tables 5 and 6, respectively. They are also provided in the IPCC Emission Factor Data Base (http://www.ipcc-nggip.iges.or.jp/EFDB/main.php) which is regularly updated.

Table 5. Source of defaults in IPCC guidance documents for factors associated with estimating change in biomass carbon stocks.

Default parameter	IPCC 2003 GPG	IPCC 2006 GL	IPCC 2013 WS
Carbon fraction of above ground forest biomass	Default = 0.5	Table 4.3	
Ratio of below ground biomass to above ground biomass	Table 3A.1.8	Table 4.4	
Above ground biomass stocks in natural and plantation forests	Tables 3A.1.2 & 3A.1.3	Tables 4.7-4.11 (excl. 11B)	
Above ground biomass for various types of perennial croplands	Table 3.3.2	Table 5.3	
Biomass carbon stocks present on Land Converted to Cropland in the year following conversion	Table 3.3.8	Table 5.9	
Above ground biomass for various types of grasslands	Table 3.4.2		
Ratio of below-ground biomass to aboveground biomass for the major grassland & savanna ecosystems of the world	Table 3.4.3	Table 6.1	
Biomass stocks present on grassland, after conversion from other land use	Tables 3.4.2 & 3.4.9	Table 6.4	

Above ground biomass stocks in mangroves			Table 4.3
Ratio of below ground biomass to above ground biomass in coastal wetlands			Tables 4.5, 4.9 & 4.10

Table 6. Source of defaults in IPCC guidance documents for factors associated with estimating change in litter and dead wood carbon stocks.

Default parameter	IPCC 2003 GPG	IPCC 2006 GL	IPCC 2013 WS
Forest litter and dead wood carbon stocks	Table 3.2.1 & 3.2.2[A]	Table 2.2	
Litter and dead wood stocks in mangroves			Table 4.7

[A] Dead wood stocks are given as dry matter.

6.2 National approaches

Tier 2 and 3 methods use nationally-derived data and more disaggregated approaches and/or process models, which allow for more precise estimates of changes in carbon stocks in biomass. It is good practice to ensure that models are tested against field measurements (IPCC 2006).

Under Tier 2 methods, country-specific data on ratios of below-ground to above-ground biomass can be used to estimate below-ground stock changes. For land converted to a new land cover category, Tier 2 methods to calculate annual change in biomass stocks replace Equation 2.4 by Equation 2.15 (Vol. 4, IPCC 2006), where the changes in carbon stock are calculated as a sum of increase in carbon stock due to biomass growth, changes due to actual conversion (difference between biomass stocks before and after conversion), and decrease in carbon stocks due to losses. Tier 2 methods for estimating carbon stock changes in dead organic matter (DOM) pools calculate the changes in dead wood and litter carbon pools (Equation 2.17, Vol 4, IPCC 2006). Two methods can be used: either tracking inputs and outputs (the Gain-Loss Method, Equation 2.18) or estimating 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. The same equation is used for dead wood and litter pools, but their values are calculated separately.

As for SOC stocks, in most cases it is envisaged that estimates of changes in carbon stocks above and below ground associated with land degradation activities will be made using a combination of remotely-sensed and ground-based data. Remotely sensed and auxiliary ground-based data in combination are likely to be useful for stratification in order to increase sampling efficiency. If sufficient national inventory data are available over space and time and at sufficient spatial resolution, repeated inventories can be used to directly estimate stock changes associated with activities. It will often be best to use national inventory data in combination with remotely-sensed data. Data from national inventories are also a potentially valuable source of information for estimation of biomass using gain-loss methods, and for developing modelling approaches (empirical, process-based or other types of advanced models) at Tier 3. A model-based inference approach, where carbon stock is inferred from models, and change in carbon stock modelled for each land cover change, can also be used.

6.3 Biomass products

6.3.1 Global/regional products

A recent review of the potential for estimation of forest biomass by remote sensing (GFOI 2016) suggests that existing large-scale biomass maps derived from remote sensing data need extensive in-country testing to confirm that they are reliable for application in specific forest types and at the spatial scale of interest. Because biomass estimation error using remote sensing is high at plot scale (< 1 ha) and scales of up to 100 ha (e.g. Saatchi et al. 2011), robust field estimates of biomass based on adequate plot size, sufficient spatial sampling, and use of appropriate allometrics are needed (e.g. Chave et al. 2004; Avitabile et al. 2011). This means that currently the method is unlikely to be cost efficient (GFOI 2016).

Examples of existing global and regional biomass map products include:

- **New IPCC Tier-1 Global Biomass Map for the Year 2000** (Ruesch and Gibbs 2008; http://cdiac.ornl.gov/epubs/ndp/global_carbon/carbon_documentation.html). This used the IPCC Tier 1 methodology (created using the IPCC Good Practice Guidance for reporting national greenhouse gas inventories) and GLC2000 land cover data to provide a new global map of biomass carbon stored in above and belowground living vegetation at 1 km resolution.
- **The National Biomass and Carbon Dataset (NBCD2000)** (Woods Hole Research Center, WHRC; http://whrc.org/publications-data/datasets/national-biomass-and-carbon-dataset/). This provides basal area-weighted canopy height, aboveground live dry biomass, and standing carbon stock for the year 2000 at 30 m resolution for the conterminous United States. NBCD2000 is based on a combination of data from the USDA Forest Service Forest Inventory and Analysis (FIA), the 2000 Shuttle RADAR Topography Mission (SRTM) and Landsat-7/ ETM+. This provides a model for how national forest inventory plot data can be combined with remote sensing data to produce maps of biomass.
- **National Level Carbon Stock Dataset (Tropics)** (WHRC; Baccini et al., 2012). This provides maps of above-ground live woody biomass at 500 m resolution for the tropics 2007-2008. A combination of field measurements and space-borne LIDAR observations at 70 m spatial resolution from the Geoscience Laser Altimeter System (GLAS) instrument on board the Ice, Cloud and land Elevation Satellite (ICESat), and optical MODIS imagery at 500 m spatial resolution, were used.
- **JPL Carbon Maps** (Saatchi et al. 2011; http://carbon.jpl.nasa.gov/). The Jet Propulsion Laboratory of NASA and the California Institute of Technology provide a biomass product similar to that of the WHRC National Level Carbon Stock Dataset. The maps provide forest above-ground carbon and biomass for sub-Saharan Africa, the Americas south of latitude 30° N, and South-East Asia and Australia between the latitudes of 40° N and 30° S at 1 km resolution. Point-based estimates of biomass generated from a combination of field data and space-borne LIDAR data from ICESat/GLAS were extrapolated using optical data from MODIS and RADAR data from SRTM and QuickSCAT.
- **Integrated pan-tropical biomass map** (Avitabile et al. 2016). This combined two existing datasets of vegetation aboveground biomass (Saatchi et al. 2011; Baccini et al. 2012) into a pan-tropical map at 1-km resolution using an independent reference dataset of field observations and locally calibrated high-resolution aboveground biomass maps, harmonized

and upscaled to 14,477 1-km estimates. The data are available at: http://www.wur.nl/en/Expertise-Services/Chair-groups/Environmental-Sciences/Laboratory-of-Geo-information-Science-and-Remote-Sensing/Research/Integrated-land-monitoring/Forest_Biomass.htm

A global biomass map is currently being developed by the **GlobBiomass project** (http://globbiomass.org/products/global-mapping/). The map will have specified requirements to spatial resolution (150-500 m) an accuracy of 70% or better with the reference year 2010. The map will be based on the combination of several SAR, LiDAR and optical datasets and established algorithms for the retrieval of forest variables at regional to continental scale.

6.3.2 National products

There is potential for integration of ground-based data with remote sensing to estimate biomass at local level. Airborne LIDAR, calibrated using ground based estimates of biomass, can be used to produce reliable high resolution biomass maps, and can be cost effective in some national circumstances, such as where terrain makes access difficult (GFOI 2016). Examples of how to use airborne LIDAR data together with ground measurements to estimate biomass are provided by Asner et al. (2010) (IPCC-compliant estimates of carbon stocks and emissions in the Peruvian Amazon); Nelson et al. (2004) (biomass estimation in Delaware, United States); Næsset et al. (2013) (biomass change estimates in boreal forests, Norway); and Lefsky et al. (1999) (biomass estimation in deciduous forests in Maryland, United States).

Under the GlobBiomass project, subnational mapping is underway, where biomass stock and change maps with better spatial resolution than the global reference map (50 – 150 m) and with a multi temporal approach comprising three epochs: 2000 or 2005, 2010 (reference year), and 2015 will be produced. The regional (subnational) maps will aim for an overall accuracy of at least 80% in five different regional mapping sites:

- Mexico (tropical-woodland; http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-mexico/)
- Poland (temperate zone; http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-poland/)
- Sweden (boreal zone; http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-sweden/)
- Indonesia/Kalimantan (tropical zone; http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-indonesiakalimantan/)
- South Africa (savanna mosaic; http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-south-africa/).

6.3.3 Limitations

One limitation of the space-borne LIDAR data used to derive several of the biomass products described above is that there is a data gap in observations between 2009 and 2015, and as yet, replacement missions (ICESat-2 scheduled launch 2017; GEDI scheduled launch 2019) have not been launched. Another limitation of space-borne LIDAR is that, while it is possible to estimate tree height from ICESat/GLAS data which in turn can be regressed to obtain biomass estimates (Sun et al. 2008), estimating tree height from GLAS data is less straightforward compared to using airborne, small footprint LIDAR data. On slopes, topographic information is required to estimate tree height because of the elliptical shape of the GLAS footprint (Lefksy et al. 2005).

Synthetic Aperture RADAR (SAR) for biomass estimation has demonstrated potential in the estimation of aboveground biomass, and is being used in the GlobBiomass project. However, currently there are limitations arising from 1) rapid saturation of the signal at low aboveground biomass stock for some bands, 2) terrain, 3) rainfall and soil moisture effects, 4) localised algorithm development (single biome or mono-specific stands), and 5) lack of consistency in estimates as a function of sensor parameters (GFOI 2016). Consequently, estimation of aboveground biomass using SAR has been more successful in temperate forests than in tropical forests, due largely to fewer species and lower biomass (Castro et al. 2003).

6.3.4 Deriving biomass carbon stocks from Earth Observation maps

Some caution should be exercised in applying biomass C stocks from biomass maps which have been derived from spectral indices such as the Normalized Difference Vegetation Index (NDVI). These estimates are unlikely to be sufficiently independent of the land productivity sub-indicator which uses NDVI to infer NPP.

7 Comments and Limitations

Lorenz and Lal (2016) reviewed the potential of SOC stock as an indicator for land and soil degradation, and assessed its relevance and feasibility as an indicator for the implementation of the SDGs. They highlighted that several associated challenges would need to be addressed before SOC stock can serve as a globally relevant and feasible indicator for monitoring degradation in the context of the SDG framework. These included: the limited availability of datasets on SOC stock at national and regional levels, the uncertainties associated with the suitability of existing data for monitoring SOC stock changes, and insufficient quantitative evidence linking SOC stock changes to the various land and soil degradation drivers and processes.

The defined monitoring period is from 2016-2030, however, intermediate monitoring points at an interval of 4-5 years have been suggested (Orr et al. 2017). For land cover, global data sets are now available annually. However, in the context of SOC change, this frequency is likely to be too short to detect change where an on-ground monitoring approach is used, because under current land management practices, it would be difficult to register change in less than 10 years (Smith 2004).

Measurements of carbon stocks are subject to various sources of error and the observed data may give a falsely positive or negative reflection of the true conditions. This could lead to land being falsely classified.

Using IPCC defaults requires soil types to be used for stratification. These are the seven default IPCC soil types defined in IPCC 2006, Annex 3A.5. For a national approach using country-specific defaults and the default equations (Tier 2), it will be hard to get agreement on what soil classification system to use. There are problems with the existing global maps of soil types including their very broad scale. Further, soil types are not necessarily highly covariant with soil carbon stocks.

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