Good Practice Guidance

SDG Indicator 15.3.1

Proportion of land that is degraded over total land area

Version 2.0 – Advanced unedited version
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Foreword

(TBP)

Executive Summary

This Good Practice Guidance (GPG) document provides guidance on how to calculate the extent of land degradation for reporting on United Nations (UN) Sustainable Development Goal (SDG) Indicator 15.3.1: the proportion of land that is degraded over total land area. This guidance supports implementation of the Tier I methods for Indicator 15.3.1 adopted by the UN Statistical Commission[1], and the development of analytical methods for measuring its three sub-indicators, which are:

1. Trends in land cover
2. Trends in land productivity
3. Trends in carbon stocks (above and below ground), which is currently represented by soil organic carbon (SOC) stocks.

The Indicator is calculated by integrating the sub-indicators using a one-out-all-out (1OAO) method, in which a significant reduction or negative change in any one of the three sub-indicators is considered to comprise land degradation. Significant reductions can be identified using statistical criteria, or by a qualitative assessment of the magnitude of change. The Indicator is reported as a binary quantification (i.e., degraded/not degraded) of the extent of degraded land in hectares, and expressed as the proportion (percentage) of land that is degraded over total land area.

Version 2 of the GPG incorporates a number of advances in the quality and availability of datasets, as well as analytical methods for calculating Indicator 15.3.1 and its sub-indicators that have emerged since publication of Version 1 of the GPG (Sims et al. 2017). These advances have been identified through research, stakeholder engagement, including analysis of recommendations from countries reporting on Indicator 15.3.1 in the first reporting period in 2018, and reviews of drafts of this report by global experts in relevant fields. This report also incorporates new developments from the growing number of publications and initiatives focussed on improving the quality and availability of data and analytics for the SDGs in general, and Indicator 15.3.1 and Land Degradation Neutrality (LDN) in particular. While the measurements of Indicator 15.3.1 form only one part of the assessment of LDN, the relationship between the Indicator and LDN is discussed in more detail in Version 2 (this document), and additional guidance on the calculation and use of measurements during the baseline period should clarify the interpretation of Indicator 15.3.1 for monitoring LDN.

The guidance covers three sub-indicators. The Land Cover sub-indicator reports degradation in land cover change based on a national assessment of the positive or negative aspects of transitions from one land cover type to another. In Version 2, this chapter highlights the need for countries to first consider the main drivers of land cover change, and then to determine which transitions to identify as degraded for reporting on Indicator 15.3.1. This chapter incorporates updates to the quality of available land cover datasets and classification methods.

[1] https://unstats.un.org/sdgs/metadata/files/Metadata-15-03-01.pdf

The Land Productivity sub-indicator reports productivity degradation using Earth Observation (EO) data to monitor changes in Net Primary Productivity (NPP) of vegetation. This assessment is based on three metrics, calculated from a time series of annual NPP observations, that are designed to identify changes in the trajectory and level of productivity. The statistical methods for assessment of each of the three metrics have been simplified and improved in Version 2 of the GPG, and they can now be interpreted in terms of the severity of degradation and the confidence of the assessment. A revision of the methods for combining the metrics also enables degradation to be identified in a range of additional phases of the long-term productivity cycle, including situations in which productivity is stable for a long period of time, or is increasing but where the level of productivity is low.

The Carbon Stocks sub-indicator has been significantly revised in light of updates and new guidance from the 2019 Refinement to the Intergovernmental Panel on Climate Change (IPCC) 2006 Guidelines for National Greenhouse Gas Inventories, and now includes expanded guidance on the methods for assessment of 'significant' change in Soil Organic Carbon (SOC) stocks. This chapter now also incorporates updates to the data sources available for estimating change in SOC stocks since the publication of version 1 of the GPG.

In addition to improved guidance on the calculation of the methods, Version 2 provides more guidance on the interpretation and reporting of degradation, based on country recommendations following the 2018 reporting period. This includes guidance on how to identify false positive or false negative outcomes in cases where the degradation analysis of the 1OAO process may produce a counterintuitive outcome, such as where land remediation activities to remove invasive weeds reduces the apparent NPP in EO data, which would normally indicate degradation despite this being an activity to improve the condition of the land.

Additional guidance is provided on recalculating the time-series data sets, following the adoption of new and improved datasets into the analysis, based on similar guidance provided by the IPCC. In most cases there is likely to be an overlapping period where both the former and new datasets are available, and the differences measured between them can be used to interpret or estimate missing values.

Guidance on assessing the magnitude of degradation, and on identifying 'brightspots' and 'hotspots' is a new addition to the GPG. This information can be used to balance 'losses' to degradation against 'gains' in the area that improves from a degraded state. It can also be used to identify local areas of the highest degradation severity, which may be useful in optimising efforts to restore degraded lands, or avoid degrading new land in future, consistent with the achievement of LDN.

Contents

Figures

Tables

Abbreviations and acronyms

1OAO - One-out-all-out

AVHRR - Advanced Very High Resolution Radiometer

BRDF - bi-directional distribution function

CCI-LC - ESA Climate Change Initiative on Land Cover

CEOS - Committee on Earth Observation Satellites

CGLS-LC100 – Copernicus Global Land Service Land Cover at 100m

CLC - CORINE Land Cover

DPSIR - Driver-Pressure-State-Impact-Response ‘causal framework’

DQS - data quality standards

EO - Earth Observation

ESA - European Space Agency

ESM - Equivalent Soil Mass

EVI - Enhanced Vegetation Index

FAO - UN Food and Agriculture Organization

fAPAR - Fraction of Absorbed Photosynthetically Active Radiation

GAES - Global Agro-Environmental Stratification

GEO - Group on Earth Observation

GEO LDN - GEO Land Degradation Neutrality Initiative

GHG - Greenhouse Gas

GIMMS - Global Inventory Monitoring and Modelling System

GLC-SHARE - FAO Global Land Cover-SHARE

GPG - this Good Practice Guidance report

GPP - Gross Primary Productivity

GSOC - FAO Global Soil Organic Carbon map

GSP - Global Soil Partnership

IAEG-SDG - Inter-agency and Expert Group on SDG Indicators

IGBP - International Geosphere–Biosphere Programme

IPCC - Intergovernmental Panel on Climate Change

ITPS - Intergovernmental Technical Panel on Soils

JRC - Joint Research Centre of the European Commission

LCEU - Land Cover/Ecosystem Functional Unit

LCCS - FAO Land Cover Classification System

LCML - Land Cover Meta Language [ISO 19144-2:2012]

LDN - Land Degradation Neutrality

LPD - JRC Land Productivity Dynamics

MODIS - Moderate Resolution Imaging Spectrometer

NALCMS - North American Land Change Monitoring System

NIR - Near Infra-Red

NPP - Net Primary Productivity

NSO - National Statistical Office

RUE - Rainfall use efficiency

SDG - UN Sustainable Development Goal

SEEA – UN Statistical Commission's System of Environmental and Economic Accounting

SOC - Soil Organic Carbon

SOM - Soil Organic Matter

UML - Unified Modelling Language

UN - United Nations

UNCCD - UN Convention to Combat Desertification

UNSD – UN Statistics Division

WAD – JRC World Atlas of Desertification

WUE - Water Use Efficiency

Glossary of terms, definitions and concepts

Above ground biomass

The biomass of living vegetation, both woody and herbaceous, above the soil including stems, stumps, branches, bark, seeds, and foliage (IPCC 2003).

Baseline

The baseline period, during which baseline conditions should be calculated, is the 16 years from 1 January 2000 to 31 December 2015. This period was selected because of the improvements in the availability of high frequency, moderate resolution global Earth observation (EO) data in the year 2000 (from the Moderate Resolution Imaging Spectrometer (MODIS) satellites) and because a period of about 15 years is typically sufficient to encounter most of the variability in natural systems (Kennard et al. 2010). Subsets of the baseline period may be used depending on the availability of data, the statistical requirements of the sub-indicator or metric, and the perception by countries of the representativeness of conditions during this period as a benchmark for comparison of future changes.

The extent of degraded land measured in the baseline provides the benchmark against which change in the extent of degraded land is compared in subsequent reporting periods. The baseline is necessary to assess progress towards achieving Sustainable Development Goal (SDG) Target 15.3 and Land Degradation Neutrality (LDN). The baseline year is 2015, which was the year that the UNCCD made the decision to pursue LDN (Orr et al. 2017), and when the 2030 Agenda for Sustainable Development (the SDGs) was adopted by all United

Nations (UN) Member States[2].

Below ground biomass

All biomass of live roots. Fine roots of less than 2 mm diameter are often excluded because these often cannot be distinguished empirically from soil organic matter or litter (IPCC 2003).

Biochar

The solid carbonised product produced by the thermochemical conversion of biomass through pyrolysis (heating with limited air). Here biochar only refers to materials that have been produced under process conditions in which relatively easily mineralisable organic materials are converted to more persistent forms by heating to above 350 °C with limited air through a gasification or pyrolysis process (IPCC 2019).

Carbon stock

The quantity of carbon in a pool or a reservoir that has the capacity to accumulate or release carbon. Ecosystem carbon pools are composed of biomass (above and below ground), dead wood and litter (above and below ground), and soil organic matter (IPCC 2003; Figure 0-1).

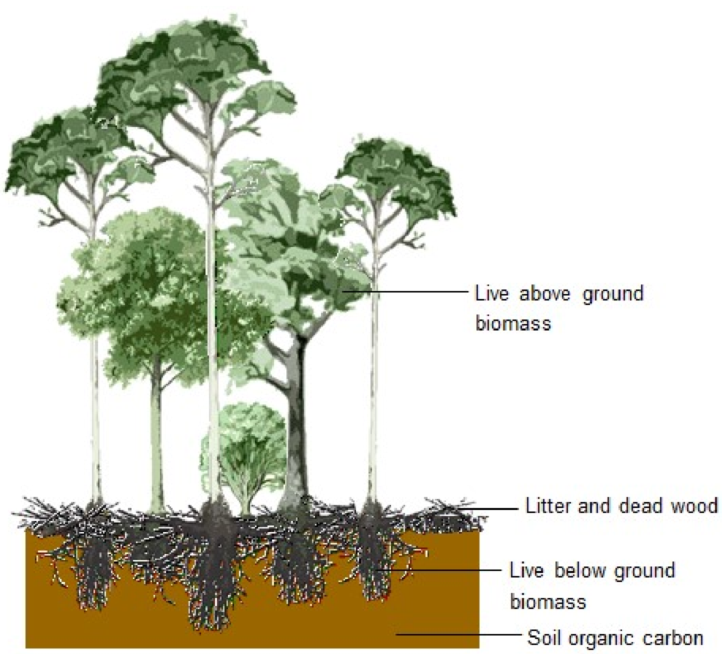


Figure 0-1. Schematic of live and dead ecosystem carbon pools.

[2] https://sdgs.un.org/goals

Classification [ISO 19144-1:2009, 4.1.4]

Abstract representation of real-world phenomena using classifiers (**see classifier, class**)

Classification system [ISO 19144-1:2009, 4.1.5]

System for assigning objects to classes

Classifier, class [ISO 19144-1:2009, 4.1.6]

Definition used to assign objects to legend classes (**see land cover element, landscape element**)

NOTE Classifiers can be algorithmically defined, or defined according to a set of classification system (**see classification system**) specific rules.

Dead wood

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 generally larger than or equal to 10 cm in diameter (IPCC 2003).

Equivalent Soil Mass (ESM)

The reference soil mass per unit area (Mg ha^{-1}) chosen in a layer. Equivalent C mass is C mass stored in an ESM (Ellert et al. 2001). SOC. Several methods for calculating ESM are available that differ in their approach to the calculation of the reference mass and/or the depth at which the mass of soil is adjusted. A simple method is proposed by Wendt and Hauser (2013), where for any soil sample depth layer (d) the dry sample mass is divided by the area sampled by the probe or auger, which is the cross-sectional area of its inside diameter.

Inorganic soil carbon

Either primary minerals in the parent material from which the soil was formed (e.g., limestone), or secondary minerals (i.e., pedogenic carbonates) that arise during soil formation (IPCC 2006).

Key category

Source or sink category that is prioritised within the national inventory system because its estimate has a significant influence on a country's total inventory of greenhouse gases in terms of the absolute level, the trend, or the uncertainty in emissions and removals (IPCC 2006). In the context of this GPG, a key category relates to a carbon pool that is prioritised because its estimate has a significant influence on estimation of degradation in the carbon stocks sub-indicator for a given land cover class.

Land-based natural capital

The natural capital of land resources. This includes the properties of the soil (chemical, physical and biological factors), geomorphological, biotic and hydrological features, that interact with each other and with the climate to determine the quantity and nature of ecosystem services provided by the land (Orr et al. 2017).

Land cover [UNFAO LCCS 2:2005]

Observed (bio)physical cover on the Earth's surface.

NOTE: Land cover is distinct from land use.

The distribution of vegetation types, water bodies and human-made infrastructure (Di Gregorio 2005). Land cover also reflects the use of land resources (i.e., soil, water and biodiversity) for agriculture, forestry, human settlements and other purposes (FAO-GTOS. 2009).

There is an international standard for the sub-indicator on land cover (ISO 19144-2:2012)[3] which includes the LCML, a common reference structure (statistical standard) for the comparison and integration of data for any generic land cover classification system. LCML is also used for defining LCEUs used in the SEEA, and closely linked to the IPCC classification on land cover/land use.

Land cover class

Class (**see classifier, class**) of land cover (**see land cover**) within a broader set of classes defined within a land cover classification system (**see classification system**). It is specified by the properties of the elements that constitute a particular class.

Land Cover Classification System (LCCS)

Framework to define and organize the land cover types or classes (**see land cover class**) used in a specific application (Di Gregorio & O'Brien 2012). The LCCS framework of the UN Food and Agriculture Organization (FAO) uses consistent, unique and systematically-applied principles for classification. The framework should use objective "logical" class definitions, rather than subjective "cognitive" definitions of land cover. Hence, logical classes are defined by the actual biophysical elements present, their arrangement and their properties. A land cover classification system should also be capable of describing the whole range of earth surface features.

Land Cover/Ecosystem Functional Unit (LCEU)

An area with relatively homogenous environmental characteristics that control plant productivity potential such as land cover, soil type, climate conditions, elevation etc. This definition is consistent with the LCEU described in the UN Statistical Commission's System of Environmental and Economic Accounting (SEEA) Ecosystem accounting units, but here explicitly includes land cover and climate conditions as potential inclusions.

[3] https://www.iso.org/standard/44342.html

Land cover element, landscape element

Feature or basic component in the landscape which can be assigned a single classification. Elements may be abiotic (e.g., water, soil, rock and man-made surfaces) or vegetation (e.g., grasses, shrubs, bushes and woody plants). Within a map or region, a particular land cover class (see land cover class) may be instantiated in one or more land cover elements.

Land Cover Meta Language (LCML; [ISO 19144-2:2012])

Logical general model used to describe land cover features (**see feature**) from which more specific rules can be described to create a *particular* classification system (**see classification system**)

The **Land Cover Meta Language** (LCML) (ISO 19144-2: 2012)[4] uses Unified Modelling Language (UML) classes to represent a framework for land cover elements and their attributes, arranged in a structured way, to ensure that classes can be clearly understood and readily compared within and between user groups and communities.

Land cover transition

Change in the type of land cover, described by a change in the classification of land cover elements. A transition that reduces the biological or economic productivity and complexity of the land is considered degradation.

Land degradation

The reduction or loss of the biological or economic productivity and complexity of rain fed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from a combination of pressures, including land use and management practices. This definition was adopted by and is used by the 197 Parties to the United Nations Convention to Combat Desertification (UNCCD).[5]

Land Degradation Neutrality (LDN)

A state whereby the amount and quality of land resources necessary to support ecosystem functions and services, and enhance food security, remain stable or increase within specified temporal and spatial scales and ecosystems (Decision 3/COP.12, UNCCD, 2015a).

Land productivity

The biological productive capacity of the land - the source of all the food, fibre and fuel that sustains humans. This is most effectively measured in the Land Productivity sub-indicator using satellite EO datasets representing NPP (see **Net Primary Productivity**). Changes in land productivity point to long-term changes in the health and productive capacity of the land and reflect the net effects of changes in ecosystem functioning on plant and biomass growth. This assessment includes only above-ground productivity and can be applied to all

[4] https://www.iso.org/standard/44342.html

[5] United Nations Convention to Combat Desertification. 1994. Article 1 of the Convention Text http://www2.unccd.int/sites/default/files/relevant-links/2017-01/UNCCD_Convention_ENG_0.pdf

natural and anthropogenic terrestrial environments. ISO 19115-1:2014[6] will guide the development of a new international standard.

Land unit

The finest-resolution spatial unit. In most cases this will typically be the extent of land occupied by an image pixel. This definition is consistent with Orr et al. (2017).

Land use [UNFAO LCCS 2:2005]

The arrangements, activities and inputs that people undertake in a certain land cover (**see feature**) type to maintain it or produce change.

NOTE This definition of land use establishes a direct link between land cover and the actions of people in their environment. Multiple land uses can coexist at the same location (e.g. forestry and recreation). This is contrary to the term land cover classes, which are mutually exclusive.

EXAMPLE "Recreation area" is a land use term that can be applicable to different land cover types, e.g. sandy surfaces such as a beach; a built-up area such as a pleasure park; woodlands etc.

Legend [UNFAO LCCS 2:2005]

Application of a classification (**see classification**) in a specific area using a defined mapping scale and specific data set.

The classes constituting a suitable legend should be:

I. Unambiguous: being mutually exclusive and unique
II. Complete: in terms of spatial coverage for the region of interest
III. Exhaustive: providing complete thematic coverage for the full range of land cover classes in the region of interest.

The level of detail for a given legend will depend on the application of the classification exercise and the thematic and spatial accuracy of available data.

Examples: Some of the more commonly used land cover legends range from coarse thematic detail, such as the six class land cover/use legend used by the Intergovernmental Panel on Climate Change (IPCC) (Penman et al. 2003), to more complex hierarchical legends such as the 22 class European Space Agency's Climate Change Initiative Land Cover (CCI-LC) dataset (Defourny et al. 2012).

Legend class [ISO 19144-1:2009, 4.1.16]

The class (**see classifier, class**) resultant from the application of a classification (see classification) process.

[6] https://www.iso.org/standard/53798.html

NOTE: In order to avoid confusion with respect to the term "class", the result of a classification process will be termed a "legend class". This use of the term "class" is distinct from the term "class" as used in UML modelling.

Litter

All non-living biomass - with a size greater than the limit for soil organic matter (2 mm) and smaller than the minimum diameter chosen for dead wood (10 cm) - lying dead and 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 (less than 2 mm diameter) are included in litter where they cannot be distinguished from it empirically (IPCC 2003).

Method of computation

The extent of degradation is calculated for each of the sub-indicators during the baseline and reporting periods. The One Out, All Out (1OAO)[7] principle is applied to the sub-indicator estimates to determine the extent of land that is degraded over total land area. 1OAO is applied to account for changes in the sub-indicators which are depicted as (i) positive or improving, (ii) negative or declining, or (iii) stable or unchanging. If one of the sub-indicators is negative (or stable when degraded in the baseline or previous reporting period) for a particular land unit, then it would be considered as degraded subject to validation by national authorities. Specific details of the methods for calculating each of the sub-indicators and the Indicator are presented in the relevant chapters in this report.

Net primary productivity (NPP)

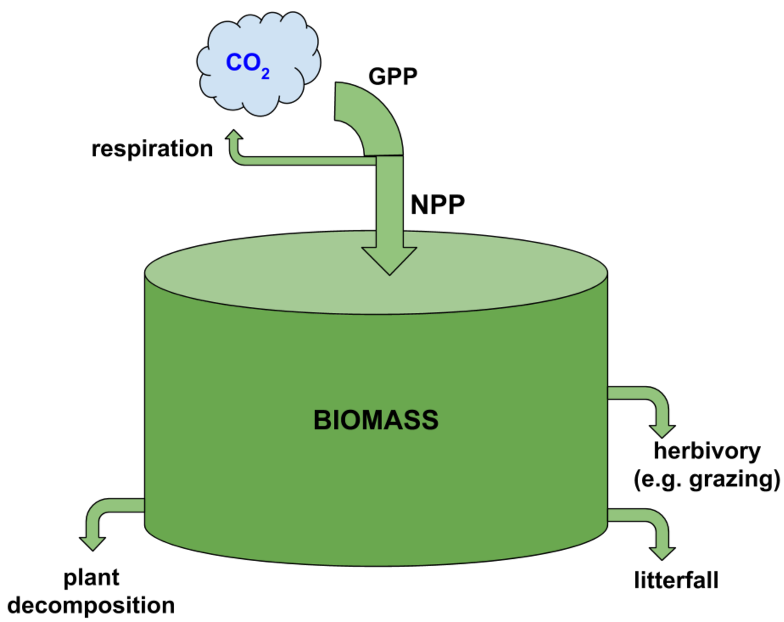
The net amount of carbon assimilated after photosynthesis and autotrophic respiration over a given period of time (Clark et al. 2001). NPP is measured in mass of carbon per area per unit of time (for example kg C/ha/year or g C/m^2/day). Remote sensing is the most effective way to estimate NPP in fine detail at national scales, but it is not directly measured by EO sensors. NPP is estimated from known correlations between the fraction of absorbed photosynthetically active radiation (fAPAR) and plant growth vigour and biomass within specific land cover types and locations (see Box 1).

[7] https://circabc.europa.eu/sd/a/06480e87-27a6-41e6-b165-0581c2b046ad/Guidance%20No%2013%20-%20Classification%20of%20Ecological%20Status%20(WG%20A).pdf

Box 1. Net Primary Productivity, Biomass and Normalized Difference Vegetation Index: How are they related and what are their differences?

Biomass is the total mass of living plant organisms in a given area. It is generally measured in units of dry mass per area (i.e. after removing the water) or units of Carbon per area. For example, kg ha^{-1} or gC m^{-2}. In the figure below it is the contents of the large cylindrical container, or “bucket”. Net Primary Production (NPP) is the amount of biomass gained (as a result of photosynthesis) in a given period of time. NPP is the difference between gross primary productivity (GPP) and plant respiration. NPP is measured in the same units as biomass, but also per unit of time, e.g. kg ha^{-1} $year^{-1}$ or gC m^{-2} day^{-1}. In the figure, NPP is the arrow showing “new” biomass entering the cylinder, akin to water filling the bucket. There are also drainages (losses of biomass) due to herbivory, litterfall, and plant decomposition. The size of the bucket can, therefore, increase, decrease or remain equal in a given period of time, depending on the relative sizes of NPP and the drainage losses. Biomass and NPP are generally positively correlated, as more biomass means more leaves producing photosynthesis and therefore more NPP. There are, however, many exceptions to this. For example, a tropical forest next to a sugarcane plantation may have a much higher biomass, but a similar amount of NPP.

Normalized Difference Vegetation Index (NDVI) is a unitless index calculated from the reflectance measured by remote sensors. NDVI does not measure Biomass nor NPP directly. NDVI tends to be linearly related to the fraction of radiation absorbed by green leaves during photosynthesis, which in turn determines the value of NPP. Therefore, NDVI has been used in many studies to estimate NPP. The relationship between NDVI and Biomass tends to be also positively correlated, but NDVI saturates (i.e. stops responding) when Biomass is high.



Organic soils

Identified on the basis of criteria 1 and 2, or 1 and 3 listed below (FAO 1998; IPCC 2006):

1. Thickness of organic horizon ≥10 cm. A horizon of <20 cm must have ≥12% organic carbon when mixed to a depth of 20 cm.
2. Soils that are never saturated with water for more than a few days must contain more than 20% organic carbon by weight (i.e., about 35% organic matter).
3. Soils are subject to water saturation episodes and has either:
    a. At least 12% organic carbon by weight (i.e., about 20% organic matter) if the soil has no clay; or
    b. At least 18% organic carbon by weight (i.e., about 30% organic matter) if the soil has 60% or more clay; or
    c. An intermediate, proportional amount of organic carbon for intermediate amounts of clay.

All other types of soils are classified as **mineral soils** (IPCC 2006).

Physiognomy

General appearance of an object or terrain, without reference to its underlying or scientific characteristics.

Productivity index

The algorithm used to estimate land productivity levels from image data. There are many vegetation indices that can be calculated from image data which have been shown to be effective surrogates for fAPAR and highly correlated with NPP. One of the oldest and most commonly used surrogates of primary productivity is the Normalised Difference Vegetation Index (NDVI) which is an indicator of green leaf productivity and biomass (Tucker 1979). The NDVI and other similar indices typically use spectral wavelengths correlated with aspects of plant cover, biomass and/or growth vigour, though each index may be better suited to some landscapes and vegetation types than others.

For the purposes of reporting on SDG Indicator 15.3.1, it is not necessary to quantify the magnitude of change in productivity in units of NPP, but only to know whether productivity is increasing (positive), decreasing (negative), or stable for the land unit at a particular time. The relative change in a unit-less index, such as the NDVI, is often sufficient to determine land degradation, in accordance with the methodology presented in this GPG. This also reduces the sampling effort required by countries to convert index values into finite units for NPP assessments.

Note however that an increase in NPP or productivity index values does not necessarily indicate improvements in land condition. A typical example is found in shrub or bush encroachment, which may increase NPP levels in native, formerly sparsely-vegetated areas (Orr et al. 2017) but have negative effects on biodiversity, habitat provision or the ability to restore land to its former land cover type. The interpretation of changes in productivity levels should always be conducted in the context of additional local data and information (see Sims et al. 2020 for more information).

Reporting Period (tn)

The time period over which the sub-indicator is measured and quantified for the reporting period using the same methods employed for the baseline period.

The UNCCD has approved a four-year reporting frequency,[8] and therefore a four-year reporting period. However, reporting every four years may not be practical or offer a reliable detection of change for many practices for slow changing variables, such as SOC stocks.

Reporting unit

An aggregation of land units for the purpose of analysis or reporting. Reporting units may be aggregated based on administrative boundaries, environmental management areas, large scale natural features (e.g. river basins) and other factors relevant for reporting purposes such as national parks or other protected areas, statistical areas. This definition is analogous to the SEEA Ecosystem Accounting Units[9].

SDG indicator 15.3.1

The proportion of land that is degraded over total land area. Determined as a binary - degraded/not degraded - quantification based on the analysis of available data for three sub-indicators to be validated and reported by national authorities. The sub-indicators (Trends in Land Cover, Land Productivity and Carbon Stocks) were adopted by the UNCCD's governing body in 2013 as part of its monitoring and evaluation approach.[10]

Soil Organic Carbon (SOC)

The amount of carbon stored in soil. SOC is the main component of soil organic matter (SOM). The persistence of SOC is seen as an ecosystem property, in that its level reflects the biogeochemical functioning of the ecosystem. Often, in several modelling approaches, SOC is conceptually divided into sub-pools with fast (Active sub-pool), intermediate (Slow sub-pool), and long (Passive sub-pool) turnover times (IPCC 2019). In observational studies however, 'short-lived' SOC can persist for long periods in the soil if it is, for instance, physically protected from degradation within the soil matrix. Similarly, 'long-lived' SOC forms can be rapidly degraded given favourable microbial conditions.

SOC stock

The mass of SOC per unit area for a reference soil layer. The reporting standard is SOC stock in tonnes of organic carbon per hectare to a depth of 30 cm (IPCC 1997). Determination of

[8] By its decision 15/COP.13, the UNCCD Conference of the Parties has approved a four-year frequency for countries to provide information on the strategic objectives and the implementation framework of the UNCCD 2018-2030 strategic framework. https://www.unccd.int/sites/default/files/sessions/documents/2019-08/15COP13_0.pdf

[9] https://unstats.un.org/unsd/envaccounting/workshops/eea_forum_2015/91.%20SEEA%20EEA%20Tech%20Guid%201%20Functional%20approach%20to%20ecosystem%20accounting%20(30March2015).pdf

[10] By its decision 22/COP.11, the Conference of the Parties established a monitoring and evaluation approach consisting of: (a) indicators; (b) a conceptual framework that allows for the integration of indicators; and (c) indicators sourcing and management mechanisms at the national/local level. http://www.unccd.int/en/programmes/Science/Monitoring-Assessment/Documents/Decision22-COP11.pdf

SOC stock requires measurements of SOC concentration in soil, corrected for water content, soil bulk density and gravel content:

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

Equation 0-1

Where SOC_m is the concentration of organic carbon in the oven-dry 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).

Quantifying SOC stock at fixed depths as the product of soil bulk density, organic carbon concentration, proportion of coarse fragments and depth (Equation 0-1) provides a simple approach for reporting change in SOC stock. However, in the context of land use/management change, this method can systematically overestimate or underestimate SOC stocks where bulk densities have changed (e.g., under changes from full to minimum tillage in croplands). Where bulk densities differ between management practices or over time periods, more accurate estimates of SOC stock can be derived based on quantification in equivalent soil masses (Wendt and Hauser, 2013; Australian Government, 2014). Thus, recent IPCC guidance (IPCC 2019) recommends expressing carbon stocks on an **equivalent soil mass** basis.

An extended ISO 28258:2013 (Soil quality - Digital exchange of soil-related data)[11] will be the core model for exchanging soil data.

SOC stock change

The change in SOC stocks between the reporting period (t_n) and the baseline (t_0), in the units of tons of carbon per hectare (t C ha^{-1}) and include the uncertainty of the change if derived from repeat measurements.

Soil Organic Matter (SOM)

Organic carbon in mineral and organic soils (including peat) to a specified soil layer chosen by the country and applied consistently through the time series. Live fine roots (of less than 2 mm diameter) are included with soil organic matter where they cannot be distinguished from it empirically (IPCC 2003). Note: The definition here does not explicitly mention soil microfauna and microbes, however, these are also included where they cannot be distinguished from the SOM empirically.

Sub-indicators

Proxies to monitor the essential variables that reflect the capacity to deliver land-based ecosystem services. The sub-indicators are globally agreed upon in definition and methodology of calculation and deemed both technically and economically feasible for

[11] https://www.iso.org/standard/44595.html

systematic observation under both the Global Climate Observation System[12] and the integrated measurement framework of the SEEA.[13]

The sub-indicators are few in number, complementary and non-additive components of land-based natural capital and sensitive to different drivers and mechanisms of degradation. While not comprehensive in their assessment of land degradation, together the three sub-indicators can represent the quantity and quality of land-based natural capital and its associated ecosystem services. They address changes in different yet synergistic and highly relevant ways. Change in land cover is, in ecological terms, a transformational variable and addresses, among other potential drivers of change, land conversion. Land productivity trends is directly reflected in the definition of land degradation, and is a "fast" ecological variable that can capture relatively fast changes in land-based natural capital, while trends in carbon stocks above and below ground is a "slow" ecological variable, which reflects slower changes that suggest a trajectory or proximity to thresholds (Orr et al. 2017). The three sub-indicators of SDG Indicator 15.3.1 are:

1. **Land cover** (**see land cover**), which serves two functions for SDG indicator 15.3.1: (1) changes in land cover may point to land degradation when there is a loss in productivity in terms of ecosystem services considered desirable in a local or national context; and (2) a land cover classification system can be used to disaggregate the other two sub-indicators to potentially increase the relevance of summary statistics for policy or environmental use.

2. **Land productivity** (**see land productivity**), which refers to changes in the health and productive capacity of the land as measured using EO data representing total above-ground NPP.

3. **Carbon stock** (**see carbon stock**)**:** in UNCCD decision 22/COP.11, *soil organic carbon (SOC) stock* (**see SOC stock**) was adopted as the metric to be used with the understanding that this metric will be replaced by *total terrestrial system carbon stocks*, once operational.

Total carbon stock

The quantity of carbon in all of the components of ecosystem carbon pools (IPCC 2003).

Total land area

The total surface area of a country excluding the area covered by inland waters such as major rivers and lakes.[14]

[12] https://library.wmo.int/opac/doc_num.php?explnum_id=3854
[13] https://seea.un.org/
[14] Food and Agriculture Organization of the United Nations

1 Introduction

The 2030 Agenda for Sustainable Development provides a framework for countries to determine how best to improve the lives of their people now, while ensuring that these improvements are sustained for future generations. The 2030 Agenda[15] was adopted by all United Nations (UN) Member States in 2015, and includes 17 Sustainable Development Goals (SDGs) which are an urgent call to action by all countries to improve health and education, end poverty, reduce inequality and spur economic growth, while at the same time tackling climate change and preserving the terrestrial, aquatic and marine environment. Within each of the 17 Goals there are 'Targets' (174 in total) which define the tasks required to achieve each Development Goal, and within each Target there are 'Indicators' (231 unique Indicators in total[16];) which are the measurable attributes to be monitored to determine progress towards achieving the 2030 Agenda.

UN SDG 15 is *'Life on Land'*, which aims to 'Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss'. Target 15.3 aims to '*By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world'*.

This report presents methods and guidance to calculate and interpret the sole indicator of Target 15.3, SDG Indicator 15.3.1, which is the *'Proportion of land that is degraded over total land area'*. The United Nations Convention to Combat Desertification (UNCCD) is the custodian agency for SDG indicator 15.3.1, which was proposed by the Inter-Agency and Expert Group on SDG indicators (IAEG-SDGs) and adopted by the UN Statistical Commission in March 2017 to monitor progress towards achieving SDG Target 15.3.

Version 1 of this Good Practice Guidance report (GPG) was published in 2017 and has been made available to all countries wishing to report on SDG Indicator 15.3.1 as a guide to the calculation, analysis and interpretation of the Indicator since that time. Indicator 15.3.1 was elevated to Tier I in November 2019, meaning that the *'Indicator is conceptually clear, has an internationally established methodology and standards are available, and data are regularly produced by countries for at least 50 per cent of countries and of the population in every region where the indicator is relevant*'[17], in part due to the availability of supporting analytical tools and methods such as the GPG. The upgrade to Tier 1 was granted after the first round of reporting, which culminated in early 2019 with the first global assessment of land degradation based on 123 country submissions and 40 estimates derived from global data sets[18].

1.1 The definition of land degradation

The definition of land degradation for SDG Indicator 15.3.1 was adopted and is used by the 197 Parties to the UNCCD and the IAEG-SDGs. The definition is: '*the reduction or loss of the biological or economic productivity and complexity of rain fed cropland, irrigated cropland, or range, pasture,*

[15] https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf
[16] https://unstats.un.org/sdgs/indicators/indicators-list/
[17] https://unstats.un.org/sdgs/iaeg-sdgs/tier-classification/
[18] https://unstats.un.org/sdgs/report/2019/goal-15/

forest and woodlands resulting from a combination of pressures, including land use and management practices'[19]. Under this definition, the extent of land degradation for reporting on SDG Indicator 15.3.1 is calculated using its three sub-indicators which are:

1. Trends in land cover
2. Trends in land productivity
3. Trends in carbon stocks (above and below ground), currently represented by soil organic carbon (SOC) stocks.

The results of the degradation analysis for each of the sub-indicators are integrated using a one-out-all-out (1OAO) method in which a significant reduction or negative change in any one of the three sub-indicators is considered to comprise land degradation. Significant reductions can be identified using statistical criteria, or by a qualitative assessment of the magnitude of change, such as for Land Cover.

This GPG provides details on how to calculate the extent of land degradation for reporting on SDG Indicator 15.3.1 according to the Tier I methods adopted by the UN Statistical Commission[20]. While it is difficult for a single indicator to fully capture the state or condition of the land, the sub-indicators are proxies to monitor the essential variables that reflect the capacity of the land to deliver ecosystem services. The Indicator is reported as a binary quantification (i.e., degraded/not degraded) based primarily, and to the largest extent possible, on comparable and standardized national official data sources.

1.2 Version 2 revision of the GPG

Version 2 of the GPG updates the datasets and methods recommended for calculating SDG indicator 15.3.1, and responds to suggestions from 141 country parties reporting on the Indicator, collated via the 17th session of the UNCCD Committee for the Review of the Implementation of the Convention (CRIC) providing requests and suggestions to improve the GPG and Indicator calculation processes[21].

1.2.1 Key concepts remaining unchanged from Version 1

- Indicator 15.3.1 remains a binary calculation based on the three sub-indicators of Land Cover, Land Productivity and Carbon stocks as a minimum.
- The Indicator remains calculated by integrating the sub-indicators using the 1OAO process.
- SOC stock remains as the surrogate for the carbon stocks above and below ground sub-indicator.
- The international standards underpinning the assessment of each of the sub-indicators remain unchanged.

1.2.2 Revisions implemented in Version 2

- Additional guidance is provided on how to interpret Indicator 15.3.1 to support the achievement of Land Degradation Neutrality (LDN). LDN uses Indicator 15.3.1 to measure

[19] United Nations Convention to Combat Desertification. 1994. Article 1 of the Convention Text http://www2.unccd.int/sites/default/files/relevant-links/2017-01/UNCCD_Convention_ENG_0.pdf
[20] https://unstats.un.org/sdgs/metadata/files/Metadata-15-03-01.pdf
[21] https://www.unccd.int/sites/default/files/sessions/documents/2019-05/ICCD_CRIC%2817%29_9-1904478E.pdf

the extent of degradation for target setting and progress monitoring. Achieving LDN requires countries to implement actions to stabilize or reduce the extent of degraded land. Monitoring LDN requires a range of analytics in addition to the binary assessment of degradation provided by Indicator 15.3.1, some of which can be interpreted from the datasets and analytics presented here. Other elements required for LDN, such as the trade-off mechanism to achieve neutrality, are not discussed in this document.

- References to key datasets relevant to each sub-indicator have been updated.
- The methodology for the Land Cover sub-indicator has been revised to first consider the mechanisms of degradation to guide the determination of positive and negative land cover transitions.
- Additional guidance is provided on stratifying the landscape to calculate one of the three metrics of the productivity sub-indicator - productivity performance - which compares local productivity levels between similar land units spatially. The graphical representation of productivity performance has been revised to improve clarity.
- Some additional detail is provided on assessing the relationship between a time series of net primary productivity (or surrogates for it such as a vegetation index calculated from remotely-sensed image data) and a time series of productivity that has been calibrated to minimize the effect of changes in moisture availability.
- Comprehensive incorporation of the 2019 refinement of the Intergovernmental Panel on Climate Change (IPCC) 2006 Guidelines for National Greenhouse Gas Inventories into the Carbon Stock sub-indicator methods.
- Additional guidance is provided on the process for identifying and reporting on false positive and false negative degradation assessments.
- Guidance is provided on recalculation of the time series and baseline to enable different, new and/or improved datasets to be introduced as they emerge.

1.3 The context of this GPG

While the GPG is, at its core, a methodological document, it is important to note that it is also a key element of an overall strategy agreed upon by both data providers and end users at the national level, through the Group on Earth Observations (GEO) Land Degradation Neutrality (LDN) Initiative, commonly known as the GEO LDN Initiative.[22] This strategy seeks to engage stakeholders ranging from data providers to end users at the national and sub-national levels in a process to ensure that:

I. Minimum data quality standards are identified and adhered to by all data providers.
II. Companion data analytics tools can be developed in a federated approach so that the methods and datasets can be used in a cohesive way to ensure that utility of Indicator 15.3.1.
III. Capacity can be developed to increase national ownership of all aspects of indicator development and reporting.

This multilateral and inter-organizational approach ensures that the global methodological standards documented here are critically assessed by all relevant stakeholders.

[22] Group on Earth Observations Land Degradation Neutrality (GEO LDN) Initiative http://earthobservations.org/geo_ldn.php

These efforts are also working to ensure that the steps and algorithms used to calculate Indicator 15.3.1 are translated into open-source code for software tools to support reporting. The primary implementation of these methods is in Trends.Earth[23], an open-source GIS plugin which countries have used to compute SDG Indicator 15.3.1 and its sub-indicators. Trends.Earth makes it possible for end users to analyse estimates provided at the global level, compare these to national estimates, and then produce their own country estimates based on country-specific data and nationally determined assumptions, while employing the same standardized methodologies described in this GPG. These resources help countries adhere to global standards while taking end-to-end ownership of the process, even when local capacity for analysis may be limited.

Through the working groups of the GEO LDN Initiative and a range of other aligned activities (see Section 1.4), additional potentially-relevant support tools that are inter-operational with Trends.Earth are being developed. These aim to broaden the utility of SDG Indicator 15.3.1 and its sub-indicators for environmental analysis and decision support at the global, national and sub-national levels. This strategy has led not only to a high rate of reporting (141 countries reporting in 2018[24]), but also to a significant expansion of the larger innovation ecosystem interested in capitalizing on the potential impact these data sets can have.

Box 2. SEPAL for calculating SDG Indicator 15.3.1

SEPAL[1] is a free and open source geospatial data processing platform that combines an easy-to-use GUI, powerful open-source software (e.g. Google Earth Engine, R, python, GDAL) and a cloud computing environment available to users anywhere in the world via their computer or mobile phone. SEPAL facilitates access to satellite imagery and processing algorithms allowing users to create their own data, analyses, and results. Custom pre-processing can be applied to optical and synthetic aperture radar (SAR) to create image mosaics, time series and multi-dimensional time series. This Analysis Ready Data can be used to classify land cover and create land cover change maps. Training data, collected within SEPAL or uploaded from another source, can be iteratively improved based on the classification output, which is run on the fly each time a new sample is added. SEPAL provides additional tools for classification and post-classification, such as object-based image analysis, morphological filtering and others. Complete land cover and land cover change maps can be assessed using the accuracy assessment tools available in SEPAL.

A new module in SEPAL calculates SDG 15.3.1 and its sub-indicators, consistent with the methodology in the GPG. The SDG monitoring module in SEPAL utilizes Landsat and Sentinel data to estimate the indicator at a sub-national scale. Project scale monitoring using SDG 15.3.1 can provide consistent information across multiple scales making global, national, sub-national and project scale data comparable. The module, when finalized, will be made easily accessible to SEPAL users worldwide.

[1] https://sepal.io/

[23] http://trends.earth/docs/en/
[24] https://prais.unccd.int/

1.4 SDG Indicator 15.3.1 and Land Degradation Neutrality

The LDN programme of the UNCCD strives to achieve the primary objective of SDG Target 15.3, which is '…*to achieve a land degradation-neutral world*'. LDN is "*a state whereby the amount and quality of land resources, necessary to support ecosystem functions and services and enhance food security, remains stable or increases within specified temporal and spatial scales and ecosystems*"[25].

Based on the lessons learnt from a pilot project involving 14 countries[26], in 2016 the UNCCD, in collaboration with multiple international partners, launched the LDN Target Setting Programme.[27] Since then, the programme has been supporting interested countries with their national LDN target setting process, including setting national baselines, evidence-based targets and associated measures to achieve LDN. By November 2020, 124 countries were participating in the LDN Target Setting Programme, over 80 of which had established and validated a baseline for the indicator.

These efforts, coupled with a series of capacity building workshops which were implemented as part of a GEF-financed Global Support Programme and trained over 300 government representatives from 140 countries[28], set the foundation for a first successful national reporting process to the UNCCD in 2018. The provision of clear methodological guidance, default data prepared in a globally consistent manner, and dedicated data analytic tools has helped countries report in an increasingly harmonized way while taking ownership of the process.[29] Country data collected through the UNCCD national reporting process, including reporting on SDG Indicator 15.3.1 along with regional and global aggregates, were then submitted to the UN Statistics Division (UNSD) for inclusion in the SDG Report 2019.

Global efforts to achieve LDN are also supported by both governments and Earth Observation (EO) organizations who are members and partners of the GEO, through their participation in the GEO LDN Initiative and other aligned activities striving to the improve the quality and availability of EO datasets for measuring and monitoring LDN and the SDGs. The use of EO and geospatial information can significantly reduce the costs of monitoring the aspirations reflected in the Goals and Targets, and make SDG monitoring and reporting more achievable with the limited resources available to governments. These activities include the work of the Committee on Earth Observation Satellites (CEOS) Ad Hoc Team on SDGs, which focuses on four SDG Indicators including 15.3.1[30], the CEOS Open Data Cube platform[31] based on freely available CEOS datasets, the GEO Earth Observation for SDGs program[32], and the Tools4LDN initiative[33]. Beyond the SDG framework, end-users in developing countries and regions are also strongly invited to use these EO data to increase their capacity to acquire, analyse and utilise information for a broad range of policy-making purposes at a national scale.

[25] https://www.unccd.int/sites/default/files/sessions/documents/2019-08/3COP12_0.pdf
[26] https://knowledge.unccd.int/knowledge-products-and-pillars/ldn-target-setting-building-blocks/lessons-learned-14-pilot-4
[27] http://www2.unccd.int/actions/ldn-target-setting-programme
[28] https://www.unccd.int/sites/default/files/inline-files/report%20on%20the%20capacity%20building%20workshops.pdf
[29] https://www.unccd.int/sites/default/files/sessions/documents/2019-03/ICCD_CRIC%2817%29_2-1822319E.pdf
[30] http://ceos.org/ourwork/ad-hoc-teams/sustainable-development-goals/
[31] https://www.opendatacube.org/ceos
[32] http://eo4sdg.org/wp-content/uploads/2018/09/EO4SDG_for_GEO.Highlights.Report.pdf
[33] https://www.tools4ldn.org/

This GPG is the document of methodological reference providing a standardized and consistent approach for the *monitoring* of LDN, national reporting to the UNCCD and reporting on SDG indicator 15.3.1. As the sole Indicator of Target 15.3, the extent of degraded land for assessing LDN is calculated using SDG Indicator 15.3.1. This GPG does not explicitly provide guidance on the *assessment* of LDN, which is addressed in other guidance documents developed for the Parties of the UNCCD.[34] Moreover, because the number and maturity of activities supporting the achievement of LDN worldwide has evolved considerably since the production of GPG Version 1, this GPG version 2 includes guidance on how data calculated for reporting on SDG Indicator 15.3.1 can be interpreted to inform LDN efforts.

[34] In September 2017, through decision 18/COP.13, the UNCCD Conference of the Parties endorsed the scientific conceptual framework for land degradation neutrality summarized in document ICCD/COP(13)/CST/2, and called upon Parties pursuing land degradation neutrality to consider the guidance provided by the scientific conceptual framework for land degradation neutrality and observe the principles summarized therein, taking into account national circumstances. Since that time, a number of other supporting guidance documents have been published which support country efforts to assess LDN and implement appropriate interventions designed to achieve or exceed LDN.

Box 3. The potential of SEEA Ecosystem Accounts to derive land degradation indicators

The *System of Environmental-Economic Accounting - Ecosystem Accounting* (SEEA EA) (UN Statistics Division 2020) is an integrated statistical framework for organizing biophysical information about ecosystems, measuring ecosystem services, tracking changes in ecosystem extent and condition, and linking this information to measures of economic and human activity. The SEEA EA consist of five core accounts: extent, condition, ecosystem services (in both physical and monetary units), and a monetary asset account. In addition, there are several connected thematic accounts, such as for carbon and biodiversity. The three sub-indicators of SDG Indicator 15.3.1 and the approaches to the underlying spatial units, are, in principle, aligned with the SEEA EA framework, as summarized here based upon UN (2019).

The **extent account** requires the delineation of areas within a country into mutually exclusive and collectively exhaustive spatial units that represent ecosystem assets. The ecosystem extent account change matrix (Table 4.1 in SEEA EA, UN Statistics Division 2020) has the same structure as the land cover change matrix described in Figure 3-2 of this report, and can be used to report on the land cover change sub-indicator of SDG Indicator 15.3.1. National ecosystem types must be linked to the 6 IPCC classes, or to an IPCCSX scheme (see Section 3.2.2) and include a description of all possible transitions in terms of whether it constitutes degradation.

The UNCCD definition of land degradation is also clearly aligned to that of ecosystem condition. The ecosystem **condition account** describes the quality of ecosystems and how they have changed during the accounting period, with respect to a reference condition, using a combination of relevant variables and indicators organized in a condition typology (see below, adapted from SEEA Table 5.1 of UN Statistics Division 2020).

	ECT groups	**ECT classes**
Ecosystem condition	Abiotic ecosystem characteristics	1. Physical state characteristics (including soil structure, water availability)
		2. Chemical state characteristics (including soil nutrient levels, water quality, air pollutant concentrations)
	Biotic ecosystem characteristics	3. Compositional state characteristics (including species-based indicators)
		4. Structural state characteristics (including vegetation, biomass, food chains)
		5. Functional state characteristics (including ecosystem processes, disturbance regimes)
	Landscape level characteristics	6. Landscape and seascape characteristics (including landscape diversity, connectivity, fragmentation, embedded semi-natural elements in farmland)

Both soil organic carbon (SOC) and net primary productivity (NPP) are reflected in condition accounts as chemical and functional state characteristics respectively. In addition, the SEEA EA also contains a thematic carbon stock account (section 13.4), which provides a comprehensive overview of the different types of carbon in the areas (e.g. geocarbon, biocarbon - above and below ground) and their change over time. Due to the spatial nature of the SEEA, condition indicators are typically derived from underlying maps. While there are specifics to be worked through (e.g. resolution of the maps, alignment of reference year with UNCCD requirements), information from the condition account can be used to report on the SOC and land productivity sub-indicators of SDG Indicator 15.3.1.

The SEEA EA defines **ecosystem degradation** as the decrease in the monetary value of an ecosystem asset (core account 5) over an accounting period that is associated with a decline in the condition of an ecosystem asset, thereby excluding ecosystem conversions which refer to changes in ecosystem extent. This differs from the physical UNCCD concept of **land degradation** that is defined through an overlay of the 3 sub-indicators.

By arranging land degradation statistics in a format that is compatible with national statistical systems, it is possible to more readily associate trends in land degradation with economic statistics, particularly for the agricultural sector. By presenting this information alongside key socio-economic statistics on unemployment, poverty and population, decision-makers will get a better picture of where people may be most impacted by land degradation.

2 SDG Indicator 15.3.1: Proportion of land that is degraded over total land area

2.1 Methodology

The UNCCD reporting template includes the indicator and sub-indicators. The methodology for the indicator is universal, allowing countries to select the most appropriate datasets and national methods for estimating the sub-indicators and determine the most suitable pathway for deriving the indicator. In this regard, this GPG helps countries access and interpret a wide range of data sources for the sub-indicators, including EO and geospatial information, whilst ensuring national ownership. At the national level, the institutions that specialize in environmental data are able to work synergistically with National Statistics Offices (NSOs). Thus, the use of the UNCCD's national reports provides a practical and harmonized approach by which countries can report on the indicator, beginning in 2018 and every four years thereafter.[35]

2.1.1 Rationale

By analysing changes in the sub-indicators in the context of local assessments of the climate, soil, land use and any other factors influencing land conditions, national authorities can identify which land units are to be classified as degraded, sum the total, and report on the indicator providing the appropriate justification (as described in Section 2.2). The indicator is derived from a binary classification of land condition (i.e., degraded or not degraded) based primarily, and to the largest extent possible, on comparable and standardized national official data sources. However, due to the nature of the indicator, EO and geospatial information from regional, national and global data sources can play an important role in its derivation, subject to validation by national authorities in conjunction with ground measurements and assessments wherever possible.

2.1.2 Calculating the Indicator

The indicator is calculated by evaluating changes in the sub-indicators over time, to determine the extent of land that is degraded over total land area. The extent of degradation measured in each of the reporting periods is compared to the extent of degradation measured in the baseline period to identify whether this area is increasing or decreasing over time. The baseline sets the benchmark extent of degradation against which progress towards achieving SDG Target 15.3 and LDN is assessed.

As a result, the 1OAO principle is applied in the method of computation where changes in the sub-indicators are depicted as:

(i) Positive or improving;

(ii) Negative or declining; or

(iii) Stable or unchanging.

[35] In September 2017, the UNCCD governing body (196 countries that make up the Conference of the Parties) requested the UNCCD secretariat, as the custodian agency for Sustainable Development Goal indicator 15.3.1, to use the information submitted to it by Parties in their national reports that is relevant to the implementation of the 2030 Agenda for Sustainable Development as a contribution to the overall follow-up and review by the High-level Political Forum on Sustainable Development.

If one of the sub-indicators is declining or negative (or stable when degraded in the baseline or previous reporting period) for a particular land unit, then it may be considered potentially degraded subject to validation by national authorities (and see Section 2.2.2).

In practical terms, for the purposes of calculating the Indicator, tracking change in the extent of degraded land is a three-step process:

1. Calculate the extent of degradation in the baseline period (t_0) from 1 January 2000 to 31 December 2015. This sets the benchmark against which progress towards achieving SDG Target 15.3 is assessed in each of the reporting periods.
2. Calculate the extent of degradation in the reporting period (t_n), which indicates the recent extent of degraded land.
3. Calculate the change in extent of degradation between the baseline and reporting periods.

Each sub-indicator, and the metrics used to define them, may be calculated using a subset of the baseline period depending on the requirements of the statistical methods implemented for their calculation. Each reporting period considers a unique set of years extending up to the reporting date.

For both the baseline and reporting periods, the extent of land that is degraded is derived from a quantification and assessment of time series data for all land units in each of the sub-indicators. National authorities report the Indicator for the baseline and subsequent reporting periods by summing the area where changes in the sub-indicators are considered to indicate new degradation, and areas identified as degraded in previous assessments that remain degraded (i.e. have not improved to a non-degraded state) in this reporting period. Land classified as degraded will retain that status unless it improves relative to the baseline.

The sub-indicators are then combined using the 1OAO process to determine the Indicator, which is the extent of land that is degraded in hectares (ha) represented as a proportion of the total land area. Although the indicator will be reported as a single figure, it can be spatially disaggregated by sub-indicator, land cover class or other policy-relevant units, which may assist in interpreting the drivers and mechanisms of land degradation for each land unit.

The method of computation for SDG indicator 15.3.1 is illustrated in Figure 2-1. Detailed methods for calculating the extent of degradation in the baseline and reporting periods for each of the sub-indicators are presented in Chapters 2 to 5 of this report.

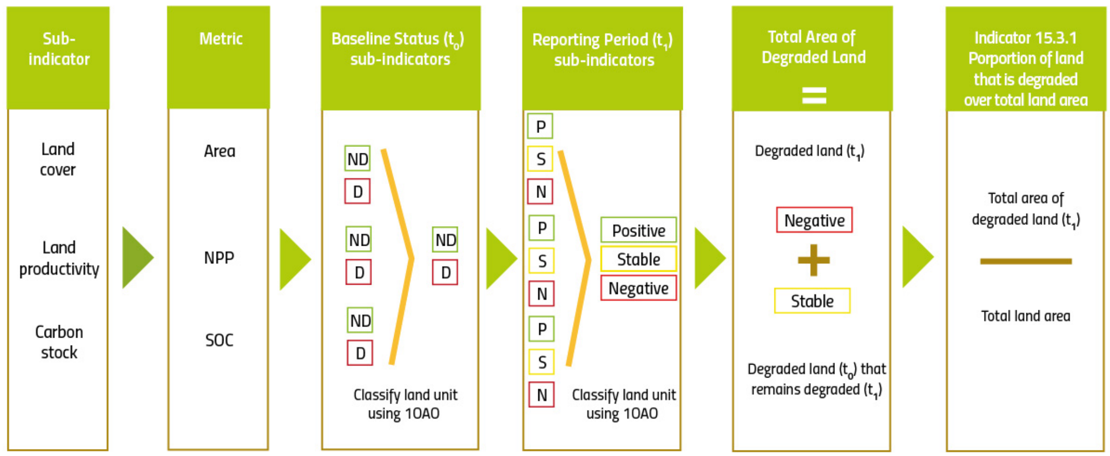


Figure 2-1. Steps to derive the indicator from the sub-indicators where ND is not degraded and D is degraded.

We define P_n as the proportion of land that is degraded at time t_n since the baseline period t_0. P_n is calculated by dividing the total area degraded *A(Degraded)*$_n$ at t_n, by the total national land area *A(Total)* including surface water extent.

Where possible *A(Degraded)*$_n$ should be reported specifically for each land cover class *i* and is made up of three components:

1. Areas of land that have persisted in a degraded state since the baseline period *A(persistent)*$_{i,n}$,
2. Areas that have degraded since the baseline period A(recent)$_{i,n}$
3. Areas that have improved from a degraded state to a non-degraded state wince the baseline period A(improved)$_{i,n}$.

The total area of degraded land for class *i* at time *n* is calculated as follows:

$$A(Degraded)_{i,n} = A(persistent)_{i,n} + A(recent)_{i,n} - A(improved)_{i,n}$$

Equation 2-1

Where $A(Degraded)_{i,n}$ is reported in hectares;

The proportion of land cover type *i* that is degraded is then given by:

$$P_{i,n} = \frac{A(Degraded)_{i,n}}{A(Total)_{i,n}}$$

Equation 2-2

The total area of land that is degraded over total land area is the accumulation across the *all* land cover classes within the reporting period *n* is given by:

$$A(Degraded)_n = \sum_i A(Degraded)_{i,n}$$

Equation 2-3

Where

The total proportion of land that is degraded over total land area is given by:

$$P_n = \frac{A(Degraded)_n}{A(Total)}$$

Equation 2-4

Note that once the indicator has been calculated, the data and map products generated during this process can be used to monitor Indicator 15.3.1 and also in the LDN planning process. This would likely involve an integration of land degradation status (an assessment of degradation) and LDN status (and assessment of significant change), as suggested in the Conceptual Framework for Land Degradation Neutrality[36]

2.1.3 Data sources

2.1.3.1 Default datasets

Global default data on the three sub-indicators is available from a range of existing sources (e.g., databases, maps, reports), including participatory inventories of land management systems as well as remote sensing data collected at the national level. The aim of this data provision is solely to assist countries in complementing and enhancing national data, subject to validation and reporting by national authorities (decision 22/COP.11[37]). However these datasets may be the most comprehensive and detailed available for some countries. A comprehensive inventory of all data sources available for each sub-indicator is contained in the relevant sub-indicator chapters of this report.

Table 2-1 shows the default global datasets that were provided by the UNCCD for calculating Indicator 15.3.1 for the 2018 reporting period, along with some alternative datasets that have become available since then, and may be preferable in some cases. For Land Cover, the default European Space Agency's Climate Change Initiative Land Cover (ESA CCI-LC) full time series has been extended to include data for 2016, 2017, 2018 and 2019[38], and while the updated alternative Copernicus Global Land Service Land Cover at 100m (CGLS-LC100) data commenced only in 2015, it provides improved spatial resolution and a range of analytical improvements over the CCI-LC.

For assessing land productivity, the Land Productivity Dynamics **(**LPD) of the Joint Research Centre (JRC) of the European Commission product remains the only global product that classifies observations of plant productivity into classes indicating the level and trend over time, as far as the authors are aware. Trends.Earth enables these classes to be calculated from other time series datasets, including the MODIS MOD13Q1 250m vegetation index product. The MODIS instruments were launched in 1999 and 2002 with a designed life of 6 years, but they are expected to continue to provide data beyond 2020[39]. Alternative near-global and freely-available time series observations

[36] https://knowledge.unccd.int/publication/ldn-scientific-conceptual-framework-land-degradation-neutrality-report-science-policy
[37] https://www.unccd.int/sites/default/files/sessions/documents/2019-08/22COP11_0.pdf
[38] http://maps.elie.ucl.ac.be/CCI/viewer/download.php
[39] https://nsidc.org/nsidc-monthly-highlights/2017/08/modis-viirs-building-time-series

that can be processed into vegetation indices include Landsat Analysis Ready Data (ARD)[40] and the Sentinel2 MultiSpectral Instrument (MSI) data[41], which can be processed using the free SNAP toolbox[42]. These can then be ingested into Trends.Earth to calculate land productivity degradation consistent with the GPG.

The SoilGrids250m default data for SOC have been significantly upgraded to version 2 (released in May 2020) and now include pixel-scale uncertainty estimates. A potential alternative dataset is the Global Soil Organic Carbon (GSOC) maps, which are developed by the Global Soil Partnership (GSP) of the FAO in conjunction with an extensive user engagement process. The GSOC maps show SOC stock in the upper 30cm of the soil profile maps at 1km resolution, and have been developed under GSOC's mapping Guidelines to ensure global comparability. A very recently developed new data source that may be of interest is Soils Revealed, which implements the methods described in version 1 of this GPG to show historic, recent and future SOC stocks and stock change globally at 250m resolution between 2000 and 2018. At the time of writing it is not clear whether there are plans to make these datasets downloadable.

Table 2-1. Global default datasets for each of the sub-indicators, and potential possible alternatives.

Sub-indicator	Default data provided for 2018 reporting	Alternatives
Land Cover	**ESA-CCI-LC**[43] 300m annual global from 1992 to 2019	**Copernicus CGLS-LC100 (Collection 3)**[44] 100m annual global from 2015 to 2019
Land productivity	**JRC Land Productivity Dynamics (LPD)**[45] 1km annual global from 1999-2013	**MODIS vegetation index (MOD31Q1, MYD13Q1)**[46] 250 m global, 16-day integration period since 2000 **Copernicus Global Land Service NDVI,**[47] 1km annual global since 1998.
SOC	**ISRIC SoilGrids250m**[48] 250 m global spatial predictions for selected soil properties at six standard depths	**ISRIC SoilGrids250m version 2** (de Sousa et al. 2020), updated global product at 250 m spatial resolution with spatial uncertainty. **FAO Global Soil Organic Carbon Map**[49], global and national maps of SOC stocks at 1 km spatial resolution; latest version 2019. *https://soilsrevealed.org/

[40] https://glad.geog.umd.edu/ard/glad-landsat-ard
[41] https://sentinel.esa.int/web/sentinel/sentinel-data-access
[42] https://step.esa.int/main/download/snap-download/
[43] https://climate.esa.int/en/projects/land-cover/
[44] https://land.copernicus.eu/global/products/lc
[45] https://wad.jrc.ec.europa.eu/landproductivity
[46] https://modis.gsfc.nasa.gov/data/dataprod/mod13.php
[47] https://land.copernicus.eu/global/products/ndvi
[48] https://www.soilgrids.org/
[49] http://www.fao.org/global-soil-partnership/pillars-action/4-information-and-data-new/global-soil-organic-carbon-gsoc-map/en/

2.1.3.2 Data Quality Standards

Global default datasets are provided to assist countries that may not have the appropriate datasets or capacity to calculate the sub-indicators at national scale. The SDG process emphasizes a preference for nations to develop their sovereign datasets, or to validate available datasets for accuracy in their national context, and it is hoped that data availability and processing capacity will improve in many countries to enable them to use their national datasets. There is therefore a need to support countries to identify datasets that are suitable for reporting Indicator 15.3.1 and LDN at national and sub-national scales.

This GPG provides guidance on how to calculate each of the sub-indicators from any relevant dataset of suitable quality. The availability and quality of EO and other spatial data suitable for calculating the sub-indicators is constantly improving, and rather than recommend specific datasets, a more adaptable approach is to define the data quality attributes that make a dataset suitable for use in calculating the sub-indicators. The data quality standards can be used to interrogate the suitability of any existing or future dataset for calculating Indicator 15.3.1 at finer scales.

In early 2020 the GEO LDN Initiative conducted a series of interviews and workshops to determine end user and data provider perspectives on data quality standards (DQS) for calculating Indicator 15.3.1 and LDN. The result of this process is a report (the DQS report[50]) describing a series of agreed minimum DQS for a range of data attributes (Table 2-2).

Some of these standards are aspirational, identifying key data needs for assessing SDG indicator 15.3.1 as a guide for data providers, particularly for supporting national scale assessments. At the time of writing none of the default global datasets meet all of these standards, such as the 100 m minimum grid cell size for SOC datasets. On small islands, for example, a grid cell size of 100 m may not be sufficient to enable accurate assessment.

In addition to the standards themselves, the DQS report also presents four decision trees that visually guide end users through the process of determining the suitability of a dataset for use in calculating Indicator 15.3.1, its sub-indicators and LDN, and provides pointers to additional information sources including this report, shown as pale blue pentagons.

The first decision tree guides potential users exploring the need and capacity to develop and/or use EO data at national and sub-national scales (Figure 2-2). If the production of datasets at this scale is not of interest or not possible, then countries may simply choose to use the global default datasets, noting that the default datasets are likely to be less representative of local conditions. To achieve full coverage of larger areas it may be necessary to create mosaics of images with a scene size smaller than the area of interest. Creating a mosaic or compositing of images is a highly technical task, and the steps required may vary depending on the datasets being joined and the processing tools being used to create the mosaic. While the DQS report indicates that guidance on this process can be found in this GPG, a detailed description of how to mosaic images is beyond the scope of this report. Readers are recommended to source this guidance from resources related to the image data sets and software tools being used. Further links are provided to the other DQS decision trees

[50] http://earthobservations.org/documents/ldn/20200703_GEOLDN_TechnicalNote_FINAL_SINGLE.pdf

included in this report for the analysis of land cover change (Figure 3-4), land productivity (Figure 4-4) and SOC (Figure 5-1).

Table 2-2. Summary of recommended minimum data quality standards (adapted from Table 5 of the DQS report)

Topic	Minimum quality standard	Further information
Grid cell size	100 m	DQS report
Temporal coverage	Specific to sub-indicator	Chapters 3, 4 & 0 of this report
Analysis ready data (ARD)	Use ARD	CEOS Analysis Ready Data
Land cover classes	User decision	Section 3.2.2 of this report
Land cover change assessment	Accuracy > 85%	Section 3.2.3 of this report; ISO 19144-2:2012(en), Geographic information - Classification systems — Part 2: Land Cover Meta Language (LCML)
Lagend translation	Land Cover Meta Language (LCML)	Chapter 3 of this report
Growing season definition	Proportional	Section 4.2.4.1 of this report
Productivity Index	Normalised Difference Vegetation Index (NDVI)	Section B.1.1 of this report
Climate calibration/normalisation	Use uncalibrated data	Section B.2 of this report
Linking time series	Linear regression	Section B.4 of this report
SOC data uncertainty	Pixel-based	Section 5.2.6.3 of this report
Harmonise and compare indices	Report change	Chapter 6 of this report
Soil inventory update period	10 years	DQS report

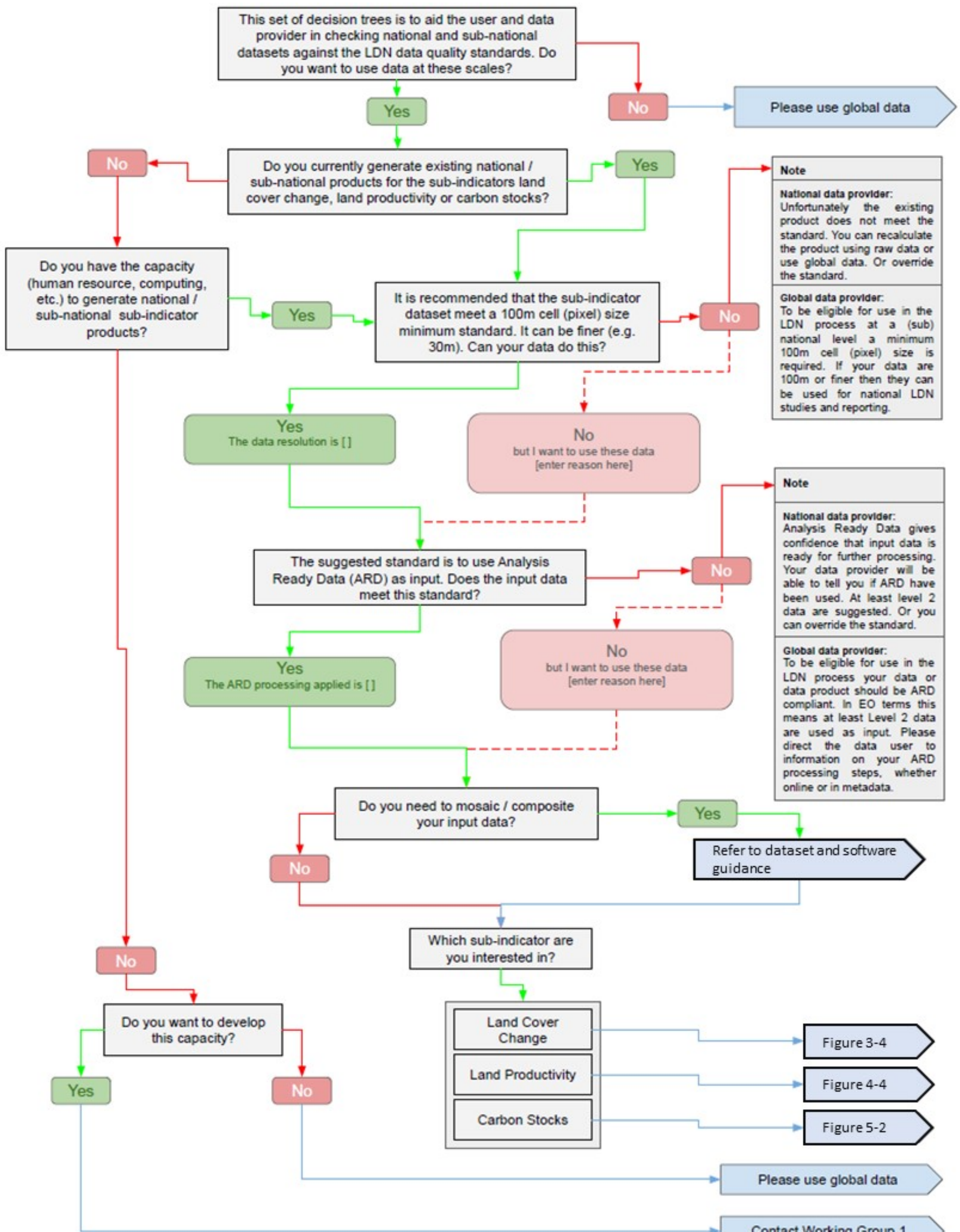


Figure 2-2.Decision tree to determine the suitability of national and sub-national datasets for calculating Indicator 15.3.1 (GEO-LDN Initiative 2020). Note that Working Group 1 is one of three Working Groups in the GEO LDN Initiative, focussing on Capacity Development. See link in reference for more details).

2.2 Reporting degradation

2.2.1 Data flows and validation

Multiple decisions by the UN Statistical Commission have stressed that official statistics and data from national statistical systems constitute the basis needed for the global SDG indicator framework. In cases where custodian agencies see a need to adjust or estimate country-specific values to ensure compliance to internationally agreed concepts, definitions or classifications, to fill data gaps or to harmonize data from different national official sources, they are requested "to consult with concerned countries to produce and validate modelled estimates before publication".[51] The IAEG-SDG has prepared a series of documents defining "guidelines of how custodian agencies and countries can work together to contribute to the data flows necessary to have harmonized statistics" for monitoring the SDG targets.[52]

For SDG Indicator 15.3.1, the data flows and validation mechanism are unique as they leverage the UNCCD national reporting and review process.

In the absence of, to enhance, or as a complement to national data sources, the UNCCD facilitates national reporting through the provision of default data derived from global data sources to be interpreted and validated by national authorities. The most comprehensive validation approach involves the use of national, sub-national or site-based indicators, data and information to assess the accuracy of the sub-indicators derived from these regional and global data sources. This could include a mixed-methods approach which makes use of multiple sources of information or combines quantitative and qualitative data, including the ground-truthing of remotely sensed data using Google Earth images, field surveys or a combination of both.

Every four years beginning in 2018, national authorities (the "main reporting entity") submit data on the indicator and sub-indicators to the UNCCD as part of their national reports following a standard format. Ideally, the reports should include the original data and reference sources, descriptions of how these have been used to derive the indicator and sub-indicators, with additional detail provided on areas identified as 'false positive' or 'false negative' errors in the identification of degradation.

Eligible countries receive financial and technical assistance to help them prepare their national reports from the UNCCD and its partners. In 2018, this support was provided through a Global Support Programme funded by the Global Environment Facility, implemented by the UN Environment Programme and managed and executed by the Global Mechanism of the UNCCD.[53] Additionally, countries have received dedicated financial resources to be used at the country level to support coordination among national institutions, acquire human resources if required, and ensure timely submission of the national reports, through a GEF-funded Umbrella Project implemented by UN Environment Programme. Under this programme, the UNCCD has provided technical backstopping and capacity development support to countries. Regular contacts between the main reporting entity and UNCCD secretariat via a help desk system, and through regional/sub-regional workshops, have formed part of this support. Similar financial and technical assistance is expected to

[51] https://undocs.org/A/RES/71/313
[52] https://unstats.un.org/sdgs/iaeg-sdgs/data-flows/
[53] https://www.unccd.int/sites/default/files/sessions/documents/2019-07/ICCD_CRIC%2818%29_6-1910512E.pdf

be provided for future reporting cycles with the aim of further strengthening the capacities of countries for monitoring and reporting. Once received, national reports undergo a review process by the UNCCD to ensure the correct use of definitions and methodology, enable data adjustments when needed, and contribute to building national capacities.

Since national data and the information used to report on SDG Indicator 15.3.1 generally come from outside the NSOs, the UNCCD consults with the NSOs and requests them to review and validate the data submitted by their country as part of their national report, prior to submitting the data to the UNSD. For those countries that have not submitted a national report, the UNCCD provides the NSOs with national estimates derived from global data sources for review and validation.

Once the countries have signed off the data, the UNCCD submits country data, as well as sub-regional, regional and global aggregates to the UNSD for publication in the SDG Report and Global Database.

By leveraging an already established reporting mechanism, this data flow and validation mechanism increases the efficiency with which UNCCD can gather data from countries. In addition, since the definitions and methodologies for reporting on SDG Indicator 15.3.1 are aligned with those adopted by the UNCCD, the reporting burden on countries and the need for harmonization/validation of the indicator values is reduced.

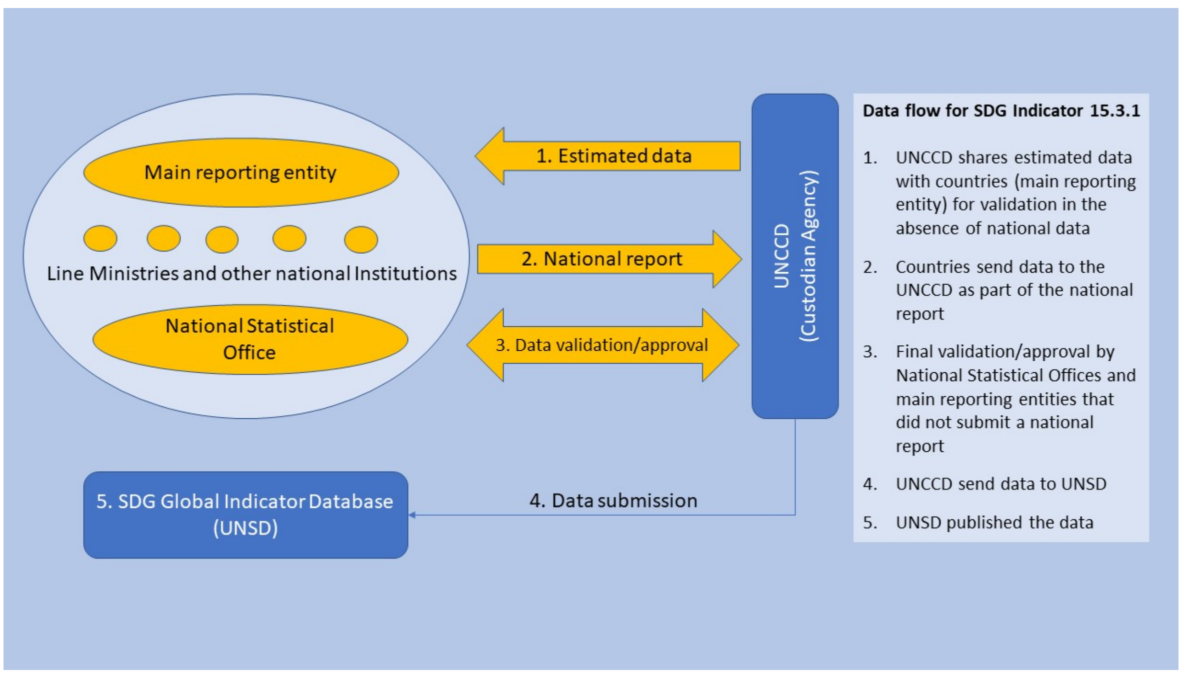


Figure 2-3. Data flow for SDG Indicator 15.3.1 (Illustration adapted from UN Water, Data flow for SDG 6, available at: https://www.sdg6monitoring.org/activities/roles-and-responsibilities/)

2.2.2 Identifying false positives and false negatives

Version 1 of the GPG considered a range of land cover scenarios in which, using the 1OAO framework, change in the degradation status of the sub-indicators might result in a counterintuitive degradation determination. The example in Version 1 described woody weed invasion of a grassland, which may raise the apparent plant productivity even though the outcome in terms of the change in land condition would normally be considered to be negative. In fact, the 1OAO deals with this situation correctly provided there is sufficient land cover information to identify a negative change in the land cover sub-indicator, which would result in this area being identified as degraded. A more challenging example is where woody weeds are removed as part of a remediation process, causing a reduction in apparent NPP. This would normally lead to an indication of degradation even though the intention is to restore degraded lands.

In these situations, countries have the option to identify areas of 'false negative' degradation, in which the outcome of the 1OAO process has incorrectly resulted in an area being identified as degraded. A similar opportunity is also available to identify areas of 'false positive' degradation, where the 1OAO process has incorrectly indicated that an area is not degraded even though the change in land condition is considered to be sufficiently negative to qualify as degraded in the context of Indicator 15.3.1.

Readers are referred to Sims et al. (2020), which provides more guidance on how to address false positives and false negatives for reporting on Indicator 15.3.1 and LDN, including an interpretation matrix to guide countries in labelling areas where the outcomes of the 1OAO process appear counterintuitive. Figure 2-4 shows a degradation interpretation matrix that can be used with any of the sub-indicators. The quantitative Land Productivity and SOC sub-indicators should be interpreted using the 'Increase' and 'Decrease' y-axis labels. As a typically categorical description of a complex of biophysical features, it can be difficult to rank land cover types to identify transitions that lead to an 'increase' or 'decrease' in condition, hence we recommend the 'Positive' and 'Negative' y-axis labels for use with the Land Cover sub-indicator as opposed to the more intuitively quantitative alternative of Increase and Decrease.

The interpretation matrix is underpinned by a conceptual model that perceives land as a socio-ecological system (a coupled human-natural system); hence, labelling a land unit as degraded requires a synergy of utilitarian (human-driven) and ecological (ecosystem function and structure) views. The y-axis indicates the direction of change in the sub-indicator: either a decrease, no change or an increase for land productivity or SOC stocks, or in the case of land cover, a negative change, no change or a positive change. The x-axis is the desirability, which reflects the interpretation of whether the condition of the area in question is desirable or undesirable at the time of assessment. Desirability might be determined following consideration of national development objectives and/or in consultation with local stakeholders, and should be justified in the national reports.

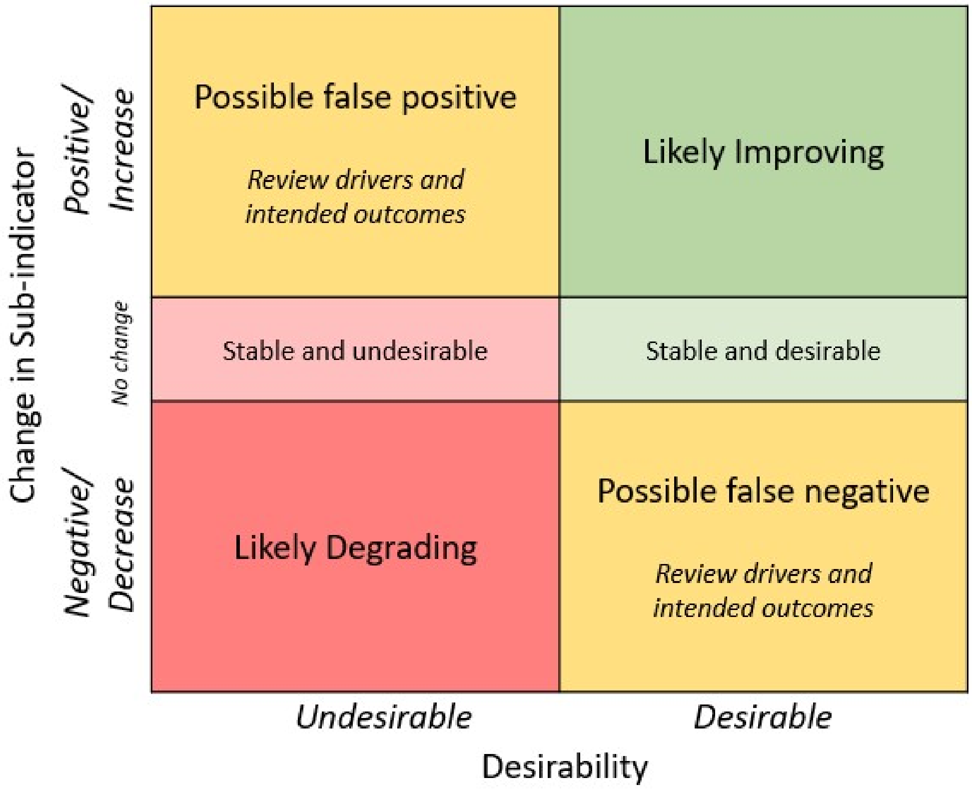


Figure 2-4. Generic degradation interpretation matrix for any sub-indicator of Indicator 15.3.1. The 'Increase' and 'Decrease' y-axis labels should be used for the Land Productivity and SOC sub-indicators, and the 'Positive' and 'Negative' labels for Land Cover.

Sectors of the interpretation matrix where the relationship between sub-indicator levels and the interpretation of condition may be counterintuitive are shown in yellow, with possible false positives in the upper left sector, and possible false negatives in the lower right. In these cases, the degradation interpretation matrix reminds countries of their opportunity to examine the drivers and pressures of change in land condition to inform the degradation decision-making process. Countries can then assess whether to label these areas as degraded or not in their maps and other reporting documents.

The Driver-Pressure-State-Impact-Response (DPSIR) 'causal framework' presents an iterative and hierarchical process to identify the impacts of land degradation (changes in the provision of services to humans and the environment), the drivers (broad categories of factors that influence the direction of ecosystem change (Oesterwind et al. 2016), and pressures (land use and management choices) leading to the degradation, and the appropriate responses.

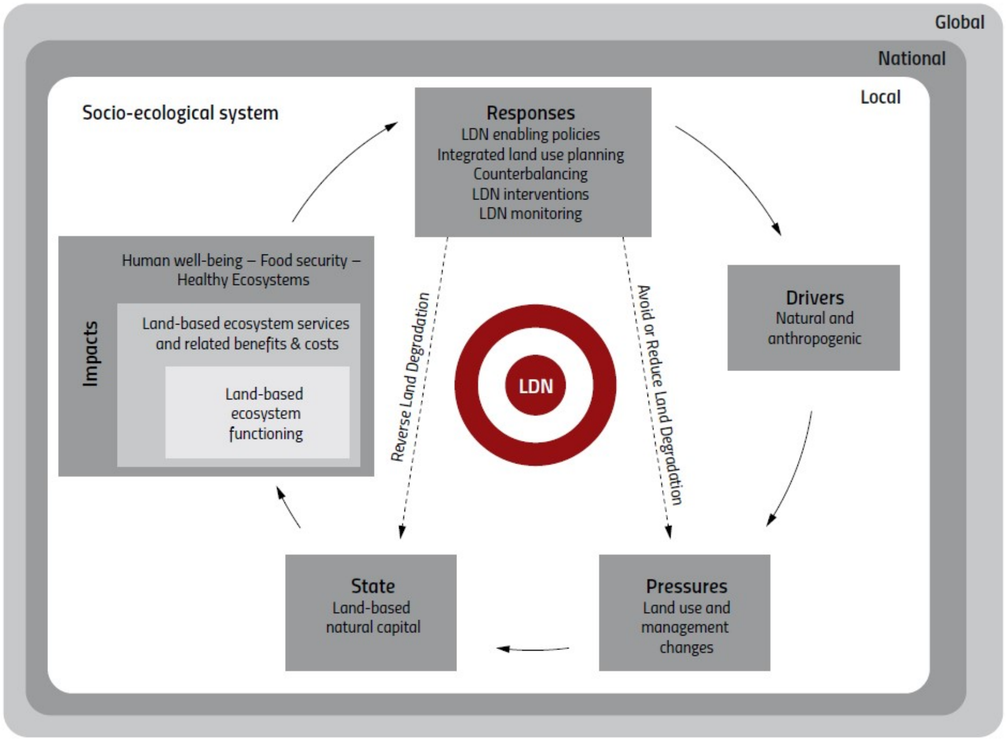


Figure 2-5.Causal framework for identifying drivers and pressures leading to land condition change, and identifying appropriate human responses. From Orr et al. (2017) & Cowie et al. (2018)

In the context of the LDN causal framework (Figure 2-5), the interpretation matrix (Figure 2-4) principally supports decisions on identifying the degradation state, which underpins the decision to initiate responses to address land degradation. The inclusion of this process in determining degradation state could support an improved understanding of land degradation at specific locations using ecological, socio-economic and policy knowledge through multi-stakeholder engagements, which may in turn lead to improved LDN outcomes at larger spatial scales and over longer time periods.

In areas where a false positive or false negative degradation outcome is identified (the upper left and lower right quadrants of the interpretation matrix, respectively), the decision to reinterpret the outcome of the 1OAO process should be justified in the report. Relevant supporting materials may include documentation of the methods and objectives of activities that have led to the false positive or negative, evidence of the extent over which these activities have been implemented, a review of the socio-economic and biophysical drivers and pressures influencing land degradation in the area using the DPSIR causal framework, a plan for, or statement of, future activities to reduce land degradation based on the DPSIR review, and a description of the intended land condition when the program of works is complete.

2.3 Comments and Limitations

The assessment and quantification of land degradation is generally regarded as context-specific, making it difficult for a single indicator to fully capture the state or condition of the land. The sub-indicators are proxies to monitor the essential variables that reflect capacity to deliver land-based ecosystem services. Nevertheless, the ultimate determination by national authorities of the extent of degraded land should be contextualized with other data and information for ground-based verification. For slow changing variables such as SOC, reporting every four years may not be practical or offer reliable change detection for many countries. The ability to interpret changes in more detail and at finer time steps is increasing, however, via improved modelling measurements at the national level, such as from WorldSoils[54], iSDAsoil[55] the FAO's GSP[56] and others.

While access to remote sensing imagery has greatly improved in recent years, there is still a need for essential historical time series that are currently only available at coarse to medium resolution. Through the efforts of aligned initiatives including the CEOS Ad Hoc Team on SDGs[57], and feedback to data providers from the UNCCD in response to identified needs in national reports, the expectation is that the availability of high-resolution, locally-calibrated datasets will increase in future. There is also a strong need to develop national capacities to process, interpret and validate geospatial data, which is being supported through Working Group 1 of the GEO LDN Initiative and capacity building training workshops for Trends.Earth.

[54] http://www.world-soils.com/
[55] https://www.isda-africa.com/isdasoil/
[56] http://www.fao.org/global-soil-partnership/en/
[57] http://ceos.org/ourwork/ad-hoc-teams/sustainable-development-goals/

3 Land Cover and Land Cover Change

3.1 Executive Summary

Land degradation for the SDG 15.3 target is defined as 'the reduction or loss of the biological or economic productivity and complexity of rain fed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from a combination of pressures, including land use and management practices'. The intention of the SDG 15.3.1 land cover sub-indicator is to identify where degradation has occurred specifically as a result of land cover change.

3.1.1 Role and calculation of the sub-indicator

The guidance given in this chapter is designed to promote a consistent and objective approach for reporting land degradation as indicated by land cover changes. The following **good practice principles** are described to guide the development of a national method for computing the land cover change sub-indicator.

- **Identify key degradation processes** that should be included in the country's assessment of land degradation.
- **Select a land cover legend** that allows key degradation processes to be monitored.
- **Generate a transition matrix** that specifies land cover changes as being either degradation, improvement or neutral transitions.
- **Assess available data** that can be used to map the legend classes over the total land area for the country and be updated and used for reporting at least every 5 years. An assessment should include documenting the source data, any pre-processing, the classification algorithm, and the accuracy assessment procedure.
- **Determine the baseline** extent of land cover degradation for assessing SDG Target 15.3 and LDN.
- **Generate reports of land degradation** based on an assessment of change using the same data and legend as the baseline period.

3.1.2 Changes from version 1 of the GPG

Version 1 of the land cover and land cover change sub-indicator chapter indicated that the six IPCC land cover classes were the preferred basis for reporting. This was to support consistency between national reports. However, in some cases, important degradation processes may not be detectable by monitoring these six broad IPCC classes. So in this revision there is a greater focus on the identification of important degradation processes, and the use of an appropriate legend so that degradation can be more easily monitored.

In some cases, countries will not be in a position to produce land cover products in line with the reporting cycle for SDG 15.3.1 and with a legend that is more detailed than the IPCC classes. In this case the IPCC legend is the default.

However, when a more detailed land cover legend is used, the number of possible transitions increases exponentially with the number of classes. Thus, to minimise complexity, only those classes that are important in monitoring land degradation should be used for reporting, and where possible classes should be aggregated using the FAO's Land Cover Classification System (LCCS) hierarchical structure. Nevertheless, land cover change at the level of the IPCC classes should be included in annual reporting even if a more detailed legend is used.

3.1.3 Interpretation and further work

1. Degradation identified using the land cover and land cover change sub-indicator should not be interpreted as comprehensive. The land cover and land cover change sub-indicator is supplemented by other sub-indicators that may be more appropriate, less-ambiguous or less prone to error than identification using land cover change.
2. Links between land cover change and degradation can be subjective. Degradation processes that are appropriately detected and monitored using the land cover and land cover change sub-indicator should be the subject of broad discussion and more detailed guidance in the future.
3. A review of national, regional and global land cover products is now included as an appendix. The set of products relevant to SDG 15.3.1 will change over time and regular review of new products is advisable.

3.2 Methodology

This chapter sets out guidance for national authorities to implement measurement, validation and reporting of land degradation processes associated with land cover change. The guidance is designed to promote a consistent and objective approach for any reporting period. The following are **good practice principles** to guide the development of a national method of computation for the land cover sub-indicator.

- **Identify key degradation processes** that should be included in the country's assessment of land degradation.
- **Select a land cover legend** that allows monitoring of key degradation processes that are detectable using land cover change.
- **Generate a transition matrix** that specifies land cover changes as being either degradation, improvement or neutral transitions.
- **Assess available data** that can be used to map legend classes over the total land area for the country and be updated and used for reporting. An assessment should include documenting the source data, any pre-processing, the classification algorithm, and the accuracy assessment procedure. Note that it may not be possible to map some legend classes due to limitations of available data. In such cases, other sub-indicators may be more appropriate for monitoring the specific degradation process.
- **Determine the baseline** extent of land cover degradation for assessing SDG Target 15.3 and LDN.
- **Generate reports of land degradation** based on an assessment of change using the same data and legend as the baseline period.

Each of these principles is described in detail in the following sub sections.

3.2.1 Identifying key degradation processes

The intention of SDG indicator 15.3.1 is to monitor the proportion of land degraded within a country. While the land cover change detection methodology and sub-indicator must be suitable to support an assessment of the proportion of land degraded, comprehensive land cover mapping is not the primary intention of this methodology.

As a basis for objective and consistent reporting, it is good practice to state the key degradation processes relevant to a country and to create a table of these processes prior to defining a land cover legend. Key processes might include deforestation, urban expansion, loss of soil fertility. Some of these processes may be detectable through analysis of land cover change. Others may require a different sub-indicator, and some may be detectable using multiple indicators. For those processes that may have an impact on land cover, it is good practice to include possible starting and ending land cover classes as shown in Table 3-1.

Table 3-1. Example of processes that may be identified by a country and the corresponding land cover transitions. Note that these are simplistic examples and attributing a change in state to degradation requires careful assessment at the national scale in the context of the definition of land degradation given in Section 1.1.

Degradation process	Likely detectable using Land Cover Change	Starting Land Cover state	Ending Land Cover state
Urban expansion	Yes	Grassland, cropland, other land	Settlements
Deforestation	Yes	Forest land	Grassland, cropland, settlements
Vegetation loss (other)	Yes	Forest land, grassland, cropland	Other land
Inundation	Yes	Vegetated, settlements, bare soil	Wetland
Woody encroachment	Yes	Wetland, grassland	Forest Land
Wetland drainage	Yes	Wetland	Grassland, cropland, settlements, other land
Soil Erosion	No	-	-
Invasive species encroachment	No	-	-
Loss of soil fertility			

3.2.2 Select a Land Cover Legend

In order to support the identification and assessment of land cover transitions, a set of land cover classes must be selected as a *legend* to classify the national land cover. This legend must be:

- *Competent* for capturing the degradation transitions identified as significant;
- *Usable*, such that available observational data can distinguish between the classes in the legend;
- *Exhaustive*, such that the entire land area of the country can be attributed to classes from the legend and monitored through time..

The six classes in the IPCC land use change legend (Penman et al. 2003) are used for aggregate reporting of the SDG 15.3 target, and therefore provide a minimum or default legend. However, there are some degradation processes that are not easily captured with reference to the IPCC legend, so national authorities should consider extending this in order to capture important land degradation processes occurring in their country, taking into account these three criteria. For example, Table 3-2. shows a (notional) legend devised to include start and end classes to allow specific degradation processes to be monitored. *IPCCSX* specializes the IPCC classification scheme and can still be generalised to IPCC classes for the purpose of aggregated reporting.

Table 3-2. An alternative land-cover legend (notional). Note that some classes in the IPCC legend need to be specialized in the notional IPCCSX legend to ensure important degradation processes can be captured, while others may remain unchanged.

IPCC	IPCCSX
Forest Land	Native forest Exotic forest
Grassland	Native grassland Improved pasture Managed parkland (incl. sports grounds)
Cropland	Plantation Cereals Horticulture
Wetlands	Inland wetland – permanent Inland wetland – ephemeral Coastal wetland
Settlements	Settlements
Other Land	Other Land

A clear and unambiguous definition of land cover classes is imperative in order to ensure that changes can be identified. Land cover classes from national schemes should be aligned with existing Land Cover Meta Language (LCML) based classifications wherever possible. FAO provides software tools to help in harmonising non-LCML classes, though these tools require users to have some prior understanding of the object-based structure of the meta-language. While LCML provides the most structured approach to class definition, Di Gregorio & Jansen (2000) also provide guidance on how to translate from conventional descriptive class definitions to a LCML-based schema.

Existing general classification schemes might guide the development of a national scheme and legend. The SEEA (UN, 2012) defines a set of 14 land cover classes for the description of land cover. FAO Global Land Cover-SHARE (GLC-SHARE) simplifies this to 11 classes, aggregating the croplands and the water bodies into single classes (Latham et al. 2014). A broad alignment of GLC-SHARE to the 'dichotomous' part of the LCCS (Di Gregorio and Jansen, 2000) was provided by Latham, which is adapted in Figure 3-1 to include both SEEA CF and GLC-SHARE numbering.

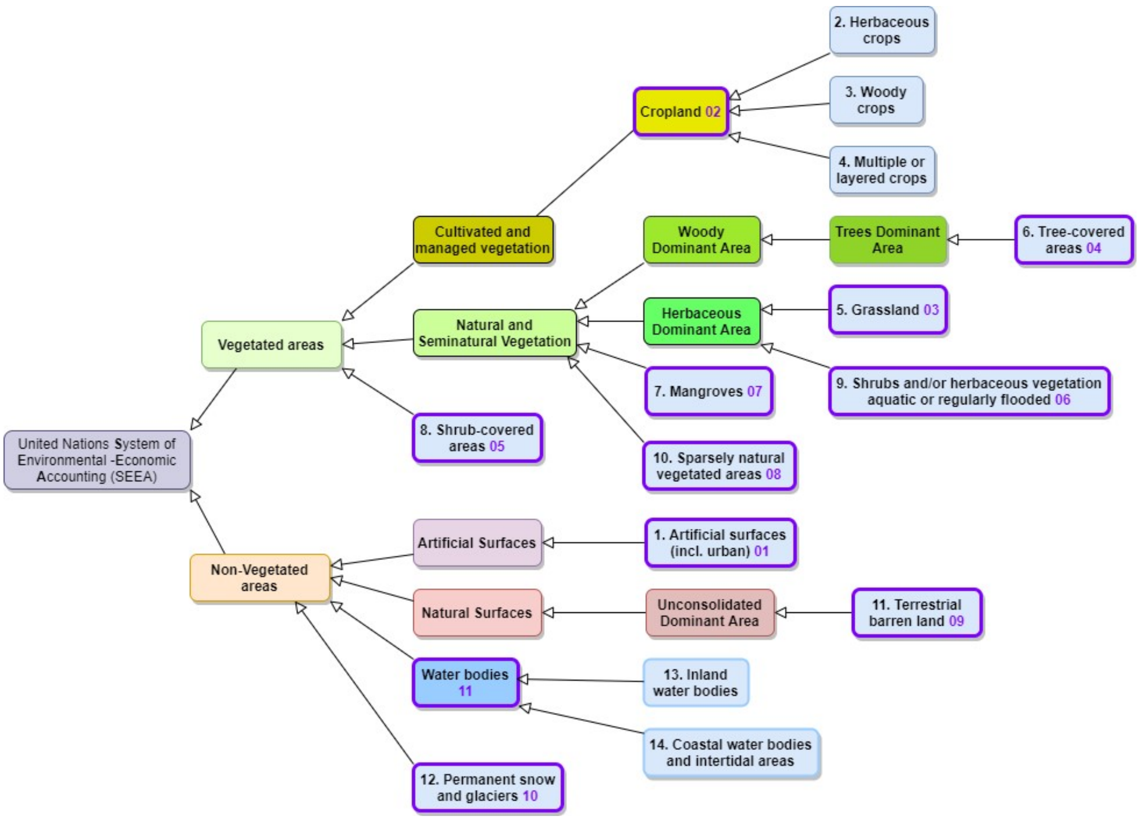


Figure 3-1. The System for Environmental and Economic Accounting (SEEA) Central Framework (CF) Land cover classification (pale blue shading) and UN FAO Global Land Cover Share (GLC-SHARE) (purple outlines and codes) in an approximate alignment to the Land Cover Classification System (LCCS) hierarchy (Di Gregorio & Jansen, 2000) (diagram adapted from Latham et al. 2014)

In contrast, the ESA Climate Change Initiative developed a typology of 22 land cover classes (ESA CCI-LC). This is based on the FAO LCCS class definition methodology, but oriented to the Plant Functional Types used in Earth System Models. Notice that while CCI-LC *differentiates* between several tree cover types, it *merges* all water-body classes. This matches the distinctions required for Earth System Models, but they might not be easily detectable using most remote-sensing data. Table 3-3. maps all the schemes mentioned to the broad classification from the IPCC legend.

Table 3-3. Mapping between land cover classes used in various legends. Table rows show how all legends can be harmonised to IPCC classes. The SEEA and GLC Share provide a classification designed to assess the natural capital while the ESA CCI-LC classification is designed around plant functional types for use in Earth system process modelling. NN correspond to the codes in the various sources. Note that aggregation of classes from ESA CCI-LC to IPCC is set out in the Reporting Manual for the 2017-2018 UNCCD reporting process[58].

SEEA	GLC-Share	IPCC	ESA CCI-LC
6 Tree-covered areas	Tree-covered areas 04	**1 Forest Land**	Tree cover, broadleaved, evergreen, closed to open (>15%) 50 Tree cover, broadleaved, deciduous, closed to open (>15%) 60 Tree cover, needle leaved, evergreen, closed to open (>15%) 70 Tree cover, needle leaved, deciduous, closed to open (>15%) 80 Tree cover, mixed leaf type, closed to open (>15%) 90 Mosaic tree and shrub (>50%)/herbaceous cover (<50%) 100
5 Grassland 8 Shrub-covered areas 10 Sparsely natural vegetated areas	Grassland 03 Shrubs covered areas 05 Sparse vegetation 08	**2 Grassland**	Grassland 130 Shrubland 120 Mosaic herbaceous cover (>50%)/tree and shrub (<50%) 110 Sparse vegetation (tree, shrub, herbaceous cover) (<15%) 150 Lichens and Mosses 140
2 Herbaceous crops 3 Woody crops 4 Multiple or layered crops	Cropland 02	**3 Cropland**	Cropland, rainfed: 10 - Herbaceous cover 11 - Tree or shrub cover 12 Cropland, irrigated or post-flooding 20 Mosaic cropland (>50%)/natural vegetation (tree, shrub, herbaceous cover) (<50%) 30 Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%)/cropland (<50%) 40
9 Shrubs and/or herbaceous vegetation, aquatic or regularly flooded 7 Mangroves	Herbaceous vegetation, aquatic or regularly flooded 06 Mangroves 07	**4 Wetlands**	Shrub or herbaceous cover, flooded, fresh/saline/brackish water 180 Tree cover, flooded, fresh or brackish water 160 Tree cover, flooded, saline water 170
1 Artificial surfaces (including urban and associated areas)	Artificial surfaces 01	**5 Settlements**	Urban areas 190
11 Terrestrial barren land 12 Permanent snow and glaciers	Bare soil 09 Snow and glaciers 10	**6 Other Land**	Bare areas 200 Permanent snow and ice 220
13 Inland water bodies 14 Coastal water bodies and intertidal areas	Water bodies 11		Water bodies 210

[58] https://prais.unccd.int/sites/default/files/helper_documents/2-Manual_EN_1.pdf

3.2.3 Generate a Transition Matrix

Within the SDG 15.3.1 indicator definition, land degradation is context specific. It depends on (a) the characteristics of the environment and (b), the values of those assessing it. Degradation might be:

1. A decline in the actual or potential **productive capacity** of the land, through a loss of biomass or a reduction in vegetative cover and soil fertility
2. A reduction in the land's capacity to provide **resources for livelihoods**
3. A loss of **biodiversity or ecosystem** complexity
4. Increased **vulnerability** of populations or habitats to destruction or crisis.

These types of degradation are not independent and mitigating one may lead to an increase in another form of degradation. National authorities must decide which changes and processes are considered to be “degradation”. This should include class transitions that are of national concern, and may include deforestation, vegetation loss or urban expansion. The identification of specific transitions will help ensure that the set of land cover classes required to monitor land degradation at the national scale is appropriate.

Land Cover and Land Cover Change is only one of the sub-indicators of SDG Indicator 15.3.1, each of which indicates unique elements of land degradation. Land cover refers to the naturally stable aspects of the land, such as its constituent elements, their structure and homogeneity. Transient aspects such as vegetation phenology, snow, flooding or burned areas are not considered transitions in the context of SDG 15.3.1. Land cover datasets used for evaluating the Land Cover and Land Cover Change sub-indicator should map classes that are linked to these stable properties using the methods described in Section 3.2.2.

National decisions about which land cover transitions are linked to a degradation process should be made in a participatory, transparent and deliberate way through a multi-stakeholder consultation process. Analysis of land cover data and visualisation of transitions will help stakeholders understand the trade-offs that exist between different types of benefits, for example food production and biodiversity. In some cases, land cover transitions will be too ambiguous to label as either degradation or improvement. In these cases, the transition should be labelled as “No Change”. In this situation, countries may wish to re-evaluate the legend being used and define finer classes that better capture transition that linked to degradation.

It is good practice to define a matrix of land cover transitions that include all classes in the national legend. For example, using the IPCC legend (Penman et al. 2003), the six classes define 6 x 5 (30) possible transitions (Figure 3-2). These changes are classified according to 12 unique land cover changes, all of which are included in Table 3-1.

Final Class

Original Class: IPCC Class	Forest Land	Grassland	Cropland	Wetlands	Settlements	Other Land
Forest Land	Stable	Vegetation loss	Deforestation	Inundation	Deforestation	Vegetation loss
Grassland	Afforestation	Stable	Agricultural expansion	Inundation	Urban expansion	Vegetation loss
Cropland	Afforestation	Withdrawal of Agriculture	Stable	Inundation	Urban expansion	Vegetation loss
Wetlands	Woody Encroachment	Wetland drainage	Wetland drainage	Stable	Wetland drainage	Wetland drainage
Settlements	Afforestation	Vegetation establishment	Agricultural expansion	Wetland establishment	Stable	Withdrawal of Settlements
Other Land	Afforestation	Vegetation establishment	Agricultural expansion	Wetland establishment	Urban expansion	Stable

Figure 3-2. Example of a land cover change matrix using the 6 IPCC classes (30 possible transitions). Unlikely transitions are highlighted in red text (see below for discussion of unlikely transitions). Land cover change processes are colour coded as improvement (green), stable (yellow) or degradation (red). Note that this is an example of a transition matrix and should not be interpreted as appropriate for countries to adopt without consideration of local conditions and key degradation processes.

An alternative transition matrix is presented in Figure 3-3 using the notional IPCCSX classification example introduced above. The transitions are not specifically named in this matrix, but it should be noted that there could be a mixture of identified transitions within each IPCC class.

Not all possible transitions between classes are logical or plausible (Gómez et al. 2016; Wehmann & Liu 2015). In fact, identification of illogical or unlikely transitions may assist the validation of land cover change maps. A comprehensive approach would consider the probability of all transitions in the matrix, and which could be incorporated into automated classifications schemes (e.g., using Bayesian prior probabilities) to improve the accuracy of subsequent land cover maps.

It is good practice in the identification and labelling of transitions to use *objective change descriptions*, and avoid attribution of cause or focus on why land cover has changed. It may be difficult to attribute specific causal factors to land cover changes.

Original class		Native forest	Exotic forest	Native grassland	Improved pasture	Managed parkland	Plantation	Cereals	Horticulture	Wetland – permanent	Wetland – ephemeral	Coastal wetland	Settlements	Other Land
		Forest		Grassland			Cropland			Wetlands				
Forest	Native forest	S	D	D	D	D	D	D	D	D	D	D	D	D
Forest	Exotic forest	I	S	NC	D	NC	NC	NC	NC	I	I	I	D	D
Grassland	Native grassland	I	NC	S	D	D	D	D	D	I	D	D	D	D
Grassland	Improved pasture	I	I	I	S	NC	I	NC	NC	I	NC	I	D	D
Grassland	Managed parkland	I	NC	I	NC	S	NC	NC	NC	I	I	I	D	D
Cropland	Plantation	I	NC	I	D	NC	S	NC	NC	I	NC	I	D	D
Cropland	Cereals	I	NC	I	NC	NC	NC	S	NC	I	I	I	D	D
Cropland	Horticulture	I	NC	I	NC	NC	NC	NC	S	I	NC	I	D	D
Wetlands	Wetland – permanent	I	D	D	D	D	D	D	D	S	D	NC	D	D
Wetlands	Wetland – ephemeral	I	D	I	NC	D	NC	D	NC	I	S	NC	D	D
Wetlands	Coastal wetland	I	D	I	D	D	D	D	D	NC	NC	S	D	D
	Settlements	I	I	I	I	I	I	I	I	I	I	I	S	I
	Other Land	I	I	I	I	I	I	I	I	I	I	I	D	S

Figure 3-3. Example of a land cover change matrix for the 13 classes from the IPCCSX scheme (156 possible transitions). Unlikely transitions are highlighted in red text (see discussion below). In this example, land cover change processes are colour coded as improvement (I green), stable (S yellow), or no change (NC yellow), degradation (D red). In this context "no change" indicates that the transition is neither degradation or improvement, or that the data is insufficient to unambiguously label as degradation or improvement.

3.2.4 Assess Available Data

A flow chart for assessing the desired standards for land cover datasets is set out in Figure 3-4. This process should be followed during the development of national datasets. In other cases the default data should be used (see Section 2.1.3).

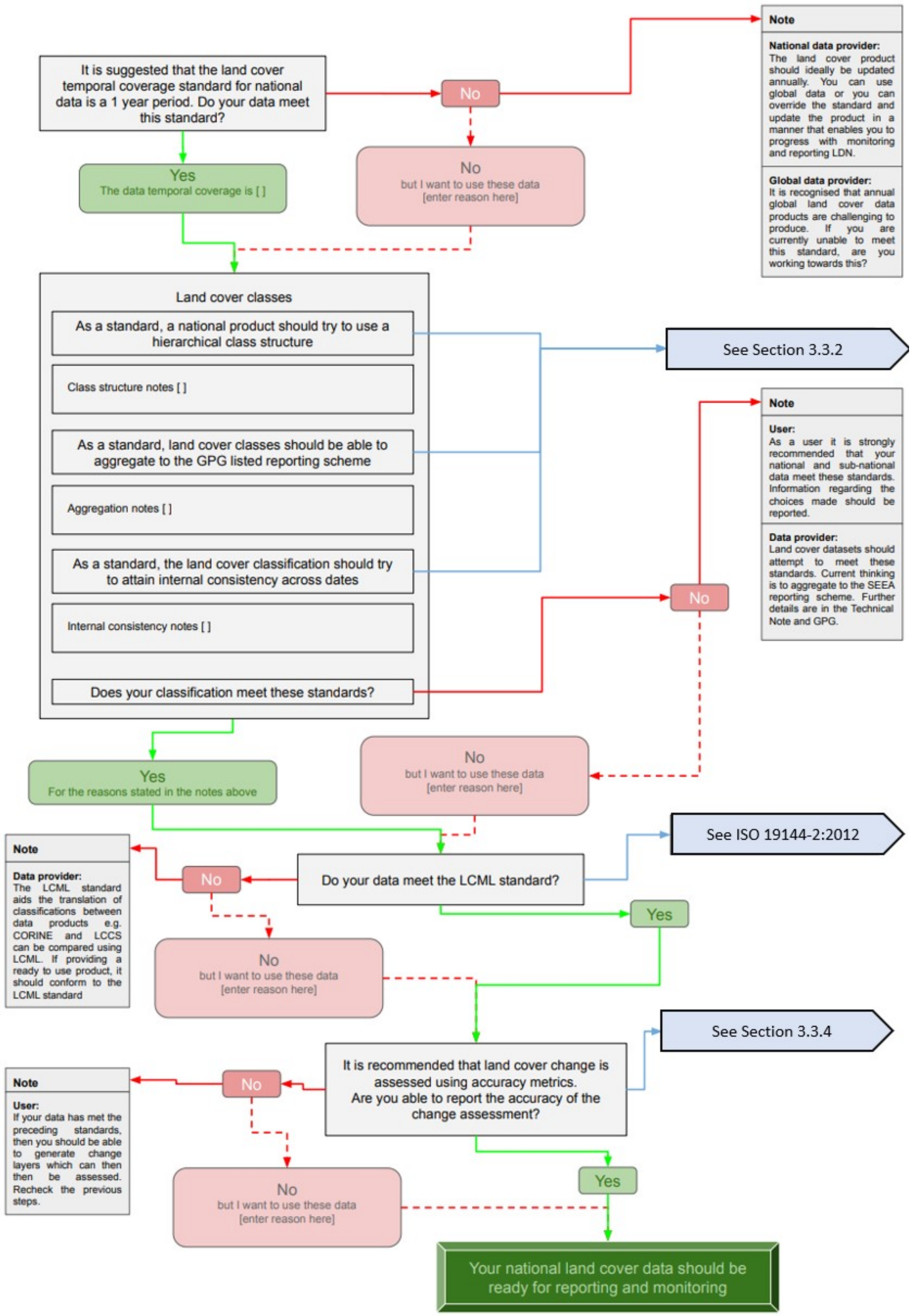


Figure 3-4. Decision tree for determining the most appropriate data for calculation of the land cover change sub-indicator (GEO-LDN Initiative 2020)

Specifically, performance against the following criteria should be assessed:

1. **Legend definition**: The land cover dataset classes should be defined using the LCML standard, have adequate classes to populate the transition matrix and be part of a hierarchical classification system to promote easy harmonisation to IPCC and SEEA legends.
2. **Temporal range and frequency**: Land cover data should be available during the SDG baseline period (2000-2015) and as close to the baseline year (2015) as possible. Ideally the land cover data should be revised on a yearly basis using the same legend.
3. **Spatial coverage and resolution**: Each epoch of land cover data should be produced for the whole country and be recorded at high spatial accuracy.
4. **Classification accuracy**: Classification accuracy should be known for each land unit at each epoch of data so that the probability of transition between classes between epochs can be calculated.

Many countries have systems in place that regularly produce land cover mapping products. Occasionally multiple land cover mapping systems exist within the one country serving different land management and reporting purposes. In cases where there is little or no capacity to regularly produce an appropriate national land cover dataset, regional or global land cover data may be used (including the UNCCD Global Default land cover data, see Section 2.1.3.1). The legend for any land cover data must be adequate to populate the transition matrix when multiple epochs are assessed. National, regional and global land cover products should not be considered mutually exclusive - multiple products can be used to build an appropriate legend, and to cross-validate to help assess classification accuracy.

Where existing land cover products do not meet the requirements of SDG 15.3.1, the UNCCD global default dataset should be used. However, given unique national context and degradation processes, it may be advantageous for a country to develop their own land cover classification. In additional to the global land cover datasets, there are many possible sources of land cover information that could be used to improve and validate the default data including:

1. Census data
2. Field observations and surveys
3. Higher resolution remote sensing imagery

While the first two data sources may be adequate for small regions, remote sensing data are the most efficient way to produce land cover data for an entire country at an update frequency required for reporting against the SDG 15.3 target. However, using remote sensing data to interpolate spatial products based on census, field observations and survey measurements is encouraged as these additional data provide a means to independently assess the accuracy of land cover products.

It is good practice to define a spatial stratification approach to help guide the selection of field samples. In some cases, ground sampling for training and validation data may be impractical. Alternative approaches to data collection may include the manual interpretation of:

- High resolution imagery (e.g., airborne, satellite, Google Earth via Collect Earth).
- Crowd-sourced data, such as those available through the Geo-Wiki (Laso Bayas et al. 2016; Fritz et al. 2012).

When using remote sensing imagery to develop new land cover datasets there are a number of aspects of pre-processing that should be considered. While many of these should already be implemented in analysis-ready (level 2) remote sensing data, any product should include consideration of:

- **Sensor spectral and radiometric variations**: While multiple sources of remote sensing imagery might be available for land cover classification, land cover products should maintain internal consistency across epochs so that variations in sensor characteristics do not lead to inaccurate identification of land cover changes. Internal consistency means that across different dates the source data and the classification algorithm used are the same. If changes are required it is good practice to re-evaluate previous assessments of land cover change prior to the current reporting cycle.
- **Geographic projection**: Topographic distortion must be removed, and imagery must be projected into an established spatial or coordinate reference system (ISO 19111: 2007)[59] to ensure that data is co-registered so that change detection can be performed over multiple dates. The choice of datum and projection is a national decision but should be consistent with that used for other sub-indicators for SDG 15.3.1.
- **Atmospheric attenuation and cloud effects**: Optical remote sensing imagery must be processed to surface reflectance prior to the generation of land cover products. Surface reflectance products correct for atmospheric effects on remote sensing imagery. These are often available from image satellite data repositories such as the ESA Copernicus Open Data Hub[60] and the USGS Earth Explorer[61]. When atmospheric attenuation is too great (e.g. due to cloud) data gaps may occur in the imagery, leading to a need for compositing of imagery (see below).
- **Bi-directional reflectance variations:** The direction of sun and sensor relative to the surface location and surface normal direction can have an effect on apparent surface reflectance. Corrections should be implemented for these effects, or products where bi-directional distribution function (BRDF) and terrain (surface normal) affects have been corrected used. The ESA Copernicus Hub and USGS Earth Explorer deliver BRDF and terrain corrected imagery. BRDF correction can also be run in Google Earth Engine or SEPAL (sepal.io) for Landsat and Sentinel-2.
- **Transient and seasonal variation:** Stable aspects of land cover include the elements, structure and homogeneity of the land, while the dynamic elements include phenology, snow and flood water coverage, and fire effects. Only changes in the stable components are considered land cover change in the context of SDG indicator 15.3.1. The challenge in developing new land cover data is to classify the source data based on these stable components in the presence of the dynamic components. In order to decouple these components, it is important to consider the intra-annual and monthly changes in land cover as captured in remote sensing time-series (Bontemps et al. 2012).

[59] https://www.iso.org/standard/41126.html
[60] https://scihub.copernicus.eu
[61] https://earthexplorer.usgs.gov/

- **Data Frequency:** Best practice is to compile appropriate land cover data on an annual basis, even though reporting to UN is only required every 4 years. This provides the opportunity for countries to assess multiple years of land cover data and maximise their ability to capture changes in the stable components of land cover. Considerations should be given to transient impacts on land cover, such as short terms drought, fire and flood impacts. If a return of the previous land cover state is considered likely within the reporting period then it is reasonable to use the land cover class prior to such transient events.

The most appropriate algorithm to use for land cover classification will depend on the land cover classes to be differentiated, and the characteristics of the data being employed. National authorities are best placed to make decisions regarding these methods once appropriate legends and source data are established. However, if national data are used, it is good practice to show how these data provide a more accurate assessment than those derived from global datasets.

Both automated and semi-automated classification methods have been developed for the generation of land cover maps. Although unsupervised methods with post-classification labelling have frequently been used (Loveland et al. 1999; Bartholomé & Belward 2005), supervised methods have become more common. These include both parametric (generally Gaussian) and non-parametric methods. Modern machine learning methods such as ensemble (support vector machines, random forests) and neural network (deep learning and convolutional NNs) approaches are becoming popular in land cover mapping and are valid considerations for automated mapping as long as adequate training and validation data is available.

Khatami et al. (2016) present a list of most to least accurate algorithms for land cover classification. In addition to variations in the performance of specific classification algorithms, they found that the inclusion of additional variables (beyond optical satellite data) can yield improvements in classification accuracy (see Table 3-4.). It is good practice to use methods of land cover mapping that not only use static indices, but also the temporal change of these indices to determine what the final state of land cover is likely to be. This will help to identify transient, as well as illogical or improbable changes (Gómez et al. 2016) to support the final land cover class specification.

Table 3-4. Improvements in the mean accuracy of land cover products after inclusion of additional data (in addition to raw spectral bands), based on the meta-analysis by Khatami et al. (2016).

Input Data	Mean Accuracy Improvement
Textural indices	12.1%
Topographic, geological, radar, lidar	8.5%
Multi-angular data	8.0%
Time-series data	6.9%
Spectral Indices	2.4%

Methods for reporting land cover classification accuracy are well established and generally begin with a confusion (or error) matrix, which is a cross-tabulation of map and validation classes (see Table 3-5). The number of samples that appear along the diagonal show those samples that are correctly classified, while those that appear off the diagonal are considered errors. Confidence intervals should be reported for each of the accuracy measures in the confusion matrix (Olofsson et al. 2014).

Table 3-5. Example of a three-class confusion matrix and accuracy statistics.

	Validation Class 1	Validation Class 2	Validation Class 3	Commission Error
Map Class 1	p_{11}	p_{12}	p_{13}	$p_{11} / \sum p_{1i}$
Map Class 2	p_{21}	p_{22}	p_{23}	$p_{21} / \sum p_{2i}$
Map Class 3	p_{31}	p_{32}	p_{33}	$p_{31} / \sum p_{3i}$
Omission Error	$p_{11} / \sum p_{i1}$	$p_{12} / \sum p_{i2}$	$p_{13} / \sum p_{i3}$	$\sum p_{ii}$

3.2.5 Establishing the Baseline

In order to track change in the extent of degraded land for the purposes of assessing SDG Target 15.3 and LDN it is necessary to calculate a baseline extent of land cover change degradation. This baseline sets the benchmark extent of land cover degradation against which the extent of land cover degradation in the reporting periods is compared.

Once the land cover transition matrix has been identified, the extent of land cover degradation in the baseline period should be calculated by comparing land cover on two dates in the baseline period: 2015 (the baseline year) and one other year between 2000 and 2014. A longer duration between dates may result in a larger extent of degradation, whereas a shorter duration may not encapsulate sufficient land cover change to identify the main degrading transitions. All transitions (likely degraded, stable and likely improving) can be reported for the baseline period, with the extent of degradation being particularly important for assessing Indicator 15.3.1.

The selection of dates may be restricted by the availability of appropriate and consistent datasets suitable for comparison with the 2015 baseline year. In particular, the archive of one of the most advanced new datasets, the CGLS-LC100 [62], extends only from 2015 to 2019. Consistent with the guidelines for recalculating the time series (Chapter 6), new and improved datasets should be adopted as the standard. However, for calculating the baseline extent of land cover degradation as

[62] https://land.copernicus.eu/global/content/annual-100m-global-land-cover-maps-available

described above, it will be necessary to use an alternative dataset with an archive of images extending throughout the baseline period, such as the CCI-LC.

The consistency of estimates of the extent of land cover degradation between the CCI-LC and CGLS-LC100 products can be assessed by comparing the extent estimates for the overlapping years of data using the overlap method described in Section 6.1.2. The spatial distribution of land cover degradation indicated by the CCI-LC data can be compared to the extent indicated by the CGLS-LC100 data, and the consistency and differences between them described in national reports using the processes described in Section 6.1.3.

3.2.6 Generate Reports of Land Degradation

Yearly reporting of land cover change will help identify areas where significant portions of land are degrading. Reporting should be detailed enough so that national stakeholders are able to determine the location, type and level of change that has occurred. The following **good practice principles** apply to the reporting process.

1) **Describe the legend and transition matrix** including the decision on key degradation processes, the classes used in the legend, a table that shows how the legend can be harmonised to IPCC classes and a land cover transitions matrix with degradation processes labelled.
2) **Provide two national land cover maps, one for the baseline year (2015) and one for the reporting year.** These maps should have the same spatial precision (e.g. pixel resolution), coordinate reference system and origin or projection. They should use the same land cover classification approach and be accompanied by an accuracy assessment for each map, including a confusion (error) matrix with accuracy and confidence intervals.
3) **Present land cover change information based on the difference between the reporting year and baseline year.** This should include:
    a) A national map that shows the type and location of land cover transitions and the confidence interval for the detected transitions.
    b) A table that identifies the total area of land that is associated with each major land cover transition.
    c) A national map that shows areas of degradation, improvement and no change, based on the land cover data. Ideally, his should be accompanied by a corresponding map that indicates the confidence in the assessment of any change from the baseline (degradation or improvement).
4) **Perform qualitative assessments of areas identified as degraded or improved.** This should assess the key land cover changes as specified above in 1) in terms of the:
    a) Location, scale and rate of degradation
    b) Direct or indirect drivers of these changes or improvements
5) **Justify why any elements identified as degraded in the land cover change data should not be included in the overall indicator calculation.** This should be based on the identification of false positives, where change in the land cover data is due to stable or improved land condition.
6) **Justify why any reporting units not identified as degraded in the land cover change data should be included as degradation in the overall indicator calculation.** This should include a

proposed improvement to the land cover classification approach or legend so that accuracy can be improved or so that such degradation processes become more apparent in future assessment periods.

3.3 Comments and Limitations

This chapter of the GPG for SDG indicator 15.3.1 outlines the key principles and considerations when implementing national scale monitoring of the sub-indicator on land cover and land cover change, drawing on a wealth of existing knowledge of good practice.

Recognizing that no sole EO dataset has yet proven to be completely adequate for rigorous land cover change detection, new satellite datasets coupled with data integration methods are increasingly challenging this notion. Furthermore, the choice or design of the classification system or legend may miss some transitions (for example, the IPCC scheme and the elaboration in Table 3-2 do not allow for consideration of the effect of invasive species). Regardless, the adoption of quantitative and repeatable methods for land cover mapping is one of the more critical tools for detecting change, which can be validated using more detailed manual interpretation of high-resolution imagery or ground based surveys or other validation methods.

By following good practice, decisions made by countries that take into account their specific land cover types and change processes will be more effective in providing a basis for setting policy responses to address land degradation. The level of data, expertise and resources available for reporting on this sub-indicator will vary immensely, and that it is not the intention of this GPG to increase the reporting burden on national agencies. Rather it is hoped that this land cover and land cover change sub-indicator can be aligned with, and find application as a tool for, both national and SDG reporting and to meet other reporting or national agendas implementing obligations.

4 Land Productivity

4.1 Executive Summary

This Chapter describes keys steps in the analysis of the default global or national land productivity data, largely derived from EO sources, to measure land productivity degradation for reporting on SDG Indicator 15.3.1.

4.1.1 Role and calculation of the sub-indicator

Land productivity is the biological productive capacity of the land, the principal source of the food, fibre and fuel that sustains humans. It 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. This can be measured at local to global scales using satellite remote sensing and image transformations that are sensitive to changes in plant productivity and are correlated with the NPP of vegetation measured in a specific timeframe.

Estimates of relative change in productivity values, such as those provided by the NDVI, are sufficient to assess and evaluate trends in land degradation in accordance with the methodology presented in this GPG. Observations of land productivity during each growing season are integrated to represent annual productivity, and these annual productivity estimates are the basis of the comparison of change in productivity over time.

The extent of land where plant productivity is improving, stable or degraded is assessed from the annual productivity estimates using three metrics:

1. **Trend**, which measures the trajectory of productivity change over the long term,
2. **State**, which compares the current productivity level in a given area to recent historical observations of productivity in that same area, and
3. **Performance**, which indicates the level of local productivity compared with other areas with a similar land productivity potential regionally.

In combination, these metrics enable land productivity degradation at different phases of the long-term productivity cycle to be identified.

The extent of land productivity degradation is first calculated in the baseline period from 2000-2015, which sets the benchmark extent of degradation that forms the basis for the comparison of degraded extent in the subsequent reporting periods.

4.1.2 Changes from version 1 of the GPG

This chapter has been extensively revised to update and improve the utility of the guidance provided for assessing land productivity degradation. Key changes include:

- Improved definitions and terms, including more information on the relationship between NPP, biomass and NDVI.
- An expanded introduction describing the range of land degradation processes and cycles that guide the methods presented in this Chapter.
- Updated guidance from the GEO LDN Initiative on the selection of suitable datasets for land productivity assessment.
- Methodological changes to each of the productivity metrics:

- **Trend** is now assessed over a moving window of 16 years for both the baseline and reporting periods, rather than 16 years for the baseline and 8 years for the reporting periods as described in Version 1. This provides a more consistent basis for the assessment of changes in productivity Trend, but at the expense of sensitivity to shorter term productivity dynamics. Trend degradation is now assessed in terms of five z-score levels, which may assist in identifying areas that are potentially degrading or improving, as well as those that are statistically significantly degraded.
    - **State** is now calculated using a five-level assessment of z-scores, rather than the decile-change method described in GPG version 1.
    - Additional guidance is provided on constraining the spatial extent of productivity Performance assessment.
- Guidance for the assessment of each of the productivity metrics now more clearly presents methods for their assessment in the baseline and reporting periods.
- Additional options are presented for combining the metrics to identify productivity degradation in a range of phases of the long-term productivity cycle, such as where productivity remains stable but below normal for a long period of time, or to ignore a declining productivity Trend where the productivity remains high if required.

4.1.3 Interpretation and further work

Countries should ultimately strive to report changes in land productivity at the highest level of detail and rigour. However, differences between countries in their capacity to conduct remote sensing analyses, access to and availability of data sets and the range and distribution of productivity conditions will make some methods more suitable in some countries than in others. Accordingly, a range of processing and analysis options are described for each of the key steps. Additional guidance on the assessment of suitable datasets and indices for measuring land productivity, methods to minimise the influence of climatic variations on productivity estimates, methods to harmonise different datasets and for validating land productivity measurements are provided in Appendix B.

4.2 Methodology

4.2.1 Land degradation patterns and processes

This Chapter presents a series of metrics and data processing methods to measure and interpret land productivity degradation from satellite observations and other ancillary data. The degradation of land productivity may occur from environmental and anthropogenic drivers, at spatial scales from local to regional, and with a rate of change that may be fast or slow. Figure 4-1 shows examples of some drivers of degradation at these different rates and scales.

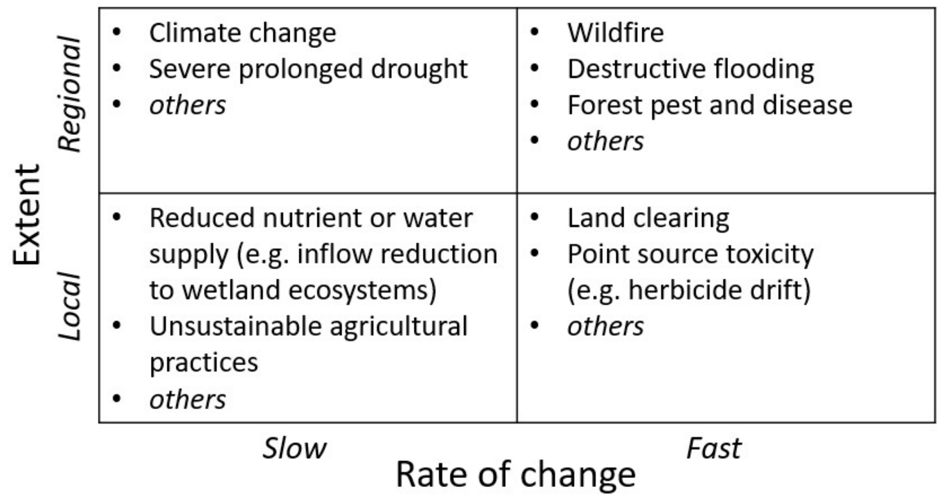


Figure 4-1 Examples drivers of land productivity degradation at different spatial extents and rate of change. There are many others that influence the long-term level and trend of land productivity at global to regional scales

Land productivity cycles exhibit phases over time. Vegetation productivity varies seasonally with annual growth and phenological cycles, and between years, in response to differences in moisture availability and other climatic factors. Over multiple years, patterns in the trajectory and level of annual productivity can be observed (Figure 4-2). A persistent decline in productivity levels, or productivity levels that remain below the long-term average may indicate potential land productivity degradation. The combination of metrics presented in this chapter enable productivity degradation to be identified in each of these phases.

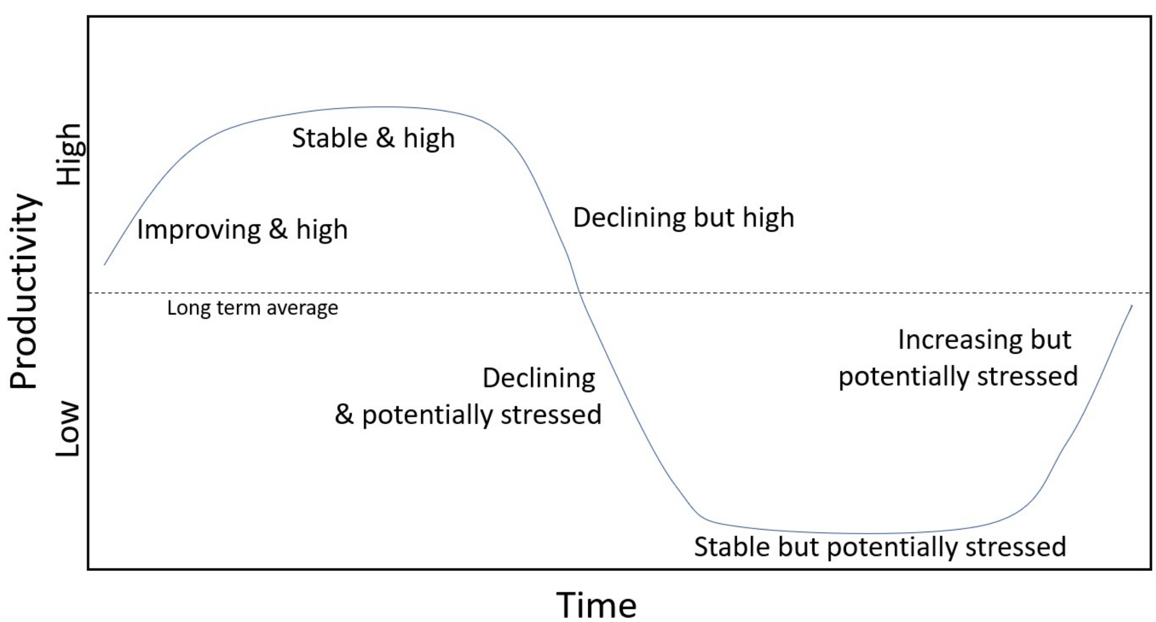


Figure 4-2. Stylised phases in the long-term average trend of land productivity. A declining trend of productivity, or productivity levels that remain below the long-term average, may indicate productivity degradation.

4.2.2 Rationale

The methods for land productivity degradation assessment presented in this GPG draw on the proposed method for assessing land productivity trends for the World Atlas of Desertification (WAD; Cherlet et al. 2018) which was developed by the JRC to measure land degradation at global scales (Figure 4-3). While the WAD method prescribes particular datasets and methods, some of these are more likely to be suited to some countries and scales of analysis than to others.

While the methods for calculating land productivity degradation presented in this GPG are largely based on the WAD method, many options are available for conducting certain aspects of this analysis. Some of the key options and considerations when making choices on the datasets and methods to use are presented throughout this chapter.

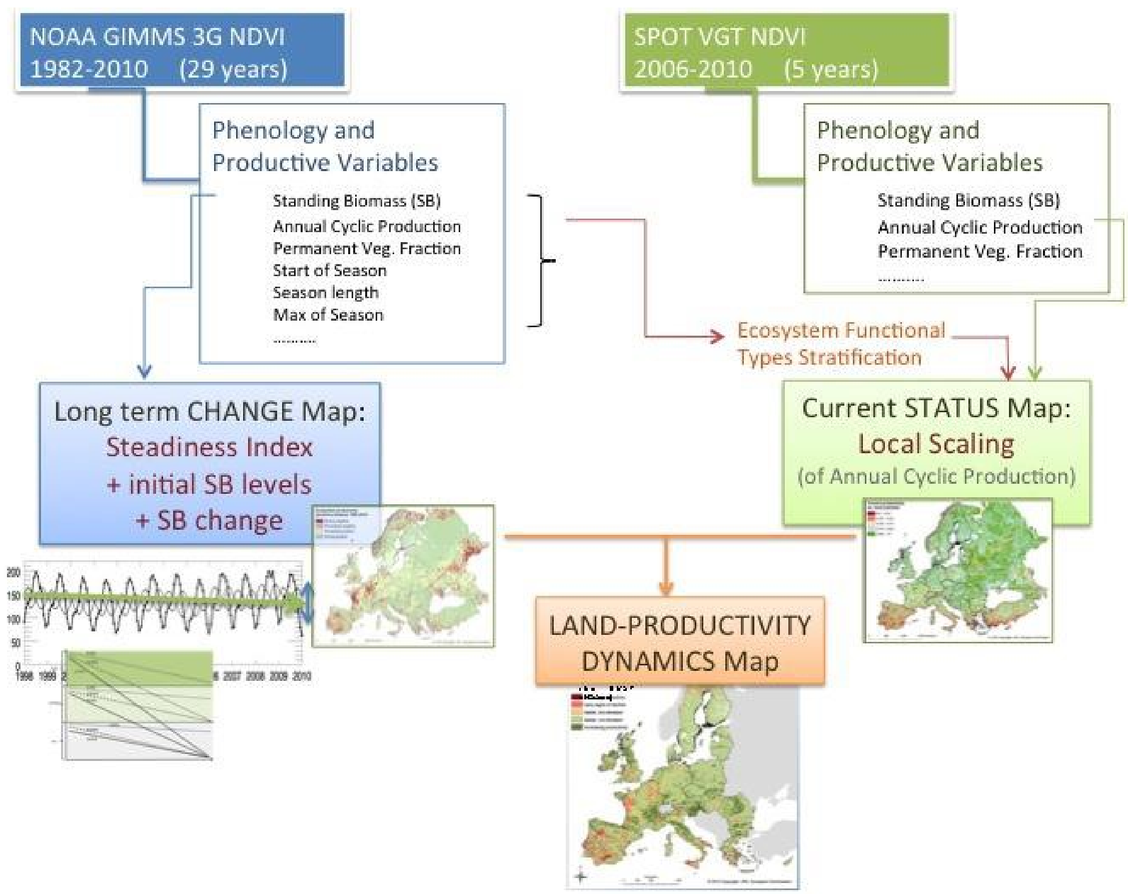


Figure 4-3. Scheme for calculating land cover productivity dynamics for the World Atlas of Desertification (Ivits and Cherlet 2016)

The assessment of land productivity in this GPG uses three metrics calculated from remotely sensed estimates of land productivity:

1. **Trend**, which measures the trajectory of productivity change over the long term,
2. **State**, which compares the current productivity level in a given area to recent historical observations of productivity in that same area, and

3. **Performance**, which indicates the level of local productivity compared with other areas with a similar land productivity potential regionally.

In combination, these three metrics can identify degradation in land units where land productivity is:

i) exhibiting a significant negative trend over the longer term
ii) exhibiting a recent change in trajectory compared to the long-term trend
iii) substantially lower than 'normal' for a given location over time
iv) substantially lower than other similar land capability units within a given region
v) increasing but remains lower than 'normal'.

Changes in the extent of land degradation are measured relative to a baseline (t_0) calculated from the baseline period which extends from 1 January 2000 to 31 December 2015. Subsets of this period may be used to assess the baseline degradation status for certain metrics. Values for the metrics and the sub-indicator calculated from the baseline period are used to determine the extent of land degradation against which the achievement of LDN is assessed.

The method presented in this chapter is comprised of six main processing steps (Table 4-1).

Table 4-1 Processing steps, recommendations, and options for assessing the sub-indicator on land productivity

Chapter Section	Processing Step	Minimum Required Standards	Options
Section 4.2.3	Select image dataset	Global default data products	High resolution and/or national datasets where available
Appendix B.1	Select a productivity index	Normalized Difference Vegetation Index unless an alternative is known to perform better	A large number of alternative vegetation indexes can be calculated from image data Calibrate for moisture availability using Water Use Efficiency or alternative (Appendix B.2). This may be important in areas with very high or very low vegetation cover.
Section 4.2.4.1	Calculate annual productivity estimates	Use TIMESAT or similar to retrieve data from time series measurements over all or part of the growing season each year	Calculate over a cloud-free period, anniversary date and/or from imagery coincident with field sampling
Section 4.2.4	Calculate land productivity metrics	Trend, Performance and State	As described in the relevant section
Section 4.2.5	Calculate the sub-indicator	Aggregate the metrics to show land productivity degradation	Metrics can be aggregated in several ways to show different aspects of productivity degradation
Appendix B.5	Validation	Collect Earth, flux tower or destructive samples	Expert opinion or concordance of evidence

4.2.3 Land productivity datasets

The main dataset required to interpret land productivity degradation is a time series of annual vegetation productivity measurements, such as the NDVI (Tucker 1979), which has been demonstrated to be well correlated with plant productivity and biomass in a wide range of ecosystems globally. The NDVI is recommended by the GEO LDN Initiative as the default index for countries to use in the absence of evidence to indicate that an alternative index is better suited to their landscape (Figure 4-4). However, there are a wide range of alternative datasets correlated with plant productivity that may be better suited to some countries than others (See Appendix B.1). In particular, the Enhanced Vegetation Index 2 (EVI2, Jiang et al. 2008) may be superior to the NDVI in comparison to a time series of land productivity observations that have been calibrated to minimise the impact of variations in moisture availability, which may be useful for identifying anthropogenic from environmental drivers of degradation (see Appendix B.2).

4.2.3.1 Default global datasets

The default dataset provided by the UNCCD for reporting in 2018 was the LPD of the JRC[63]. This product shows vegetation in 5 classes of persistent land productivity trajectories from 1999-2013 and is available through Trends.Earth. Two alternative global datasets are also available through Trends.Earth: the Advanced Very High Resolution Radiometer (AVHRR) Global Inventory Monitoring and Modelling System (GIMMS) 3rd generation NDVI dataset[64], and the Moderate Resolution Imaging Spectrometer (MODIS) dataset numbers MOD13Q1 collection 6[65]. The AVHRR GIMMS3g dataset integrates NDVI observations at 8km pixel resolution over a 16-day period from July 1981 to the present. The GIMMS processing minimises the influence of factors such as sensor degradation over time, orbital drift and volcanic eruptions (amongst others) on image quality, providing an NDVI time series that is very consistent over many years (Fensholt and Proud 2012). The large pixel size makes this dataset ideally suited for reporting at continental or global scales.

MOD13Q1 integrates NDVI observations (and EVI1) at 250m pixel resolution over 16 day periods between 18 February 2000 to the present, and builds a composite scene from pixels with the highest NDVI value, lowest view angle and lowest cloud cover during the integration period for every location on the globe. With its smaller pixel size relative to GIMMS3g, this dataset is better suited to reporting at national and sub-national scales.

4.2.3.2 National datasets

The default datasets are recommended for use only where a more suitable national dataset is not available. Ideally, countries will have, or aim to produce, a land productivity time series dataset that best suits their landscape and land productivity characteristics.

Figure 4-4 shows a decision tree to help guide the identification of datasets suitable for use for calculating land productivity degradation.

[63] https://wad.jrc.ec.europa.eu/landproductivity
[64] https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v0/
[65] https://lpdaac.usgs.gov/products/mod13q1v006/

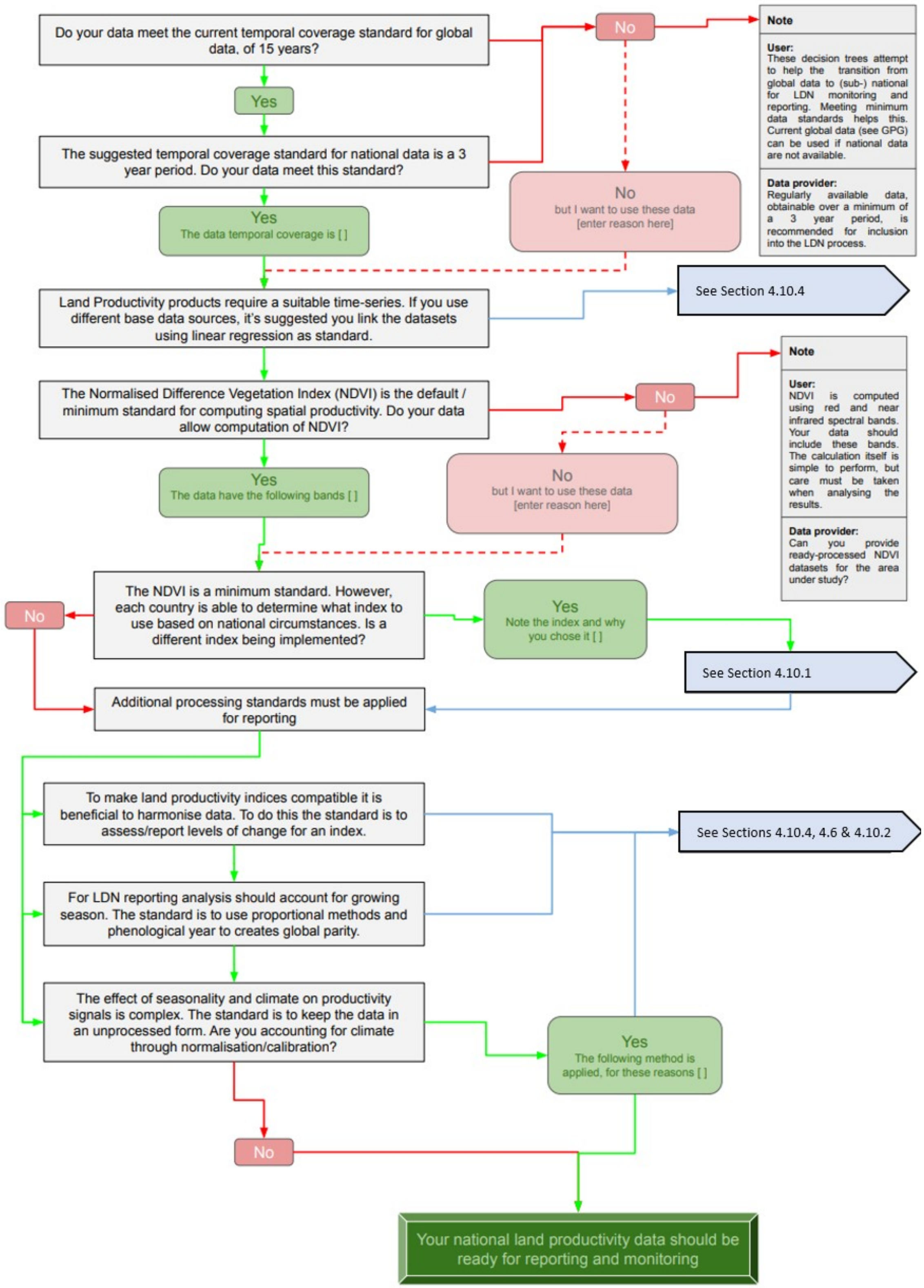


Figure 4-4. Decision tree to determine the suitability of datasets for calculating the land productivity sub-indicator (GEO-LDN Initiative 2020).

The range of available image data sources suitable for assessing land productivity is increasing as new EO satellites are being launched. The key criteria for the selection of a dataset are that it should have an archive of historical data from which baseline conditions can be calculated (ideally spanning 15 years or more including the baseline period), coverage of the entire study area, pixels small enough to represent productivity at the desired spatial resolution, and the spectral bands required to calculate the required productivity indices.

While Figure 4-4 indicates a minimum temporal coverage of only 3 years for national data, this short period is unlikely to encapsulate much of the typical variation in conditions, and a minimum period of 15 years is recommended in highly variable systems (Kennard et al. 2010). A list of alternative low or no cost datasets, and some additional guidance on dataset selection is provided in Appendix B.3.

4.2.4 Calculating the productivity metrics

4.2.4.1 Retrieving annual productivity estimates

Data can be extracted from time series image datasets, such as those shown in Table B-2. Due to the natural cycles of growth and senescence in most vegetation communities, NPP is best represented by a subset of observations captured during the period of highest plant growth each year. This is specifically captured by the integral, or the area under the growing season productivity indicator profile. This is commonly computed by summation of the productivity indicator values from start to end of the growing season.

The growing season is most easily identified from time series satellite observations in temperate regions where there is a pronounced seasonal change in productivity levels throughout the year. Such pronounced cyclical variation in productivity may not occur in tropical regions or areas with low vegetation cover. In these cases, the assessment season each year can be defined based on the expected period of highest biomass, the period of lowest cloud cover, or an arbitrary period chosen to coincide with field data collection. Ideally, the assessment period should occur at approximately the same time each year and/or represent growing conditions that are as similar as possible for each assessment period.

The freely available TIMESAT software[66] (Eklundh and Jönsson 2015a, b) includes features for automatically identifying the growing season and calculating a range of annual metrics from time series data describing the phenology. Figure 4-5 shows some of the parameters that can be calculated from time series data using TIMESAT. Field data are required to determine which of these parameters is best correlated with NPP in any particular region. In the absence of field data, the most highly correlated metric is often the 'small integral' (equivalent to area 'h' in Figure 4-5) which represents the signal associated with growing season recurrent vegetation (Fensholt et al. 2013; Ma et al. 2015; Moran et al. 2014; Olsen et al. 2015).

Recent studies have demonstrated improved correlations with field samples of NPP using absolute rather than proportional values to define the growing season. For example, Olsen et al. (2015) selected NDVI values of 0.22 for season start and 0.25 for season end. The choice to use proportional or absolute values may influence the extent over which the growing season can be identified in the time series imagery.

[66] http://web.nateko.lu.se/timesat/timesat.asp

TIMESAT also includes features to smooth noise and fill gaps in the time series, such as from missing observations or cloud cover (red line in Figure 4-5). Smoothing the data in this way can improve the comparability of NPP measurements between years, which may include more or fewer observations in different years.

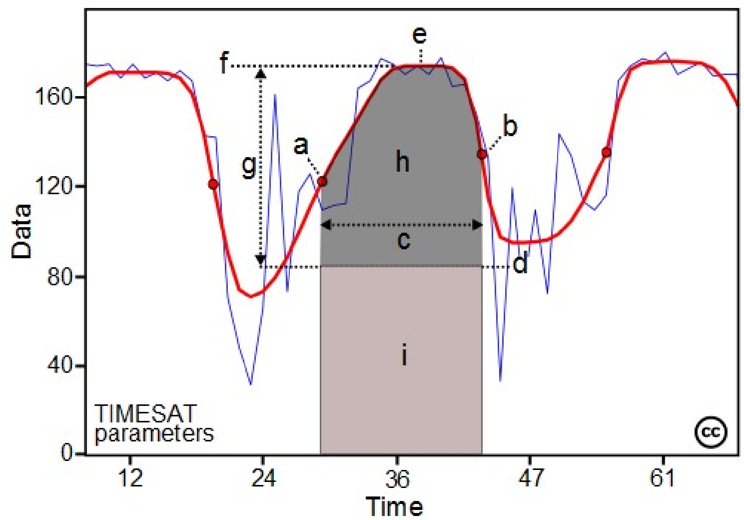


Figure 4-5. Some of the parameters generated in TIMESAT: (a) beginning of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) maximum value, (g) amplitude, (h) small integrated value, (h+i) large integrated value (source ***http://web.nateko.lu.se/timesat/timesat.asp?cat=0****).*

A range of alternatives to TIMESAT are also available, including the Software for Processing and Interpreting Remote Sensing Image Time Series (SPIRITS)[67] which is more suited to medium and coarse resolution imagery, and a system currently being implemented in Google Earth Engine which automatically selects the peak growing season each year, calculates the appropriate integrals and computes the annual trends in NPP and Water Use Efficiency (WUE) from a range of datasets[68]

4.2.4.2 Productivity Trend

Productivity Trend describes the trajectory of change in productivity over the longer term on a pixel level (Figure 4-6). Trend is calculated by fitting a robust, non-parametric linear regression model such as the Thiel-Sen median (Ivits and Cherlet 2016), which can be implemented using the 'mblm' package in R across the annual NPP values.[69] The Mann-Kendall 'Z' score[70] calculated using the 'trend' package in R can be used to determine the significance of the Trend slope (Onyutha et al. 2016). Positive Z scores indicate a trend of increasing productivity and negative scores indicate decreasing productivity. Z scores reflect the magnitude of the slope, with larger positive or negative scores indicating a more statistically significant slope. The black data points show a non-significant increasing trend in annual productivity over the baseline period. The blue points show a significant increase and the red points show a significant decrease over the same period.

[67] Software for Processing and Interpreting Remote Sensing Image Time Series (SPIRITS) | EU Science Hub (europa.eu)
[68] https://zenodo.org/record/3945802
[69] https://cran.r-project.org/web/packages/mblm/mblm.pdf
[70] https://cran.r-project.org/web/packages/trend/trend.pdf

The bins used in the five-level scale to interpret the significance of the slope of the productivity Trend gradient are based on the probability of encountering a value by chance in a normally distributed sample, such as should be expected in samples such as NPP[71]. The z-score represents the number of standard deviations from the mean of the sample. Z- values can also be interpreted in terms of the probability of a data value occurring outside of that distance from the mean (P value) and the statistical confidence that the value has not occurred by chance alone.

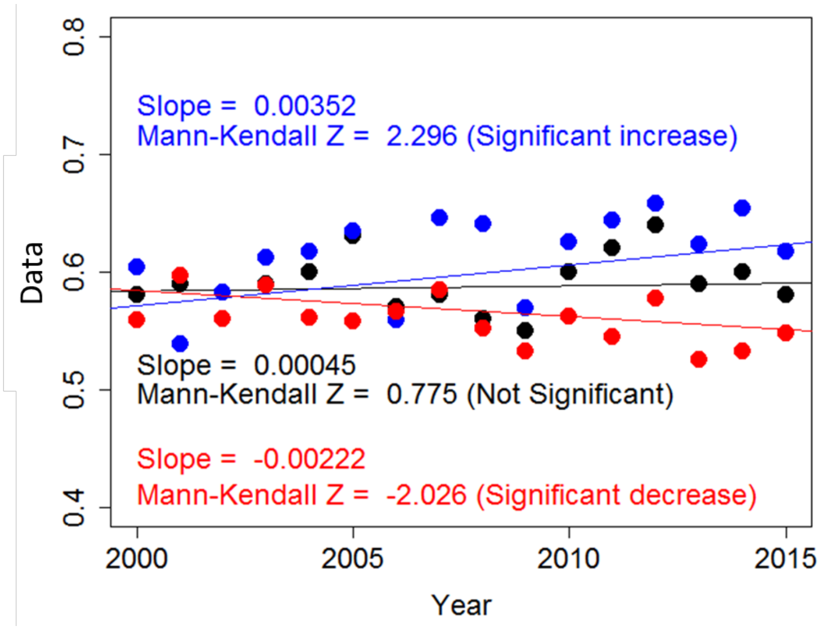


Figure 4-6. Example of productivity trend Figure to be included in the reports. The blue points and regression line show a significant increase, and the red points and regression line show a significant decrease over the same period. The trend plot provided in the report should include only one trend line per region.

Table 4-2 shows the relationship between two-tailed z-scores, p-values and statistical confidence for a normally distributed sample. We recommend the use of Z = 1.96 and Z = 1.28 as the boundary between levels as these options balance a reasonably high level of statistical confidence in the assessment of the significance of the Trend slope, with sensitivity to changes that may be indicative of potential changes in Trend direction.

Table 4-2. Relationship between two-tailed Z-scores, P-values and statistical confidence for a normally distributed sample.

Z-score	P-value	Confidence	Potential error rate of detection
< -2.58 or > +2.58	< 0.01	99%	1%
< -1.96 or > +1.96	< 0.05	95%	5%
< -1.65 or > +1.65	< 0.10	90%	10%
< -1.28 or > +1.28	< 0.20	80%	20%
< -1.04 or > +1.04	<0.30	70%	30%

[71] https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/what-is-a-z-score-what-is-a-p-value.htm

4.2.4.2.1 Calculating the productivity Trend baseline

Productivity Trend in the baseline period should be calculated using all 16 annual productivity measurements between the years 2000-2015. The significance of Trend slope Z scores for the reporting period data can be interpreted on a five-level scale:

- Z score < -1.96 = Degrading, as indicated by a significant decreasing trend
- Z score < -1.28 AND ≥ -1.96 = Potentially Degrading
- Z score ≥ -1.28 AND ≤ 1.28 = No significant change
- Z score > 1.28 AND ≤ 1.96 = Potentially Improving, or
- Z score > 1.96 = Improving, as indicated by a significant increasing trend

The 5-level scale provides a great deal of information about the direction and magnitude of the change in productivity over time for each pixel. For the purposes of monitoring LDN, these classes can be presented as a map showing the extent of land on which productivity Trend is potentially degrading (Z = < -1.28), remaining stable (Z = ≥ -1.28 AND ≤ 1.28) or potentially improving (Z = > 1.28).

For reporting on SDG Indicator 15.3.1, and for calculating the Land Productivity sub-indicator (see Section 4.2.5), it is necessary to classify productivity Trend into one of two classes; degraded or not degraded. The Potentially Degrading class has an error rate of detection of around 20% as opposed to 5% for the Degrading class (Table 4-2). Therefore, for the purposes of calculating the Land Productivity Sub-Indicator, we recommend considering only the area of the lowest negative Z-score level (< -1.96) as degraded. Areas in other Z-score classes should be reported as not degraded.

4.2.4.2.2 Calculating productivity Trend in the reporting periods

To maintain consistency with the Trend assessment in the baseline, we recommend calculating the Trend for the reporting period using a period of 16 years, ending in the last full year of data being reported. The reporting period will move forward by 4 years on commencement of every new reporting period. For example, reporting in 2022 could calculate reporting period Trend over the years 2006 to 2021 if annual productivity data is available for the full 2021 growing season.

Trend slope Z scores for the reporting period should be classified into the same five-level scale as baseline period, and for monitoring LDN these can be converted into the three-class map showing areas that are potentially degrading, remaining stable or potentially improving. As with the calculation of productivity Trend in the baseline period, for the purposes of calculating the Land Productivity Sub-Indicator, we recommend considering only the area the area of the lowest negative Z-score level (< -1.96) as degraded. Areas in other Z-score classes should be considered as not degraded.

4.2.4.2.3 Notes on reporting productivity Trend

Productivity Trend is one of three metrics used to determine land productivity degradation, and as such it is not sufficient to classify land as degraded at the sub-indicator level using Trend alone.

For the purposes of monitoring LDN, Productivity Trend in the reporting periods should be reported as potentially degrading, stable or potentially improving according to the direction and significance of the trend observed. The area of land in each of these categories should be calculated and presented as a map, and justifications for any changes in the distribution or extent of degraded land between the baseline and reporting periods should be included in the report.

This assessment could be accompanied by a scatter plot figure showing the annual productivity measurements, with a linear trend line fitted and slope indicated, as shown in Figure 4-6. The trend plot provided in the report should include only one trend line per land cover class for each reporting unit.

We do not recommend scrutinising changes in the slope of the Trend as an indicator of the magnitude of change in productivity degradation levels except in the terms described above. Additional guidance on the interpretation of degradation severity is provided in Chapter 7.

4.2.4.3 Productivity State

Productivity State represents the level of productivity in a land unit compared to the historical observations of productivity for that land unit over time (Ivits and Cherlet 2016). Productivity State degradation is determined by comparing the mean annual NPP of the three most recent years to the distribution of annual NPP values observed in the preceding 13 years. By comparing productivity in the three most recent years to the 13 earlier years, productivity State is more sensitive to the recent magnitude and direction of change in NPP than Trend, which represents the trajectory of productivity change over the longer term.

Productivity State can be interpreted as a level of productivity relative to historical observations of a given location, and as an 'early warning' indicator of the potential future trajectory of productivity change.

4.2.4.3.1 Calculating the productivity State baseline

The productivity State baseline sets the extent of productivity State degradation to which measurements in the reporting period are compared. Calculate the mean (μ) and standard deviation (σ) of the annual NPP measurements from 2000 to 2012 inclusive. These statistics are assumed to be representative of the normal distribution of annual NPP measurements over time.

$$\mu = \frac{\sum_{y-15}^{y-3} x_y}{13}$$

Equation 4-1

$$\sigma = \sqrt{\frac{\sum_{y-15}^{y-3} \left(x_y - \mu\right)^2}{13}}$$

Equation 4-2

Where *x* is the metric used for productivity (e.g. annual NDVI) and *y* is the year of analysis.

Productivity State in the baseline period is calculated by comparing the mean of the final 3 years of the baseline period to the distribution of annual NPP measurements from 2000 to 2012 as follows:

Calculate the mean of 2013-2015 inclusive

$$\bar{x} = \frac{\sum_{y-2}^{y} x_y}{3}$$

Equation 4-3

Calculate the Z statistic

$$z = \frac{\bar{x} - \mu}{\sigma / \sqrt{3}}$$

Equation 4-4

The significance of productivity State degradation in the baseline period can be interpreted from the Z scores using the same five-level scale as for productivity Trend with slightly modified class labels:

- Z score < -1.96 = Degraded, showing a significantly lower mean in the recent years compared to the longer term
- Z score < -1.28 AND ≥ -1.96 = At risk of degrading
- Z score ≥ -1.28 AND ≤ 1.28 = No significant change
- Z score > 1.28 AND ≤ 1.96 = Potentially Improving
- Z score > 1.96 = Improving, as indicated by a significantly higher mean in recent years compared to the longer term

The 5-level scale provides a great deal of information about the direction and magnitude of the change in productivity State over time for each pixel. For the purposes of monitoring LDN, these classes can be presented as a map showing the extent of land on which productivity State is potentially degrading (Z = < -1.28), remaining stable (Z = ≥ -1.28 AND ≤ 1.28) or potentially improving (Z = > 1.28).

Reporting on SDG Indicator 15.3.1, and for calculating the Land Productivity sub-indicator (see Section 4.2.5), it is necessary to classify productivity State into one of two classes; degraded or not degraded. For the purposes of calculating the Land Productivity Sub-Indicator, we recommend considering only the area of the lowest negative Z-score level (< -1.96) as degraded. Areas in other Z-score classes should be considered as not degraded.

4.2.4.3.2 Calculating productivity State in the reporting periods

Productivity State in the reporting periods is calculated from the 16 most recent years of annual NPP data up to and including the most recent year included in the reporting period. The mean of the most recent 3 years is compared to the distribution of annual NPP values in the preceding 13 years, using the method described for calculating State degradation in the baseline (Section 4.2.4.3.1).

Productivity State degradation can be classified using the five-level scale described for the baseline period, and converted into a three-class map showing areas in which productivity State is potentially degrading (Z = < -1.28), remaining stable (Z = ≥ -1.28 AND ≤ 1.28) or potentially improving (Z = > 1.28).

Reporting on SDG Indicator 15.3.1 requires land to be classified into one of two classes; degraded or not degraded. For the purposes of calculating the Land Productivity Sub-Indicator, we recommend considering only the area of the lowest negative Z-score level (< -1.96) as degraded. Areas in other Z-score classes should be considered as not degraded.

4.2.4.3.3 Notes on reporting productivity State

Productivity State is one of three metrics used to determine land productivity degradation, and as such it is not sufficient to classify land as degraded at the sub-indicator level using State alone.

Note that, while the recommended Z score (and probability and confidence levels) used to define classes of productivity State degradation are identical to those used for Trend, their descriptive labels reflect the differences in interpretation.

4.2.4.4 Productivity Performance

Productivity Performance indicates the level of local plant productivity relative to other regions with similar productivity potential. Specifically, productivity Performance compares productivity in each land unit to the productivity level of all other land units within the same LCEU in the assessment period (see definitions in Section 0). LCEUs can be defined based on any available information on factors influencing plant productivity potential such as land cover, soil type, climate conditions, elevation and aspect. A subset of the available datasets may also be used, and the decision on which variables to include should be supported by local knowledge of the factors controlling productivity in that LCEU. A range of global datasets are available to stratify the landscape into LCEUs for calculating productivity Performance (Table 4-3). Figure 4-7 shows northern South America overlaid with the Global Agro-Environmental Stratification (GAES) level 4 stratification boundaries, which are considered appropriate for Performance assessment in most locations.

Table 4-3. A subset of global datasets that may be used to support the spatial definition of LCEU regions for productivity Performance assessment

Dataset	Variables	Reference
Terrestrial Ecosystems of the World (TEOW)[72]	Climate, expert consultation	(Olson et al. 2001)
Global Homogeneous Response Units[73]	Soil, slope, altitude	(Skalsky et al. 2012)
Global Ecological Land Units[74]	Bioclimate, landform, lithology, and land cover.	(Sayre et al. 2014)
Global Agro-Environmental Stratification (GAES)[75]	Climate, elevation, soil, growing season, vegetation & other	(Mücher et al. 2016)
World Ecosystems[76]	Landform (slope, altitude), soil, climate, vege.	(Sayre et al. 2020)

[72] https://www.sciencebase.gov/catalog/item/508fece8e4b0a1b43c29ca22
[73] https://doi.pangaea.de/10.1594/PANGAEA.775369
[74] http://www.aag.org/galleries/default-file/AAG_Global_Ecosyst_bklt72.pdf
[75] http://www.fao.org/geonetwork/srv/en/main.home?uuid=a509e912-9166-407e-828c-bcb31a8109d8
[76] https://rmgsc.cr.usgs.gov/outgoing/ecosystems/Global/

The main assumption of this metric is that, in the absence of degrading factors, productivity levels in each land unit within the LCEU should be similar for a given assessment period. Productivity Performance may identify areas of long-term degradation, in which there is not necessarily a declining Trend in productivity, but where the level of productivity in a given land unit remains low relative to other land units within the LCEU. Productivity performance can indicate the impacts of land management activities, such as differences in the intensity of grazing (rangelands) or logging (forests) across fence lines, or from other localised sources.

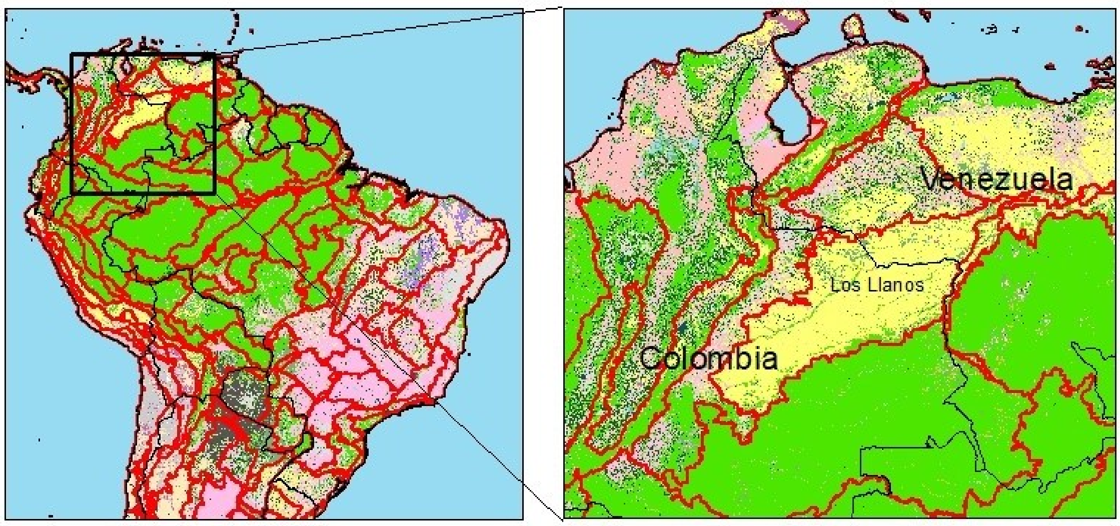


Figure 4-7. Map of South America with Agro-ecological Stratification (layer 4) in red, country borders in back and land cover classes (forest – green, grassland – yellow, croplands – pink). A zoom around the 'Los Llanos' highland grassland strata which borders Colombia and Venezuela is also shown which illustrates that this grassland strata is shared by two countries

Productivity Performance for a given land unit is calculated in comparison with the maximum productivity index value observed within the relevant land unit (NPP_{max}). In order to avoid possible overestimation of the maximum value due to the presence of outliers, it is recommended to use the 90th percentile of the productivity values within the land unit. Once NPP_{max} is obtained, Productivity performance in each pixel within the land unit is calculated as:

$$Performance = \frac{Observed\ NPP}{NPP_{max}}$$

Equation 4-5

Productivity Performance values close to 1 represent pixels in which productivity is close to the highest level for that land unit in that period of time. Performance levels well below NPP_{max} may indicate land degradation, and we suggest considering pixels with productivity values less than 0.5 of the NPP_{max} (Figure 4-8) as degraded for the purpose of calculating the land Productivity sub-Indicator.

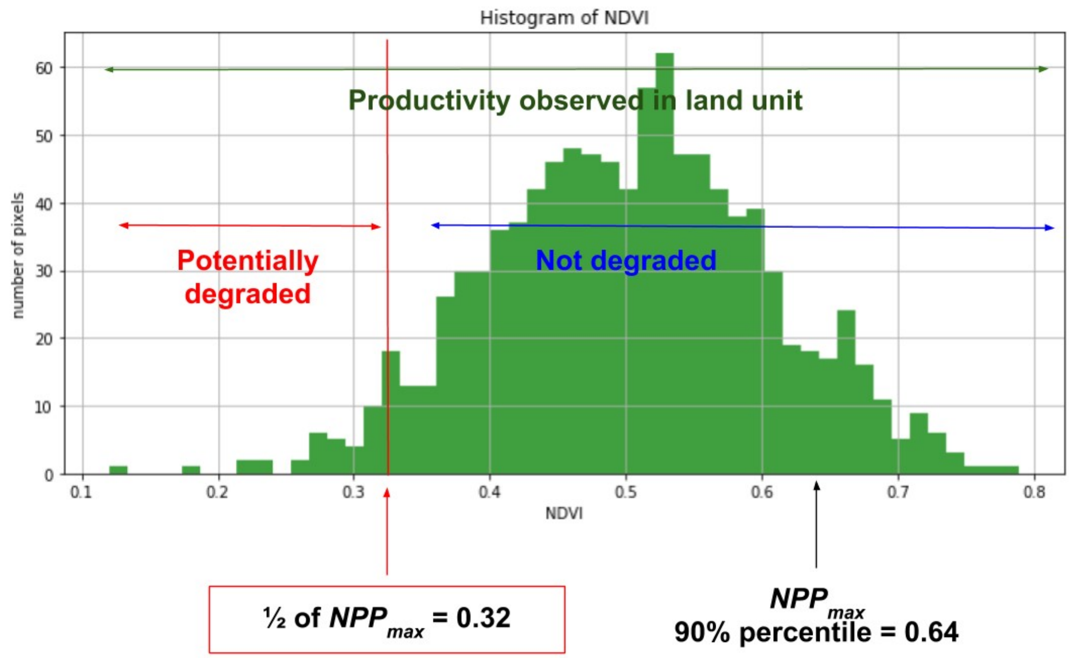


Figure 4-8. Illustration of the Productivity Performance in a hypothetical example. Performance compares productivity within a land capability unit. Pixels or regions where productivity is less than half the value of the 90%th percentile for that land capability unit may indicate potential degradation.

4.2.4.4.1 Calculating the Performance baseline

Productivity Performance during the baseline period should be calculated from the mean of the annual productivity assessments over the baseline period from 2000 to 2015. A map of performance degradation should be produced showing the spatial distribution of pixels < 0.5 NPP_{max}.

The calculation of productivity Performance is strongly dependent on the definition of the LCEU. Unlike the Trend and State metrics which assess changes over time, Performance is a spatial comparison, and the results may change if the extent over which the analysis is conducted changes. The most ecologically relevant assessment of productivity Performance should theoretically include all other pixels within the same LCEU in the local geographical region.

4.2.4.4.2 Calculating Performance in the reporting periods

Productivity performance in the reporting periods should be calculated from the mean of the annual productivity assessments over the years between the previous (or baseline) assessment up to the current year. For reporting in 2022, for example, performance could be calculated from an average of 2019, 2020 and 2021 productivity measurements if the full growing season for each of these years is encapsulated in these data.

4.2.4.4.3 Notes on reporting productivity Performance

Productivity Performance is one of three metrics used to determine land productivity degradation, and as such it is not sufficient to classify land as degraded at the sub-indicator level using Performance alone.

An important consideration when determining the extent over which productivity Performance is assessed is whether the analysis should extend across political borders. These borders are ecologically artificial and may truncate an LCEU, restricting the range of pixel values considered in the assessment. The greatest ecological relevance may be provided by extending the analysis to all areas of the LCEU across borders, which provides a more comprehensive context for assessing productivity Performance.

One potential consequence of extending across political borders, however, is that the determination of whether productivity Performance is degraded or not may be influenced by land use and management practices in areas over which the reporting country has no control. If a reporting country decides to extend the assessment of productivity Performance to include international areas and detects significant impacts from such activities in areas over which they have no control, these impacts should be justified in the national reports.

We recommend identifying pixels with an NPP (NDVI or other index value) less than 0.5 of the NPP_{max} as degraded in this assessment. Countries may adjust this threshold according to other criteria or local knowledge if required, and this choice should be justified in their national report.

4.2.5 Calculating the sub-indicator

The Land Productivity sub-indicator is calculated by assessing the indications of degradation shown by the Trend, State and Performance metrics and interpreting their combinations to determine degradation at the sub-indicator level. There are several ways that the land productivity metrics can be combined to determine degradation at the sub-indicator level. (Note that this process relates to the integration of the metrics of the Land Productivity sub-indicator only, and is entirely separate from the "One Out, All Out" principle used to estimate SDG indicator 15.3.1.)

Measurements of biological indicators are subject to various sources of error and the observed data may give a falsely optimistic or pessimistic reflection of the true conditions. When combining metrics to interpret land productivity degradation, we therefore recommend considering only the areas identified as Degrading in the Trend metric, Degraded in the State metric and Potentially Degraded in the Performance metric as these areas have the highest statistical confidence in their assessment.

Version 1 of the GPG recommended combining the metrics as shown in the lookup Table 4-4. This method identified pixels showing degradation as those with:

1. A significant negative trend in any combination of degradation metrics;
2. A trend that is not significantly negative with:
    a. Degradation indicated in the productivity State analysis;
    b. Degradation indicated in the productivity Performance analysis.

This combination of metrics placed more emphasis on the assessment of Trend than State or Performance to determine degradation, primarily because the statistical test for Trend was more rigorous than for the other metrics. In this second version of the GPG, however, the rigor of the tests for State and Performance has been increased, which provides the opportunity to identify other combinations of metrics as potential land productivity degradation.

The combination of metrics presented in Table 4-4 strictly complies with the definition of land degradation adopted by the UNCCD, which includes a reduction of biological productivity (i.e. a significantly negative Trend constitutes degradation regardless of the State or Performance metrics). It could be argued, however, that a decline in productivity may not constitute degradation where the productivity level remains high. This combination of metrics may also not detect degradation in areas where the productivity level remains low for a long period of time, as both Trend and State identify degradation based on a reduction in NPP from a previously higher level.

Table 4-4. Lookup table indicating combinations of productivity metrics for determining whether a pixel is degraded: classes 1 to 5 show degradation, where Y is degraded and N is not degraded in that metric or pixel. This combination of metrics may over-emphasise the extent of productivity degradation from declining Trend alone, and may under-emphasise degradation in areas where productivity levels remain low for a long period of time.

Class	Trend	State	Performance	Degraded
1	Y	Y	Y	Y
2	Y	Y	N	Y
3	Y	N	Y	Y
4	Y	N	N	Y
5	N	Y	Y	Y
6	N	Y	N	N
7	N	N	Y	N
8	N	N	N	N

One of the potential options provided by the improved metrics is to consider a reduction in productivity as degradation only when the level of productivity is low. The Performance metric can identify degradation in areas where the productivity remains low compared to other land units within its LCEU.

Ultimately, countries have the choice to use whichever combination of metrics and assessments of their significance they prefer to determine the extent of land degradation within their national boundaries. These choices should be justified in the accompanying report, however, preferably with maps comparing the extent of degradation identified using the different combinations. The extent of land productivity degradation identified in the reporting period should be added to the extent of degradation mapped during the baseline or previous reporting period which remains degraded in the current assessment.

Table 4-5 presents an alternative interpretation of the combination of metrics that could be used to identify pixels showing degradation, and includes as degraded any land unit with:

1. A significant negative trend with a degradation indicated in the State and/or Performance metrics; or
2. A trend that is not significantly negative with:
    a. Degradation indicated in the State and Performance metrics;
    b. Degradation indicated in the Performance metric only.

Table 4-5. Alternative lookup table indicating combinations of productivity metrics for determining whether a pixel is degraded: classes 1 to 5 show degradation, where Y is degraded and N is not degraded in that metric or pixel. This combination of metrics may not identify degradation where the Trend of land productivity is decreasing but remains high, and it may help to identify degraded areas where productivity levels remain low for a long period of time. Changes from Table 4-4 (which was included in GPG version 1) are shown in red.

Class	Trend	State	Performance	Degraded
1	Y	Y	Y	Y
2	Y	Y	N	Y
3	Y	N	Y	Y
4	Y	N	N	N
5	N	Y	Y	Y
6	N	Y	N	N
7	N	N	Y	Y
8	N	N	N	N

4.3 Comments and limitations

Much of the guidance presented in this Chapter is based on the WAD method, which is best suited to assessing land productivity dynamics in water-limited, temperate regions. The Chapter presents a process of analysing annual land productivity data in a way can be used to interpret a range of aspects of land productivity dynamics consistently between countries. In reality, the seasonal dynamics of productivity vary greatly across the globe, and decisions on the most suitable vegetation index to adopt and time of year to assess peak productivity should be based on the best available local knowledge. Each country will also differ in its land cover characteristics, access to datasets, analytical capability and development objectives. Options are available for countries to adapt this guidance on land productivity assessment to meet their circumstances and needs, and more information about how to justify and report these choices is available in Section 2.2

Degradation assessed during the baseline period will be strongly influenced by the specific climatic and land management conditions prevailing during that period, and consideration should be given to whether the baseline period is representative of 'normal' NPP conditions. In Australia for example, the millennium drought extended from the late 1990s to 2010 across the southern part of the continent, and included some of the most severe rainfall and temperature anomalies on record. Vegetation became severely water stressed in the latter part of this period, and subsequent comparison of contemporary productivity measurements with baseline conditions is likely to skew the assessment towards indicating higher recent productivity and potentially underestimate the true extent of land degradation. Calibrating the productivity measurements to adjust for moisture availability (described in Section B.2) can be used to highlight the potential influence of climatic conditions on the baseline period in this case.

The improved statistical rigour of the sub-indicator assessments in this Version 2 of the GPG provides information on the severity of degradation and the confidence in the assessments. Areas with a z-score between -1.28 and -1.96 are potentially degrading in the Trend metric, and areas that are at risk of degrading in the State metric. The statistical confidence in these areas is lower than for the Degraded level, and areas identified as being "at risk of degradation" should not be included in national reports as being degraded. These areas may be of interest for interpreting future degradation risk, which may be useful for guiding efforts to achieve LDN (see Section 1.4 on LDN and Chapter 7 on assessing the magnitude of degradation for more information).

The suitability of alternative data sources will need to be assessed as data sources expire and/or new ones emerge. The availability of high resolution and locally calibrated global time-series datasets is likely to increase in future, including through specific global efforts to support the SDGs within CEOS[77] and GEO[78], which should improve the quality and comparability of data between countries and at larger regional and global scales.

[77] http://ceos.org/ourwork/ad-hoc-teams/sustainable-development-goals/
[78] https://www.earthobservations.org/geo_sdgs.php

5 Carbon Stocks, Above and Below Ground

5.1 Executive summary

This chapter describes the methodology and data sources available for establishing baselines and evaluating change in the carbon stocks, above and below ground sub-indicator for reporting on SDG indicator 15.3.1. As outlined in the UNCCD decision 22/COP.11, *soil organic carbon (SOC) stock* is the metric currently used to assess carbon stocks and will be replaced by *total terrestrial system carbon stock* once operational.

5.1.1 Role and calculation of the sub-indicator

Carbon stocks reflect the integration of multiple processes affecting plant growth as well as decomposition, which together control 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 soil type, land use and management practices. This chapter provides guidance on approaches that countries can use to determine baseline SOC stocks and estimate change in SOC stocks. Consistent with the IPCC guidelines, supplements and refinements (IPCC 2006; 2013; 2019), a range of datasets and processing options are presented with the level of accuracy, detail and processing complexity increasing from Tier 1 (broad methods with default values) to Tier 2 (additional use of country-specific data) to Tier 3 (more complex methods involving ground measurements and modelling). Where possible, it is good practice for countries to use a national approach i.e., the highest tier practical, to reduce bias and uncertainty.

Where country-specific data and capacities are unavailable, the Tier 1 method for estimating change in SOC stocks is informed by the equations in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006), and the 2013 Wetlands Supplement (IPCC 2013) and 2019 Refinement (IPCC 2019) to the 2006 guidelines. Changes in vegetation cover, including those in response to climate or land use or management, influence SOC stocks by altering the rates, quality, and location of plant litter inputs to soils as well as the rates of output from soils via microbial decomposition and physical transport (e.g., leaching). This implementation of the Tier 1 method uses information on land cover change along with: i) climate/land cover default change factors (available for land cover change, inputs and management) to estimate changes in carbon stock for mineral soils, and ii) default annual emission factors to estimate the losses of carbon following drainage and/or fire for organic soils. The IPCC Tier 1 methodology constructs reference SOC stocks (baseline SOC stocks) based on broad global estimates of default SOC stocks under natural vegetation, stratified by climate/soil type. Current implementations of Tier 1 use some form of predicted SOC spatial distribution for the baseline state. For change factors, the Tier 1 method is strongly reliant on land cover change and/or land management change to estimate changes in SOC stocks as well as delineation of Wetland areas as a proxy for organic soils.

Where possible, the Tier 2 method should be employed to complement default values with national datasets (both for SOC baseline stocks and for change factors) even if they are only able to better specify certain components of the Tier 1 method. Reference SOC stocks can be determined from high spatial resolution digital soil maps or from measurements, for example, as part of national soil surveys. Default management systems can be disaggregated into categories that better represent country-specific management impacts on SOC stocks based on empirical data. Compared with the use of default equations, a new alternative Tier 2 ‘steady-state’ method for mineral soils in Cropland Remaining Cropland addresses the additional complexity in SOC dynamics, subdividing the SOC pool into three separate sub-pools with fast, intermediate and long turnover times (IPCC 2019). This steady-state approach may be applicable to other land uses but requires further expert development and parameterisation. While SOC stock change is estimated based on land cover and land management change, it is possible for national authorities to arrive at a different assessment of change (i.e., positive, negative, or stable) from that of land cover given additional data and information (e.g. through identification of “false positives” or “false negatives”). However, consistency and transparency in reporting of such assessments is required.

The Tier 3 method incorporates more advanced national methods which better capture annual variability in fluxes, such as country-specific digital soil mapping and time-series spatial land use/management and climate data, combined with calibrated and validated process-based models, and/or a measurement-based inventory with a monitoring network. Tier 3 provides the highest level of certainty in the estimates of SOC stock change but requires the most expertise and resources to implement and maintain.

Most countries will use a blend of methods from Tiers 1-3, depending on their national requirements and availability of expertise and resources. Regardless of the methods used, the following are **good practice principles** to guide the development of a national method of computation for the carbon stocks sub-indicator:

1. **Identify key degradation processes** that should be included in the country’s assessment of land degradation.
2. **Assess available data and estimation methods** that can be used to determine the carbon stocks over the total land area for the country. This should include documenting the source data and relevant methods.
3. **Determine the baseline carbon stocks** from which changes will be assessed.
4. **Determine the reporting period carbon stocks** using the same data sources as the baseline period.
5. **Define a change assessment method** that quantifies carbon stock changes and determines the status of change as being either an increase (improvement), decrease (degradation) or no change (neutral).
6. **Generate reports of land degradation** based on an assessment of change from the baseline to the reporting period. Identify and justify potential “false positives”, i.e., increases in carbon stocks for land use transitions that are considered land degradation, and explainable anomalies.

5.1.2 Changes from version 1 of the GPG

In this revision, updates to version 1 of the GPG (Sims et al. 2017) have been made where the science was considered to have sufficiently advanced since version 1, or where new or additional guidance was required. In particular, the previous guidance has been expanded on by providing:

- Inclusion of additional terms and definitions;
- Revisions to the methods for estimation of change in SOC stocks, including relevant updates and new guidance from the 2019 IPCC Refinement to the 2006 Guidelines;
- Expanded guidance on the methods for assessment of 'significant' change in SOC stocks
- Updates to the data sources available for estimating change in SOC stocks;
- Expanded guidance on approaches for estimating change in total carbon stocks (i.e., above and below ground biomass, litter, dead wood and soil) and available datasets, with a view to transitioning from the current sub-indicator metric SOC stock to total carbon stock over time;
- Additional guidance principles and diagrams to assist countries with the development of a national method of computation for the carbon stocks sub-indicator, including generating reports of land degradation.

5.1.3 Interpretation and further work

SOC is central to maintaining soil health and ecosystem functioning, and ensuring global food security, and is the current metric used to assess the carbon stocks above and below ground sub-indicator. There are a range of methodological approaches that countries can use to estimate change in carbon stocks depending on available data and analytical capability. Although there has been much progress made, current global or national maps for estimating SOC reference stocks are currently not dynamic. Further work is required to address this, including improvements to global gridded models (e.g. time-stamped releases over several decades), and ideally, through well-designed national monitoring networks.

Compared with other sub-indicators, changes in SOC stock associated with changes in land use and management must be measured over longer periods. These changes are small relative to the very large stocks present in the soil as well as their inherent variability. A four-year reporting frequency proposed for the indicator is likely to be too short to detect SOC stock change where an on-ground monitoring approach is used, and may even be difficult to register change in less than 10 years (Smith 2004).

Carbon stocks in non-forested ecosystems are typically largest in the soil pool, but in woody perennial systems the biomass pool tends to be largest. Further, in such systems, changes in SOC stocks may not always capture degradation. Thus, once operational, the use of total carbon stocks as the sub-indicator will provide a more comprehensive assessment of degradation, particularly in cases of conversion of forested systems to other land uses. However, further work is required to improve the spatial data available for the range of carbon pools.

5.2 Methodology

5.2.1 Rationale

The methodological approach to this sub-indicator ranges from a broad Tier 1 default approach to a highly detailed and complex Tier 3 set of approaches consistent with the IPCC guidelines, supplements and refinements (IPCC 2006; 2013; 2019). The tiered approach to the method of computation (IPCC 2006) considers a range of datasets and processing options which are categorised by the level of accuracy, detail and processing complexity increasing from Tier 1 (general methods with default values) to Tier 2 (additional use of country-specific data) to Tier 3 (more complex methods involving ground measurements and modelling).

Factors such as the significance of the source/sink (proportional contribution to national inventory), available data, and analytical capability will ultimately determine which Tier is selected. It is good practice to use higher tiers for the measurement of significant sources/sinks. Investment in monitoring of SOC should prioritise sites where SOC is the key indicator such as in croplands and grazing lands where land productivity and land cover change are less reliable indicators of land degradation (e.g. for different cropland management practices; see Chotte et al. 2019).

The default (Tier 1) method for estimating change in SOC stocks draws on the significant body of work of the IPCC, which has published the methodological guidance that Annex I countries have agreed to use in estimating greenhouse gas inventories for reporting to the United Nations Framework Convention on Climate Change. 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) and the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006) which consolidates and updates previous guidance. The 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands (IPCC 2014) fills gaps and extends the 2006 Guidelines and updates emission/removal factors including on wetlands and drained soils. Most recently, the 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2019) provides some refinement to reference and change factors, and additional approaches for Tier 2 and 3 methods.

Methodological changes and refinements over time, often driven by the development of new datasets, are an essential part of improving the quality of sub-indicator estimates. It is **good practice** to change or refine methods for estimating carbon stocks/stock change when:

- The available data have changed;
- The previously used method is not consistent with the most recent IPCC guidance;
- The category has become key;
- The capacity for sub-indicator calculation has increased;
- New methods have become available;
- Errors have been identified and corrected.

Ensuring the consistency of time series when there has been a methodological change or refinement is considered in Chapter 6.

5.2.2 Landscape stratification

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 and microbial decomposition (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, fertiliser addition) or loss (e.g., removal of crops, cultivation) change SOC stock.

The IPCC defaults for SOC stocks and change factors use 'strata' based on factors such as climate and soil type. While 'land use' refers essentially to the six land cover 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, SOC stock change factors are based on land use and management under different climatic regimes, while the defaults for reference stock, i.e., under native vegetation, are based on IPCC default climate zones and seven broad soil classes[79]. For organic soils, IPCC defaults stratify by climatic region.

The IPCC term 'stratum' is consistent with LCEU terminology, where LCEUs can be defined based on available information affecting productivity such as land cover, climate, soil type and elevation. Here the term LCEU is used instead of the IPCC term 'stratum' to avoid confusion with land cover terminology. All land in an LCEU should ideally 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 'reporting unit' is the spatial unit (e.g., watershed, polygon) reported on and is likely to be a mix of land cover classes, while an LCEU is a uniform land cover class within a reporting unit.

5.2.3 Role and function of sub-indicator in the context of the Indicator

SOC is a fundamental part of the terrestrial ecosystem and changes in SOC can be used as a proxy for ecosystem and soil health. SOC 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 SOC is central to maintaining soil health and ensuring global food security (Lal, 2004) and ecosystem functioning. Consequently, one of the greatest priorities for action concluded by the Intergovernmental Technical Panel on Soils (ITPS) in their Technical Summary[80] 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*".

In the following sections, guidance is provided to implement the measurement, validation and reporting of land degradation processes associated with change in carbon stocks above and below ground. The guidance is designed to promote a consistent and objective approach for any reporting period.

5.2.4 Key degradation processes related to this sub-indicator

[79] 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: https://data.isric.org/geonetwork/srv/eng/catalog.search#/metadata/41cb0ae9-1604-4807-96e6-0dc8c94c5d22

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

As a basis for objective and consistent reporting, it is good practice to state the key degradation processes relevant to a country and to create a table of these processes prior to determining change in carbon stocks. Key degradation processes related to the SOC metric of the carbon stocks above and below ground sub-indicator might include: urban expansion, deforestation/land clearing, overgrazing, unsustainable cropping practices, including tillage and burning or irrigation, and natural events such as intense fires or drought that substantially and/or persistently reduce vegetation cover and increase soil erosion. Some of these processes may be detectable through analysis of change in SOC stocks as methods for estimating changes in SOC stocks are strongly reliant on land cover change data, many of the degrading processes are likely to be inferred using land cover change (see Chapter 3), and some may be inferred using multiple indicators.

5.2.5 Assessing available data

For the carbon stocks sub-indicator, the primary data are:

- Ground observations and measurements, and predictions based on them;
- Spatial data including remotely sensed data or products predicted from these data.

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);
- **Transparent**, i.e., data sources, definitions, methodologies and assumptions should be clearly described.

Minimum DQS and decision trees for determining the most appropriate data for calculating SDG Indicator 15.3.1 have recently been developed through multi-phase consultation with data providers and data users (GEO LDN Initiative, 2020). These standards, which may be under development and not currently available, aim to ensure consistency, coherence and comparability of data sets supplied by various global or national data providers in support of country efforts to monitor SDG Indicator 15.3.1. Cross-cutting and sub-indicator specific minimum DQS relevant to SOC have been developed and relate to spatial and temporal resolution, data pre-processing, data uncertainty assessment and monitoring update periods (Table 5-1).

Two decision trees are provided - a cross-cutting decision tree (see Figure 2-2) which guides the user on whether to use global default data, investigate the building of additional country capacity or proceed with using national data, and a sub-indicator decision tree for assessing the desired standards for SOC datasets Figure 5-1). It is good practice to use these DQS and decision trees for verifying the best available data for calculating the sub-indicator.

In addition to data uncertainty and inventory update period, the standards (GEO LDN Initiative 2020) recognise that spatial stratification of SOC data at a national level may need to be applied, but that this should not be a standard. The importance of stratification is likely to depend on local factors including the size and heterogeneity of the country. Spatial stratification by land cover types, climatic regions and soil types is important to help differentiate changes in SOC stocks. Stratification could also be based on other factors such as NPP performance zones, prior land use, or degradation severity. The decision should be left to the individual nations.

The type and availability of SOC data will vary by country. Data may be sourced from freely available global datasets, IPCC Good Practice Guidance (IPCC 2003), Guidelines (2006) and Supplements/ Refinements (IPCC 2013; 2019), and nationally contributed datasets. Global datasets include IPCC defaults and global soil organic carbon maps. A summary of existing freely available sources is provided in Appendix C.1. National and regional products are based on EO data for land cover at finer resolutions than for global products (see Chapter 3). Examples of existing continent and country baseline maps for SOC stocks are provided in Appendix C.2.

Table 5-1. Cross-cutting and sub-indicator specific minimum data quality standards relevant to carbon stocks (from GEO LDN Initiative, 2020)

Issue	Suggested standard	Comments
Cross-cutting		
Grid cell size	100 m	National SOC stocks should aim for a 100 m grid, but this will depend in part on the *in situ* data collection. Suggested standard **suitable.**
Temporal coverage	Specific to sub-indicator	National SOC stocks should aim for temporal coverage in line with global products. Suggested standard **suitable.**
Analysis ready data (ARD)	Use ARD	Knowing the processing lineage is more important and should be provided. Suggested standard **suitable.**
Sub-indicator specific		
SOC data uncertainty	Pixel based	Datasets should aim for pixel level uncertainty. Suggested to **further consultation required.**
Soil inventory update period	10 years	Ambitious standard, probably more of a goal to strive for. Specific time period depends on local rates of change, the change methods used and local conditions. Suggested standard **suitable.**

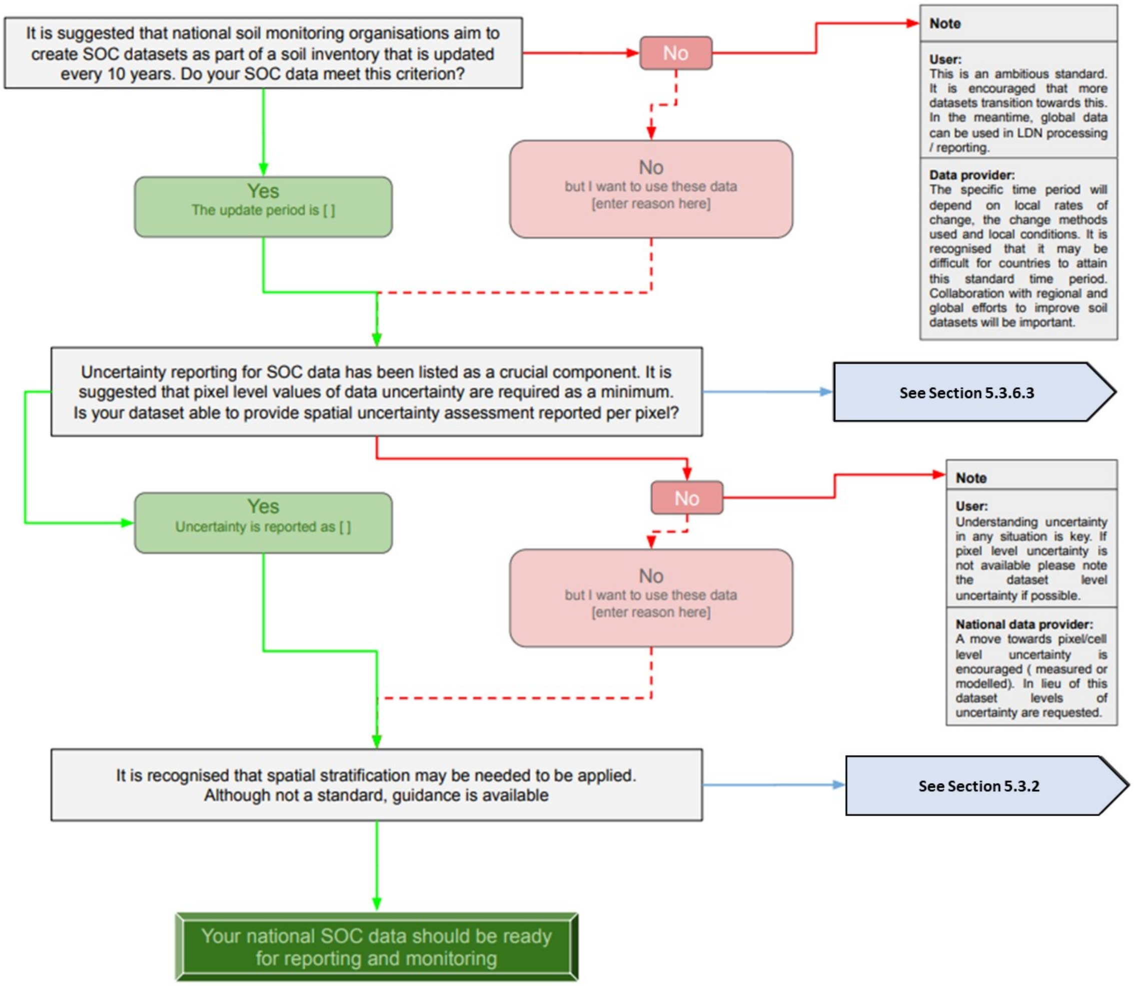


Figure 5-1. Decision tree for determining the most appropriate data for calculation of the soil organic carbon stock change sub-indicator (from GEO-LDN Initiative, 2020).

5.2.6 Calculation of the sub-indicator

A conceptual framework for quantifying changes in SOC stocks is provided in Table 5-2. The Tier 1 method for reference SOC estimates and change factors is recommended only when national data and/or processing capacity is limited. Where possible, it is good practice for countries to use a country-specific approach (Tier 2 or Tier 3 method) to reduce bias and uncertainty, even if they are only able to better specify certain components of the default approach. Progressing from Tier 1 to Tier 3 methods represents a potential reduction in the uncertainty of SOC estimates, though at a cost of an increase in the complexity of measurement processes and analyses.

Table 5-2. Conceptual framework for quantifying changes in SOC stock

Level of detail	SOC stock baseline	SOC stock changes
Tier 1	Apply IPCC Tier 1 methods that relate SOC stock to environmental and management factors, with separate approaches and defaults for mineral and organic soils. As an alternative to IPCC default values, reference stocks can be determined from global digital maps of SOC.	Apply IPCC Tier 1 methods to assess SOC stock change after default 20-year period[1]; methods differ for mineral and organic soils. Option to use global soil map data for reference stocks combined with default stock change factors.
Tier 2	Apply IPCC Tier 2 method i.e., update of SOC reference stocks with country-specific values. A blend of data sources may be used. SOC reference stocks can be determined from national digital soil maps or from measurements (e.g., national soil surveys).	Apply IPCC Tier 2 method using stock change factors with country-specific values. A blend of data sources may be used. Stock change factors can be determined from region/country-specific long-term experiments or other field measurements (e.g. chronosequence studies).
Tier 3	Two general approaches: **a)** Use a national on-ground measurement-based inventory with a monitoring network; **b)** Use calibrated and validated ecosystem (process-based) modelling which links the model and country-specific spatial datasets, such as soil maps, land use, climate, and agricultural activity (i.e. land use/management).	**a)** Apply IPCC Tier 3 national soil monitoring method with large sampling density to minimise uncertainty, and to represent all management systems and associated land-use changes, across all climatic regions and major soil types; **b)** Apply ecosystem modelling for changed land-uses and management systems, calibrated/validated at points using results from new field measurements/monitoring.

[1] Default equations are based on linear relationships and have been modified to allow for different reporting periods.

5.2.6.1 Default methods of estimation

Where country-specific data/capability are yet to be developed, a default ('Tier 1') approach can be used, noting that a higher-tiered, country-specific approach is preferable. IPCC Tier 1 methods assume that following land use/management changes, carbon stock changes occur over a 20-year period, after which a new equilibrium stock is reached. 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 (IPCC 2003; 2006), and the recent supplement and refinement (IPCC 2013;2019). Using the IPCC Tier approach, carbon stocks in organic soils are not explicitly computed using Tier 1 or Tier 2 methods which estimate only annual carbon flux from organic soils (see below). Carbon stocks in organic soils can be estimated in a Tier 3 method (IPCC 2006; 2019).

Where both mineral and organic soil types are present, the equation for estimating the change in SOC stocks (Eqn. 2) in a reporting unit is modified from Equation 2.24 (Ch. 2, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines) to exclude inorganic carbon stocks:

$$\Delta SOC = \Delta SOC_{mineral} - L_{organic} + \Delta SOC_{inorganic}$$

Equation 5-1

Where:

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

$\Delta SOC_{mineral}$ = change in organic carbon stocks in mineral soils in the reporting unit, 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 reporting period and divide by the area of the reporting unit);

$L_{organic}$ = loss of carbon from drained organic soils in the reporting unit, 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 reporting unit and multiply by the number of years in the reporting period);

$\Delta SOC_{inorganic}$ = change in inorganic carbon stocks from soils in the reporting unit, t C ha^{-1} (assumed to be 0 unless using a Tier 3 approach). (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 reporting period and divide by the area of the reporting unit).

Note: most reporting units will not include organic soils.

Mineral soils: The Tier 1 approach considers globally-established reference stocks for SOC (0-30 cm) based on land areas that are stratified by IPCC climate zones and default soil classes (see Table 2.3, Ch. 2, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines), default management factors, and rules to derive SOC stocks for defined changes in land cover (e.g., Forestland to Cropland) and land management, with consideration of broadly defined 'climate-soil' classes (IPCC 2006; 2019). SOC stock change is derived by applying these rules while assuming a default time interval of 20 years (proxy for next SOC stock equilibrium) and a simplified linear rate of change. The stock change factors are very broadly defined and include:

- A land-use factor (F_{LU}) that reflects carbon stock changes associated with type of land use;
- A management factor (F_{MG}) representing the main management practice specific to the land-use sector (e.g., different tillage practices in croplands);
- An input factor (F_I) representing different levels of carbon input to soil.

All land in an LCEU should have common biophysical conditions (i.e., climate and soil type) and management history over the time period, to be considered together for analytical purposes. It will also be necessary to ensure that these units can be aggregated to the six classes in the IPCC default land use change legend used for aggregate reporting. Many reporting units will have more than one LCEU (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 (Ch. 2, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines) and reproduced here:

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

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

Equation 5-2

Where:

$\Delta SOC_{mineral}$ = change in carbon stocks in mineral soils in the reporting unit, t C ha^{-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 with the reference carbon stocks and stock change factors 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);

$SOC_{mineral}$ = soil organic carbon stock in mineral soils in the reporting unit at a defined time, t C;

c represents the climate zones that are present in a reporting unit;

s represents the IPCC soil classes that are present in a reporting unit;

i = the set of management systems that are present in a reporting unit;

$SOC_{REF_{c,s,i}}$ = the reference soil organic 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 LCEU being estimated, ha.

IPCC default values can be used in the equations (see Appendix C.5). If using global map products, it may be necessary for source data to be adapted to meet the requirements for reporting on the sub-indicator at Tier 1. For example, baseline 0-30 cm SOC stocks will need to be derived from SOC concentration, bulk density, gravel fraction and soil depth layers (UNCCD 2018). Further, although change factors based on transitions from one land use to another (F_{LU}) can be populated from the indicator for land cover and its annual transitions, there are currently no known global data at a sufficient resolution to obtain information for management (F_{MG}) and input (F_I) change factors (UNCCD 2018). Therefore, no changes can currently be applied when using global map products (i.e., F_{MG} and F_I are set to one).

Organic soils: There are few updates to the methods for organic soils in the 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. However, some additional guidance and emissions factors are provided for flooded land in Vol. 4, Ch. 7 of IPCC (2019). The basic methodology for estimating carbon emissions from organic (e.g., peat-derived) soils is to assign an annual emission factor that estimates the losses of carbon 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 (Ch. 2, IPCC 2013 Wetlands Supplement), reproduced here:

$$L_{organic} = L_{drainage} + L_{fire}$$

Equation 5-3

Where:

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

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

L_{fire}= emissions from burning of organic soils for the reporting unit, 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 reporting period).

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

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

Equation 5-4

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 (Ch. 2, 2013 IPCC Wetlands Supplement).

Emissions from peat burning are estimated in accordance with Equation 2.8 (Ch. 2, IPCC 2013 Wetlands Supplement) as follows:

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

Equation 5-5

Where:

L_{fire} = Amount of CO_2 or non-CO_2 emissions from fire in the reporting unit, tonnes (t)

A_{burnt} = Area of peat burnt annually in the reporting unit, ha

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

f 1, 2 …*F* fire types, including wildfire and prescribed fire

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 reporting unit

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. 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).

5.2.6.2 National methods of estimation

At **Tier 2**, separate approaches are taken for mineral soils and organic soils.

For **mineral soils**, countries may choose to use the same linear equations as the 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 derived for all of these components, or any subset which would then be combined with default values. Example national datasets are provided in Appendix C.6.

Reference SOC stocks can be determined from national digital soil maps or from measurements, for example, as part of national soil surveys. These sources 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. Accepted standards for sampling and analysis of SOC concentration and bulk density (where using fixed depth) should be used and documented.

At Tier 2, the default management systems can be disaggregated into categories that better represent country-specific management impacts on SOC stocks. However, this is only possible where there is sufficient detail in the underlying data to disaggregate the land into a more detailed set of management systems. Stock change factors can be estimated from long-term experiments or other field measurements (e.g. chronosequence studies) for a country or region. The depth of measurement and time frame over which the management difference has been expressed should be provided (IPCC 2006). Further, SOC stock estimates may be improved when deriving country-specific factors for F_{LU} and F_{MG}, by expressing carbon stocks on an ESM basis rather than a fixed depth basis (IPCC 2019).

Two notable additions in the 2019 Refinement to the IPCC 2006 Guidelines are the inclusion of i) an optional alternative Tier 2 steady-state method for mineral soils of Cropland Remaining Cropland (Appendix C.3); and ii) a method *at Tier* 2/3 to estimate the change in mineral soil organic C stock due to biochar amendments to mineral soils (Appendix C.4).

For **organic soils**, the Tier 2 method for calculating 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.

An alternative Tier 2 approach to replacing defaults with country-specific reference stocks, change factors or emissions factors, is to use methods that relate SOC stock to environmental and management factors, using statistical learning methods such as state-of-the-art digital soil mapping studies, and the best available baseline data for SOC stock and environmental covariates (e.g., land cover) for a defined reference period. In this approach, relationships are derived from large databases with measurements of SOC content, bulk density and proportion of coarse fragments by layer, ideally with corresponding information on site factors (e.g., land use, land management) and environmental factors at the time of sampling (e.g. Batjes et al. 2020). Such relationships can now be derived routinely from digital soil mapping (Minasny et al. 2013; Arrouays et al. 2014; Hengl et al. 2017; de Sousa et al. 2020).

Typically, the relationships (regression models) are derived using machine learning approaches and are based on data from a large number of environmental factors (so-called 'covariates'), mainly from remote sensing and other spatial datasets representing climate, terrain, parent material and land use. These relationships can be used to estimate the baseline SOC stock as well as changes over time by inserting the changed covariates (notably land use) in the regression model that predicts SOC stock from covariates. The above soil mapping approaches make predictions at point locations. By implication, spatial aggregation is possible to any desired reporting unit.

At **Tier 3**, more advanced national methods are used which typically better capture annual variability in fluxes, unlike Tier 1 and 2 approaches that mostly assume a constant annual change in carbon 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 can capture longer-term legacy effects of land use and management.

Ideally, Tier 3 involves:

1. Nationally derived land cover classes and data for baseline SOC stocks, change factors and emission factors specific to national/local conditions;
2. National data based on the integration of ongoing ground-measurement programs, earth observation data and models.

Two general approaches using the Tier 3 method are recommended.

The first approach uses a national measurement-based inventory with a monitoring network. At Tier 3, a national soil monitoring method requires large sampling density to minimise uncertainty, and to represent all management systems and associated land-use changes across all climatic regions and major soil types. Further detail on sampling considerations is provided in Appendix C.6.

The second approach combines measurements and/or country-specific digital soil mapping with calibrated and validated process-based ecosystem models to estimate changes in SOC stocks (Figure 5-2). For example, country-scale Tier 3 assessments of SOC stocks have been developed for several countries including, Australia, Japan, Finland and USA (e.g. Shirato 2017; US EPA 2017; DISER 2020; Statistics Finland 2019). These Tier 3 approaches use calibrated and validated ecosystem (process-based) models (e.g. RothC, Century) which link the model and country-specific spatial datasets, including soil maps, land use, climate, and forest/agricultural activity (e.g. Lee et al. 2020). Detailed examples of Tier 3 mineral soil C stock change methods are provided in Ch. 2, Box 2.2D of IPCC 2019.

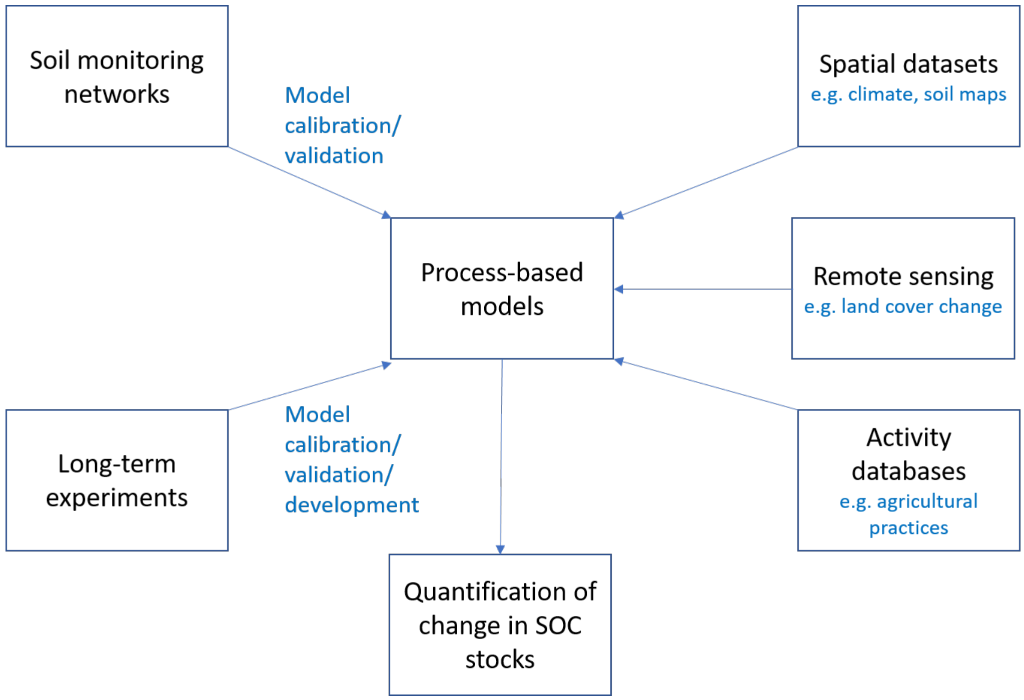


Figure 5-2. Schematic of possible national Tier 3 approach for estimating change in soil organic carbon stock.

As outlined for Tier 2 methods, countries can now estimate the change in mineral soil organic C stock due to biochar amendments to mineral soils at higher tiers (IPCC 2019; Appendix C.4). Soil erosion and/or deposition can have significant effects on measured SOC stocks (Chappell et al. 2016) but their effects on stock changes are not considered to be embedded in factors for land-use change or land management. Tier 3 methods can include lateral flows of SOC associated with soil erosion and deposition, for example, through the use of well-tested models that capture these dynamics with input data to make estimates of the effect of past erosion/deposition on SOC stocks (e.g. Van Oost et al. 2005) and evaluating the model predictions with empirical data (IPCC 2019).

At national scale different approaches can be used to derive estimates of SOC stocks, such as country-specific maps. Alternatively, global maps could be used to improve national estimates where they are used as input into national models (e.g. global data are used as another covariate in the national modelling). If new data could be collected, then design-based sampling (e.g. DotEE 2018) will produce unbiased estimates of SOC stocks over the total land area.

5.2.6.3 Estimating uncertainty

It is good practice to report uncertainties in estimates and minimise uncertainty as far as practical, even if these uncertainties are not used in a formal sense (i.e., in statistical tests). IPCC (2006; Vol. 1, Ch. 1, p 1.6) specifies two good practice guidelines for GHG inventories which are also relevant here:

(i) “neither over- nor underestimates so far as can be judged”;

(ii) “uncertainties are reduced as far as practicable”.

This means ensuring estimates are unbiased (satisfying criterion (i)), and that all of the key, nonnegligible error sources are recognised and accounted for (satisfying criterion (ii)) (Figure 5-3).

Quantifying bias can be problematic, as it requires knowledge of the 'true' underlying value, which is almost always unknown. Sources of bias can arise from measurement errors, such as incorrectly calibrated weighing scales, and biased model predictions arising from the use of incomplete or non-representative field data. When identified, bias should be corrected prior to further analysis.

Below is a brief description of 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 (e.g., in the areal estimates, change factors, emissions factors) are calculated is not provided here, but approaches to this are covered in detail elsewhere. Approaches for assessing uncertainty in Tier 2 and 3 methods are briefly discussed.

The default method recommended by IPCC (2006) is the use of a 95% confidence interval i.e., the interval that has a 95% probability of containing the unknown true value. It is good practice to report the 95% confidence interval with estimates of SOC stocks. This could 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.[81]

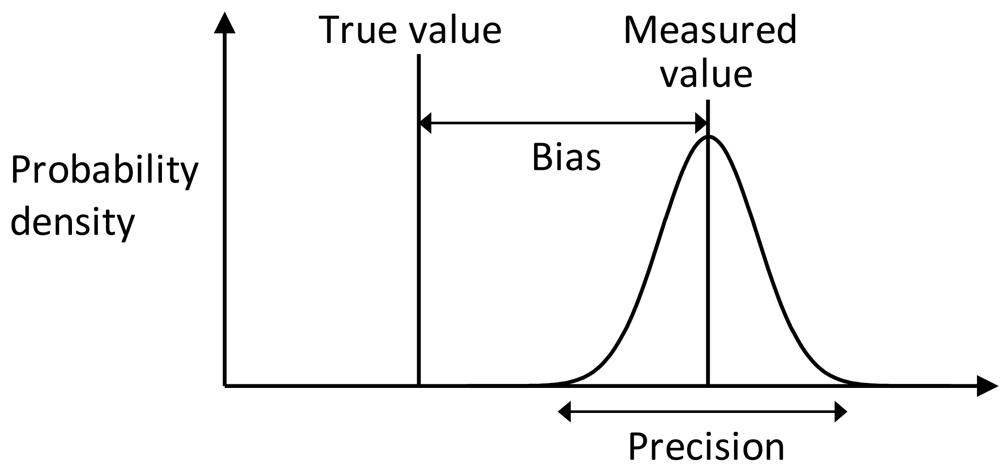


Figure 5-3. The accuracy of an estimate comprises two components. (i) Precision (referred to as uncertainty in the text) describes the variability around the estimated value. (ii) Bias describes the degree to which the estimated value deviates from the true (but often unknown) population value.

The default method for combining uncertainties is based on error propagation. Where uncertain quantities are to be combined by multiplication and they are independent, a simple equation (based on Equation 3.1, Vol. 1, Ch. 3, IPCC 2006) for the uncertainty of the product, expressed in percentage terms is:

[81] 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 on Total Carbon Stocks).

$$U_{total} = \sqrt{U_1{}^2 + U_2{}^2 + \ldots + U_n{}^2}$$

Equation 5-6

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 independent uncertainties are to be combined by addition or subtraction, a simple equation (based on Equation 3.2, Vol. 1, Ch. 3, IPCC 2006) for the uncertainty of the sum, expressed in percentage terms is:

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

Equation 5-7

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.

Worked examples of the calculation of uncertainty using default methods are provided in Appendix C.5.

For higher tiers: where map products are used, it is good practice for these to be accompanied by uncertainty quantifications (e.g. Viscarra Rossel et al. 2014; de Sousa et al. 2020). Where sampling methods are used, it is good practice to use approaches that result in unbiased estimates. Approaches based on design-based samples, where sample points selected by probability sampling (i.e. random) are assumed to be unbiased (Cochran 1977). Model-based approaches, where sample points can be systematically (i.e. non-randomly) located and need not conform to design-based principles, generally require additional validation checks to ensure estimates are unbiased (McRoberts et al. 2019). This can be achieved by comparison of the model predictions using statistical internal cross-validations and validation with independent data not used in the original model fitting. Statistics that evaluate the model's precision and bias should be used to ensure that the model shows no systematic lack of fit to the sample data, and through checks to ensure the sample data on which the modelling is based are representative.

5.2.6.4 Determining baseline stocks and degradation status

In order to measure the change in the extent of SOC degradation over time, and to assess LDN, it is necessary to calculate the extent of SOC degradation in the baseline period. This involves comparing estimated SOC stocks in the year 2015 (the baseline year) with one other previous year to measure change in SOC stocks. Years that are further apart in time may exhibit a greater difference in their SOC levels, which may result in a larger extent of apparent SOC degradation than comparing years that are closer together in time. Ideally, the previous year should be in the baseline period from 1 Jan 2000 to 31 Dec 2014. However, given the potentially slow rate of change of SOC stocks compared to the other sub-indicators, and to accommodate different data densities at the national scales, it may be necessary to include data from years before 1 January 2000 to calculate a robust estimate of SOC stocks in the previous year.

An historical averaging approach to minimize the effects of seasonal and inter-annual climate variability is the simplest option for estimating the baseline. Estimation of SOC stocks in the baseline period (SOC_{t_0}) for a given reporting unit is based on a national-level assessment of carbon stocks during the baseline period (2000-2015) or the most appropriate epochs from the period. Global land cover data sets are now available annually (see Chapter 3). The absolute numerical value of the metric for each reporting unit is quantified by averaging across an extended (10–15 year) period prior to the year 2015 (t_0), at annual or less frequent intervals depending on data availability and resources. The availability of annual land cover products also allows extrapolation of a trend fitted to historical data. This approach requires confidence that the past trend is likely to be representative of the future and is appropriate only if there is a clear trend in historical data (GFOI 2016).

An initial baseline (t_0) is required to derive the indicator. Below are two options for estimating initial baseline status at t_0 at differing temporal scales for the SOC stocks metric, both of which are likely to have large uncertainties.

Because the maximum equilibrium carbon content for a soil at a given location is determined by environmental factors, to inform the initial baseline status at t_0, a benchmarking approach (i.e., assessing whether the SOC stocks in the baseline period are low, high or average relative to some potential value for a given climate, soil type and so on) could be used. As a starting point, the updated IPCC (2019) reference SOC stocks under native vegetation, reflecting default climate regions and soil types, could be considered as the benchmark, but ideally, national benchmarks (e.g., derived from largely undisturbed systems) would be used for assessment of large spatial extents. The determination of initial baseline status would then be guided by comparing the actual average value with the benchmark or potential value within some agreed significance bounds, where baseline values less than the relevant benchmark and below agreed significance bounds would be considered degraded. However, there are a number of issues with this option. For example, although the updated 2019 IPCC defaults for SOC reference stocks for native vegetation have reduced the error bounds for a number of climate zone × soil class combinations (relative to the IPCC 2006 defaults), there are still some defaults with very large error bounds (nominally 90% expressed as 2 × SD as a percent of the mean), so a nominal bound would need to be defined, both globally as a default and nationally as each country adapts these significance bounds to their particular circumstances. Furthermore, native vegetation may not be considered the most appropriate benchmark in some situations. Land use history varies widely among countries, ranging from very recent change from native vegetation, to centuries old agricultural systems. Ideally, country-specific benchmark values with lower uncertainty would be derived and used (Batjes 2011).

Another option is similar to that used in Chapter 4 for the sub-indicator on land productivity, where change/status over only the baseline period (2000-2015) is used to inform the initial baseline status at t_0 of each land unit. While this approach may be valid for land productivity where changes occur over short (e.g. seasonal to annual) timeframes, SOC stocks are likely to change over longer (e.g. multi-year to decadal) timeframes. If this approach were used, 'epochs' (e.g., 2013-2015 SOC stock with 2000-2002 SOC stock) rather than annual values could be compared, to determine 'trajectory' and relative change. Then the same approach used to compare t_0 and t_n could be used to compare the start and end periods of the baseline.

Rather than relying on spatial analysis alone, most assessments of SOC stock 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 (FAO & 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 sampling variance (de Gruitjer et al. 2006; Chappell et al. 2013; Viscarra Rossel et al. 2016a). This can be achieved using a design-based approach. Some examples of the types of data for SOC stock that could be used to inform a baseline are provided in Table 5-3.

Table 5-3. Types of data that could be used to derive a SOC stocks baseline.

Data type	Typical scale
Default values[1]	All scales
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]	All scales

[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 or new sensing technologies such as visible–infrared spectroscopy (see Appendix C.6)
[4] calibrated/validated using ground measurements

The choice of method for estimating change in SOC stocks by a country will largely depend on the current and likely future availability of data but will also have implications for determining the SOC baseline. Baselines could be derived in two distinct ways:

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

For option 1, estimates could be derived from the global datasets or using a national approach. The global approach, where default values are applied to the land stratification data from EO to derive the baseline stocks (or reference stocks as per IPCC 2019) described in the calculations below, or using global soil maps of carbon such as SoilGrids250m v.2[82], OpenLandMap[83], or finer scale continental maps such as the 30 m pan-African iSADsoil[84]. However, it is likely that such estimates are subject to large bias and uncertainty, especially in areas with relatively unique combinations of environmental factors and/or limited representation.

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) national maps, such as the 90 m grid SOC stock baseline used in Australia (Viscarra Rossel et al. 2014; 2019) to improve the accuracy of the reference SOC stocks. This is likely to reduce bias and uncertainty in the estimates of baseline stock, but the variability of SOC stock needs to be accurately quantified.

For option 2, when deriving a spatially explicit baseline, the appropriate resolution would need to be defined. The suggested data quality standards (GEO-LDN Initiative 2020) are a minimum 100 m spatial resolution (Table 5-1), noting that this is not yet available for global datasets, but is available at continental scale (Africa) and is expected globally within this reporting cycle. Other hybrid methods are possible, such as a spatio-temporal data model assimilation approach that uses easily accessible EO data for the updating but is underpinned by on-ground monitoring. The field of SOC monitoring is rapidly evolving and numerous techniques, systems and approaches are expected to become operational in the next several reporting cycles.

Methodological changes and refinements, largely in response to scientific and technical advances in datasets, are an essential part of improving the quality of sub-indicator estimates. Where possible, all estimates in a time series should be estimated consistently, using the same method and data sources in all years. Using different methods and data in a time series may introduce bias because the estimated trend will reflect not only actual changes in carbon stocks but also those from the methodological changes/refinements. It is **good practice** to ensure **time series consistency** by making appropriate recalculations following any methodological changes or refinements (IPCC 2006, see Chapter 6).

5.2.6.5 Estimating change in SOC stocks

A hybrid approach is recommended, using the **trend** (or the direction of change) in the metric over the reporting period as well as the **magnitude** of the relative change in carbon stocks between the baseline and the current estimate to assess and evaluate change. This approach assesses whether there has been a (significant) negative change in SOC stocks between the baseline period and the reporting period for a given reporting unit, and makes no assumptions about the initial status of SOC stocks for that particular reporting unit.

Once the baseline SOC stocks and the SOC stocks at the end of the reporting period for a given reporting unit have been consistently estimated (using any of the Tier 1-3 approaches described in

[82] https://www.isric.org/explore/soilgrids
[83] https://www.openlandmap.org
[84] https://www.isda-africa.com/isdasoil

the previous sections), the relative percentage change in SOC stocks (i.e., whether carbon stocks are increasing, decreasing or stable) is calculated as:

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

Equation 5-8

Where:

r_{SOC} = relative change in soil organic carbon for reporting unit (%)

SOC_{t_0} = baseline soil organic carbon stock for reporting unit (t C ha^{-1})

SOC_{t_n} = soil organic carbon stock for final reporting period for reporting unit (t C ha^{-1}).

One approach to assessing change in SOC stocks is based on tests for statistical significance and compares the average monitored SOC stock with the upper and lower bounds of the average baseline SOC for the same 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 stable (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 reporting 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. 9.

Given the high spatial variability of the data for SOC stocks and the increasing interest in sub-national accounting, 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., resulting 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.

The 'false negative' problem is also likely to occur using higher Tier methods. For example, Box 3.0 in Vol. 1, Ch.3, IPCC (2019) provides an example of the calculation of uncertainty for SOC change using the United States as a case study for the *Croplands Remaining Croplands* land use category. Using Tier 1 and Tier 2 approaches the reported uncertainty (represented as 95% confidence intervals) was ±59% and ±40%, respectively. A Tier 3 analysis using a calibrated ecosystem model gave ±16%. Thus, relying on an approach which concludes degradation has occurred only if the reported change exceeds these confidence intervals, even using the Tier 3 approach, may result in an incorrect assessment of degradation (i.e., false negative). In the event timeseries of SOC become available, then this would allow degradation to be detected as a statistically significant trend over time, such as using the methods depicted in Figure 4-4 for changes in land productivity.

An alternative approach may be to assess both the direction of change and magnitude of the relative percentage change (Eqn. 5-9) in SOC stocks, relative to some defined threshold, between the baseline and reporting period. Then, for SOC stocks, the method of determining the status of change will be defined as:

- **Degraded**: Reporting units with more than e.g. 10% average net reduction in SOC stocks between baseline and current observations;
- **Not degraded**: Reporting units with less than e.g. 10% average net reduction, no change or an average net increase in SOC stocks between baseline and current observations.

As a starting point, an arbitrary >10% change threshold is suggested (e.g. see meta-analysis by Guo and Gifford 2002). Subsequent refinement and justification of this threshold value will be needed. This refinement is likely to be a country decision based on available information, practicalities, expert opinion and risk assessment among other factors and will be dependent on the method used. Figure 5-4 provides guidance on possible approaches that could be used to assess 'significant' change in SOC stocks for a reporting unit based on the methods described in Table 5-2. At Tier 1 where no country-specific data are available, the 10% threshold assessed against the baseline is suggested, while for Tier 2 and 3 approaches, it is suggested that countries refine the threshold value based on available country-specific information on measured, mapped and modelled datasets. For example, local climate, soil type and vegetation types regulate spatial variability of SOC. Further, similar to deriving country-specific stock change factors (Table 5-5), countries could refine the threshold based on long-term experiments or other field measurements (e.g. chronosequence studies) demonstrating the impact of land use/management change on SOC stocks. The examples provided in Appendix C.5 give some indication of the magnitude of change that might be estimated using the Tier 1 default method. Two contrasting scenarios under the default approach give both an 11% increase based on changed management (reduced tillage) of 80% of the area of a reporting unit that was annual cropland (no degradation), and a 26% decrease based on conversion of 70% of the area of a reporting unit from native forest to annual cropland (degradation).

Others have suggested that interim procedures are required so that assessments of change can be 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).

Such procedures could be used to inform refinement of the threshold value as suggested in Figure 5-4.

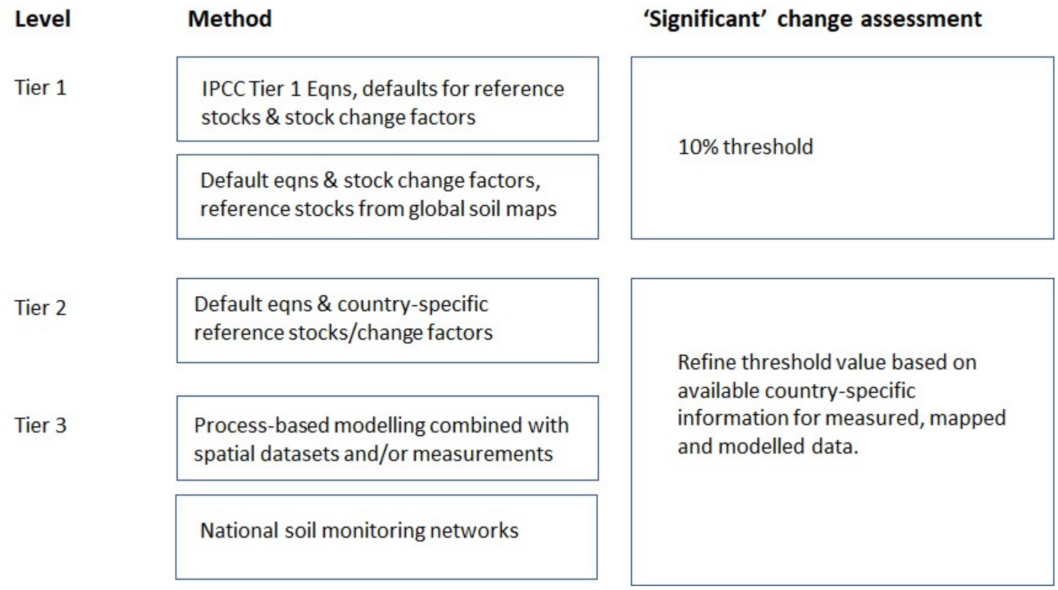


Figure 5-4. Guidance on possible approaches to assessing 'significant' change in soil organic carbon stocks for a reporting unit.

5.2.6.6 Summary of Computational Steps

1. Assess data options (see Section 5.3.5) and select estimation method (i.e., Tier 1, 2 or 3; see Table 5-2).

   a. Where a default approach (Tier 1) is used:

      a. Reference soil carbon stocks will be determined and documented for climate regions and soil types;

      b. Stock change factors and emission factors will be determined and documented for all land uses/inputs/management systems, and where needed, any additional sub-types.

   b. Where country-specific methods (Tiers 2 and 3) are used:

      i. Apply a Tier 2 method i.e., update SOC reference stocks with country-specific values. SOC reference stocks can be determined from national digital soil maps or national soil surveys;
      ii. Apply a Tier 3 method such as a national on-ground measurement-based inventory with a monitoring network and/or calibrated and validated ecosystem (process-based) modelling which links the model and country-specific spatial datasets, such as soil maps, land use, climate, and agricultural activity.

2. Assess SOC stocks within each LCEU of the defined disaggregation scheme for the baseline period. Generate an average SOC stock for each identified reporting unit for the baseline period, including the 95% confidence interval.

3. Compare the average SOC stock in the reporting period with the average baseline SOC stock for the same reporting unit by calculation of the relative percentage change (Eqn. 5-9).
4. Apply the most appropriate method to assess whether change results in a significant decrease in SOC (degradation), an increase in SOC or no change (Figure 5-4).

A wide range of methods are available for estimating uncertainty, ranging from the relatively simple Equation 5-6 and Equation 5-7 for combining uncertainties when multiplying (Equation 5-6) or adding /subtracting (Equation 5-7) values together, through to complex Monte Carlo simulations embedding complex chains of calculations. There is no one correct approach, and methods for uncertainty analysis need to be selected based on the nature of the data being combined. Appendix C.5 provides example uncertainty calculations for the default approach.

5.2.7 Reporting the sub-indicator

The following good practice principles apply to the reporting process.

- Where possible, provide two national SOC stock maps, one for the baseline period and one for the reporting period. These maps should have the same spatial precision (e.g. pixel resolution), use the same approach and be accompanied by an uncertainty estimate.
- Provide SOC stock change information based on the difference between the reporting year and baseline year. This will include:
  - Where possible, a national map that shows the location of SOC stock change;
  - A table that identifies the total area of land that is associated with each major land cover transition and SOC stock change;
  - A national map that shows where degradation has occurred, and ideally the confidence in the assessment of the degradation where possible.
- Justify why any reporting units identified as degraded should not be included in the overall indicator calculation. This should be based on the identification of "false positives", where SOC stocks may be increasing for land use transitions that are considered land degradation (see Section 2.2.2).
- Justify why any reporting units not identified as degraded should be included in the overall indicator calculation. This should be based on the identification of "false negatives", where SOC stocks may be decreasing for land use transitions that are considered land improvement (e.g. weed removal; see Section 2.2.2).

5.2.7.1 Comparison of degradation extent between baseline and reporting periods

It is good practice to apply consistent approaches for determining baseline and reporting period SOC stocks for assessment of whether SOC stocks are increasing, decreasing or stable. Where a default approach is used, the same equations used for estimating baseline SOC stocks should also be used in the reporting period. For higher tier level, direct measurement methods (see Figure 5-4), standardized spatial and temporal sampling should be used for baseline and reporting period assessments (de Gruitjer et al. 2006; Brus et al. 2014). Similarly, ecosystem process-based modelling methods should be supported by appropriate calibration and validation sampling through time. Computation of the carbon stocks sub-indicator requires that the area of land in each land unit at times t_0 and t_n is identical, and that the same pools of carbon (including reference depths for SOC) are included in all time steps. Land use categories and estimates of carbon stocks may change with improved knowledge and therefore may be retrospectively corrected (see Chapter 6).

5.2.7.2 National and sub-national contexts

In general, areas with long-term declining carbon stocks may be considered degraded while areas with increasing carbon stocks may be considered improving. In some cases, carbon stocks may be increasing for land use transitions that are considered land degradation (i.e., false positives), such as woody encroachment (i.e., land cover change from grassland to shrubland) or invasion by alien plant species (weeds). Conversely, there may also be circumstances where carbon stocks are decreasing for land use transitions that are considered improvements in terms of degradation (i.e., false negatives), such as weed removal, woody plant removal or transition from irrigated to dryland agriculture. In other cases, an average computed for a country may hide areas of intense degradation (i.e., hotspots) or improvement (i.e., brightspots).

It is good practice to contextualize global and regional data sets with national and where possible, sub-national level, information.

Assessment of false positives or false negatives, or degradation hotspots or bright spots requires knowledge and interpretation at the local level. Assessment approaches could include using:

- site-based data;
- qualitative information;
- stakeholder perspectives from surveys, workshops, in-depth interviews;
- establishment of expert panels.

With respect to false positives/negatives, the use of a degradation interpretation matrix (Sims et al. 2020) is one way to improve the transparency and consistency of degradation labelling between countries and regions. However, transparency will require that the details are clearly communicated, and consistency will require agreement on which contexts constitute false positives or false negatives (see Section 2.2.2).

5.2.7.3 Transparency in reporting

It is **good practice** for countries to provide **transparency in reporting** to:

- Allow assessment of the level and **trend** of carbon stocks over time;
- Provide information on the **drivers** of carbon stocks and changes;
- Build trust in the information provided by assuring its **quality**;
- Ensure **comparability** with reports by other countries.

To **achieve** this, repor**ting should a**im to be **complete**, **consistent**, and **accurate** with respect to the information provided.

5.2.8 Total carbon stocks

Consistent with the UNCCD 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., above and below ground biomass, litter, dead wood and soil). This section expands on version 1 of the GPG

(Sims et al. 2017) by providing further detail on the current methods and datasets that could be used to estimate total carbon stocks.

As for SOC stocks, the tiered approach to the methods for estimating change in total carbon stocks considers a range of datasets and processing options with the level of accuracy, detail and processing complexity increasing from Tier 1 (general methods with default values) to Tier 2 (additional use of country-specific data) to Tier 3 (more complex methods involving ground measurements and modelling). Frequently, national assessments combine methods from lower Tiers with those of higher Tiers for pools which are less significant or too costly to measure. Thus, a combination of tiers is usually employed for total carbon stocks.

The type and availability of data will vary by country. These data are sourced from freely available global datasets, IPCC Good Practice Guidance (2003), IPCC Guidelines (2006) and other documents (e.g., IPCC Wetlands Supplement 2013, 2019 Refinement to the IPCC 2006 Guidelines) and nationally contributed datasets. Where country-specific data are not available, it is good practice to apply the best available defaults for biomass carbon stocks to national land cover maps obtained by Earth observation data. Where available and considered robust and representative, it is good practice to use global spatial datasets for biomass carbon stocks as an alternative to using defaults.

5.2.8.1 Default Methods

Where country-specific data and capacities are currently lacking, a default or Tier 1 method can be used to estimate the total carbon pools. The IPCC provides a systematic approach for estimating carbon stock changes in biomass and debris (IPCC 2003, 2006, 2013; 2019). Changes in ecosystem C stocks are estimated for each land-use category, including both land remaining in a land-use category as well as land converted to another land use. The equation for estimating the change in total carbon stocks (Eqn. 5-10) in a reporting unit is modified from Equation 2.3 in Ch. 2, Vol. 4 of the 2019 Refinement to the 2006 IPCC Guidelines (IPCC 2019) and excludes harvested wood products:

$$\Delta C = \Delta C_{AB} + \Delta C_{BB} + \Delta C_{DW} + \Delta C_{LI} + \Delta SOC$$

Equation 5-9

Where:

ΔC = total carbon stocks in the reporting unit

ΔC_{AB} = carbon stocks in live aboveground biomass in the reporting unit

ΔC_{BB} = carbon stocks in live belowground biomass in the reporting unit

ΔC_{DW} = carbon stocks in dead wood in the reporting unit

ΔC_{LI} = carbon stocks in litter in the reporting unit

ΔSOC = organic carbon stocks in soil in the reporting unit

As outlined in IPCC (2006; 2019), depending on country circumstances, stock changes may not be estimated for all pools shown in Equation 5-10. There are simplifying assumptions about some carbon pools under Tier 1 methods (change in below-ground biomass carbon stocks are assumed to be zero, dead wood and litter pools may be combined as ‘dead organic matter’ and these stocks are assumed to be zero for non-forest land use categories) but for forest land converted to another land use, default values for estimating dead organic matter carbon stocks are provided.

Under the IPCC guidance, there are two valid approaches to estimating stock changes: The Gain-Loss Method is a process-based approach that estimates the net balance of additions to and removals from a carbon stock and the *Stock-Difference Method* which estimates the difference in carbon stocks at two points in time. Change in biomass and debris pools is estimated using either Equation 5-10 (*Gain-Loss Method*) or Equation 5-11 (*Stock-Difference Method*) (Ch. 2, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines) and reproduced here:

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

Equation 5-10

Where:

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

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

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

or

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

Equation 5-11

Where:

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

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

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

5.2.8.2 National methods for estimation of biomass carbon stocks

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 biomass carbon stocks. It is **good practice** to ensure that **models** are **tested against field measurements**. Examples of current national and sub-national biomass/biomass carbon map products are provided in Appendix C.6.

Under Tier 2 methods for **biomass carbon stocks**, 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 class, Tier 2 methods to calculate annual change in biomass stocks replace Equation 2.4 with Equation 2.15 (Vol. 4, IPCC 2006), where the changes in carbon stock are calculated as a sum of the 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.

There are no refinements to the IPCC (2006) methods to estimate change in biomass carbon stocks (above and below ground) in the 2019 Refinement to the IPCC 2006 Guidelines. Additional generic guidance is provided for Tier 2 methods around the use of: i) allometric models for estimating biomass, and ii) above-ground biomass density maps constructed from remotely-sensed data to estimate biomass. **Allometric models** can be used with country-specific data to estimate biomass carbon stocks at Tier 2 and may also form part of more complex Tier 3 approaches including measurement-based inventories and model-based inventories. **Biomass density maps** are constructed by combining remotely sensed data and field observations and have been developed at a range of scales including national, continental and global (see Appendix C.7).

5.2.8.3 National methods for estimation of debris carbon stocks

Under Tier 2 methods for **debris carbon stocks**, changes in dead organic matter (DOM, dead wood and litter) carbon pools (Equation 2.17, Vol 4, IPCC 2006) can be estimated using two methods: i) tracking inputs and outputs (the Gain-Loss Method, Equation 2.18, IPCC 2006); ii) estimating the difference in DOM pools at two points in time (Stock-Difference Method, Equation 2.19; IPCC 2006).

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. Tier 3 methods based on models of the terrestrial carbon budget that include both the production and turnover of living biomass will embed, as part of their structure, the dead wood and litter carbon pools.

For SOC stocks, in most cases it is envisaged for Tier 2 methods that estimates of changes in carbon stocks above and below ground 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 the estimation of biomass using gain-loss methods, and for developing modelling approaches (empirical, process-based or other types of advanced models) under a Tier 3 method. 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.

5.3 Comments and Limitations

5.3.1 Limitations of the sub-indicator as a degradation metric

Compared with biomass carbon, changes in SOC stock associated with changes in land use and management, or with climate change, must be measured over longer periods. These changes are small relative to the very large stocks present in the soil as well as the inherent variability. Thus, sensitive measurement techniques and due consideration for the minimum detectable difference are required, as well as cost-effective sampling schemes that use comparable soil analytical methods (Ravindranath and Ostwald 2008; Heuvelink 2014; Batjes and van Wesemael 2015). A four-year reporting frequency proposed for the indicator is likely to be too short to detect SOC stock change where an on-ground monitoring approach is used, and may even be difficult to register change in less than 10 years (Smith 2004).

Although carbon stocks in non-forested ecosystems are typically largest in the soil pool, in forested ecosystems and where woody perennial vegetation is present, the largest pool tends to be in the biomass except when growing on organic soils (GFOI 2016). Furthermore, in forested ecosystems, observed 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 (Guo and Gifford 2002), but it will substantially reduce biomass carbon stock. Thus, once operational, the use of total carbon stocks as the sub-indicator will provide a more comprehensive assessment of degradation, particularly in cases of conversion of forested systems to other land uses.

5.3.2 Applicability across land cover types

5.3.2.1 Default methods

In some cases, it may be difficult to report SOC stock changes using IPCC defaults because these do not capture all land cover changes. An alternative default method, perhaps by including IPCC defaults for stratification by climate, ecological, disturbance or management, and national proxy data, may be used as long as this stratification can be aggregated to the IPCC classes to allow global reporting.

In terms of operationalising for reporting, assuming land cover can be a stand-in for land use, then the change factors based on transitions from one land use to another (F_{LU}) can be populated from the indicator for LC and its annual transitions. However, there are currently no known global data at a sufficient resolution to obtain information for the management (F_{MG}) and input (F_I) change factors. These factors can be more reasonably applied at national and sub-national levels.

5.3.2.2 National methods

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 in FAO (2015).

5.3.3 Data limitations

5.3.3.1 Limitations of soil organic carbon datasets

Soils are the largest terrestrial store of organic carbon, yet large uncertainty remains in estimates of SOC stocks at global, continental, regional and local scales. Default values for reference SOC stocks and stock change factors provided in IPCC (2019) improve upon those in IPCC (2006) and reflect the most recent review of changes in SOC with conversion of native soils. However, limitations include the lack of relative change factors for some climates, as well as a paucity of change factors for specific management scenarios. It should be noted that, as for the IPCC defaults, the predictions of baseline SOC stocks derived from soil maps at a specified location will typically have large uncertainties. In general, the use of datasets with the highest (finest) spatial resolution and accuracy is recommended.

For baseline maps, there are several limitations with currently available maps used to construct SOC stocks. These relate primarily to predictions being based on soil legacy data and include:

- A general paucity of data on bulk density and gravel content. Misuse of these data in calculation of SOC stocks can lead to systematic overestimation (Poeplau et al. 2017).
- Data for SOC (%), bulk density, gravel content and soil depth are typically collected using inconsistent measurement methods.
- Soil data are often collected over a long time period with subsequent predictions not made for a specific year but for a span of time (but assumed so in the absence of other, more suitable global data).
- Soil data are collected for various purposes, so there will likely be sampling bias (e.g., an over-representation of agricultural areas is common; in such cases bias can be heuristically minimised by weighting; however, an underrepresentation of natural grasslands and forests poses larger methodological issues).
- Incomplete coverage of various 'global' legacy data collections (e.g., WoSIS, Batjes et al. 2020), with much existing data kept in national and institutional repositories (Arrouays et al. 2017).

Further, many global products (e.g. Harmonized World Soil Database[85]) map SOC content and bulk density but not SOC stocks which requires multiplying the maps and averaging the depths to derive the 0-30 cm SOC stocks. This is generally easily overcome: For example, GSOC map[86] is global but consists of national maps, many of which would be better alternatives to the IPCC defaults. As concluded by the ITPS in their Technical Summary of the Status of the World's Soil Resources (Action 4, page ix)[87], regional assessments frequently base their evaluations on studies from the 1990s that were, in turn, based on observations made in the 1980s or earlier. Thus, there is a strong need to improve our knowledge about the current state and trends in the condition of soil, and initial emphasis should be on improving observation systems, including for SOC. Recognising the limited availability of datasets on SOC stock at national and regional levels, the uncertainties associated with

[85] http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/
[86] http://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/global-soil-organic-carbon-map-gsocmap/en/
[87] http://www.fao.org/3/a-i5126e.pdf

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 FAO's GSP is now making a concerted effort to address these challenges and build national capacities to more accurately estimate SOC stocks within the context of SDG Indicator 15.3.1 (FAO & ITPS 2015).

The global spatial products described above for estimating SOC reference stocks are currently not dynamic. 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, such as a well-designed monitoring network (e.g. the European Union's Land Use/Cover Area Frame Statistical Survey, LUCAS[88]), 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 methods (See Appendix C.2).

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 (Parton et al. 1987; Skjemstad et al. 2004) and formed the basis for the stock change factors used in current IPCC inventory guidelines (Ogle et al. 2005; IPCC 2006; 2019). However, 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.

5.3.4 Uncertainty

The main consideration in the selection of the estimation method by a country is the current and likely future availability of data. 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 country-specific data (and/or use of higher order methods) is a more rigorous approach to generating estimates of changes in SOC stocks and requires higher levels of effort and resources. Reducing uncertainty in estimates requires improvements in the stratifications of environmental variables linked to emission factors, and/or increasing the number of soil samples used for the estimation. The capacity to do this will require improvements in analytical capabilities and analysis. Requirements include ground measurements, such as national inventories repeated through time, and intensive monitoring sites. Existing data from national inventories, or from similar bioclimatic regions, 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 the

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

development of model parameters, including emissions and removals factors. Derived estimates using such higher order methods provide information at sub-national scale and ought to have lower uncertainty.

Both land cover areas and carbon stocks 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 have 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 uncertainty for each C stock estimate for each time period include error propagation and uncertainty analysis, such as the Monte Carlo simulation (see IPCC 2003 guidance).

6 Recalculating the time series

Throughout the reporting periods it will occasionally be necessary to adopt different, new and/or improved data sources to calculate one or more of the sub-indicators. Recalculation may be necessary to incorporate the improved quality and availability of datasets, changes in the calculation methods, or to correct errors in a previous version of the data. It may also be necessary to fill data gaps by recalculating subsets of the existing time series from an alternative data source. Countries are strongly urged to transition to using the improved datasets for this analysis as they become available, consistent with the guidance provided by the GEO LDN assessment of data quality standards[89]. These datasets will evolve over time as new sensors are launched and their data is calibrated and provided for use.

Given the evolution of the sub-indicator calculation methods presented in this revised version of the GPG, it is recommended that previously submitted estimates of Indicator 15.3.1 should be recalculated and included in the next reporting period.

The methods used to create the default land cover and SOC datasets (and land productivity to a lesser degree) provided to countries for calculating Indicator 15.3.1 are complex, and it is unlikely that many countries will be able to replicate those products from the available archives of EO image data. The length of the historical archive of these products, and their likelihood of provision at no cost in the future is also dependent on the interests of third-party organisations. Filling gaps in these datasets, such as to extend a new time series dataset to the beginning of the baseline period, will therefore probably involve compilation and harmonization of products created from different EO sources or using different methods.

Improved algorithms using the previous data sources may enable a relatively straightforward back calculation of the sub-indicators, in which case values in the baseline period may be recalculated with a high level of confidence in the revised values. The emergence of a new data source makes this more difficult, and confidence in recalculated values may be lower or difficult to calculate.

Improvements in the spatial resolution, spectral composition and capture frequency between data sources may influence the extent of degradation calculated for each of the sub-indicators. Smaller pixels can better represent complex spatial patterns, increased spectral resolution can enable land features to be more accurately discern from one another, and increased observation frequency may improve the representation of dynamic processes. While it is unlikely that a new dataset of a similar type will produce very significantly different or inconsistent results compared to a previous one, it is important to assess the impact of these differences across the time series of measurements to incorporate any improvements in accuracy in the historical and current degradation assessments.

The use of a new dataset may also indicate a different extent of degradation during the baseline period than was indicated using the previous dataset. As the aim of LDN is to stabilise or reduce the extent of degraded land in future compared to the baseline period, changes to the apparent extent

[89] http://earthobservations.org/documents/ldn/20200703_GEOLDN_TechnicalNote_FINAL_SINGLE.pdf

of degraded land calculated using a newer dataset should be adopted as the new baseline degraded extent.

6.1 Recalculation Methods

6.1.1 Objective and methodology

The objective of recalculating the time series is to estimate any changes to the baseline degraded extent, based on a reasonable approximation of how the new dataset would have represented the baseline period had it been available at that time.

Good practice for incorporating new or improved datasets is to:

1. Adopt the new dataset as the standard data source;
2. Model the relationship between annual estimates from the previous and new datasets in the period of data overlap – the difference is likely to be a constant, proportion or a trend;
3. Apply the model to adjust annual estimates from the previous dataset to match the new dataset;
4. Report the difference in values and the extent of degradation between the previous and new annual estimates;
5. Document the reason for the re-calculation including any notable inconsistencies or errors in the assessment of the difference between the previous and new datasets.

Recalculation of the degraded extent using the new datasets should occur at the sub-indicator level, as each sub-indicator may have a unique pattern of response between the previous and new datasets. Integrating the sub-indicators should provide a more accurate foundation for comparison in the 1OAO process than simply adjusting measurements at the Indicator level.

Volume 1, Chapter 5 in IPCC (IPCC 2006) provides guidance for combining and comparing quantitative datasets in a range of likely data situations (summarised in Table 6-1), noting that the choice of technique should involve an expert assessment of the variability of the sub-indicator trends, the availability of data for overlapping periods, the suitability and availability of alternative data sets, and the number of years of missing data. Much of this chapter is adapted from the IPCC document for relevance to Indicator 15.3.1 and LDN.

Table 6-1. Methods for combining and comparing all or parts of time series datasets (modified from IPCC, 2006, 2019)

Approach	Applicability	Comments
Overlap	Only where measurements using both the previous and the new method are available for at least one coincident year, preferably more.	Most reliable when the difference between two or more sets of annual estimates can be compared for several year(s). If the trends observed using the previously used and new methods are inconsistent, this approach is not good practice.
Surrogate data	Sub-indicators are strongly correlated with other well-known and more readily available indicative data.	Multiple indicative data sets (singly or in combination) should be tested in order to determine the most strongly correlated. Should not be done for long periods.
Interpolation	Data needed for recalculation using the new method are available for intermittent years during the time series.	Estimates can be linearly interpolated for the periods when the new method cannot be applied. The method is not applicable in the case of large annual fluctuations.
Trend extrapolation	Data for the new method are not collected annually and are not available at the beginning or the end of the time series.	Most reliable if the trend over time is constant. Should not be used if the trend is changing (in this case, the surrogate method may be more appropriate). Should not be done for long periods.
Non-Linear Trend Analysis (Interpolation/ Extrapolation)	In cases where time series consistency is best represented by multiplicative (exponential) rather than additive (linear) relationships.	Most reliable for trend analysis of model outputs. Applicable in the case of large annual fluctuations with observed high standard deviations (see Box 3.0a, Chapter 3, Volume 1 of the 2019 Refinement for guidance on standard deviation values).
Other techniques	The standard alternatives are not valid when technical conditions are changing throughout the time series (e.g., due to the introduction of mitigation technology).	Document customised approaches thoroughly. Compare results with standard techniques.

6.1.2 Recalculating datasets with overlapping time periods

The most likely scenario under which the time series will be recalculated for reporting on Indicator 15.3.1 is to incorporate the use of an improved dataset into future calculations. In the case where a new and improved data source becomes available, it may not have a long enough archive to provide observations over the full baseline and reporting period. However, there may be a period of time during which measured data (such as observations of productivity) are available from both datasets. Under these circumstances it may be possible to calculate the relationship between the previous and new datasets to simulate the measurements that the new dataset would have made over the previous time period if it had been available.

The overlap method works best where the difference in annual estimates between the previous and new datasets is consistent, and where the previous and new datasets overlap by several years, which enables a more accurate estimation of the difference between their estimates. The overlap method is unsuitable where the period of overlap is very short or where the difference between datasets varies substantially between years. If there is no overlap between the previous and new datasets, or if the difference between annual estimates of the new and previous datasets is not constant, it may be necessary to model the difference between datasets using more sophisticated methods and additional data sources.

A simulated dataset is constructed by examining the relationship between the previous and new datasets in the period of overlap and applying that transformation to the previous dataset. The estimates from the previous dataset should be adjusted to match those of the new dataset either by adding a constant (where the difference between annual estimates is constant) or by an amount equal to the average difference between annual estimates where variation in the difference between years is small.

The suitability of the overlap method can be tested using the guidance provided in Box 5.1B of the IPCC Refinement report (IPCC 2019). Key steps in this process include:

1. For each year, calculate the ratio between the estimates calculated from the previous and new datasets (as shown in the 'Change in degraded extent' column in Table 6-2).
2. Calculate the mean and standard deviation of the differences. If the standard deviation is large relative to the mean then the overlap approach may not be appropriate. At least three overlapping years of data will be required to complete this step.
3. For a linear approximation of the missing data, multiply the previous data by the ratio (calculated from step 1, above) to estimate the values that would have been calculated had the new dataset been available during the previous time period.

It is good statistical practice to calculate an average annual difference or constant between datasets over no fewer than three years. If there are fewer than three years of data available before the current reporting period, then estimates from the previous dataset should be used in the report, noting that a new dataset is available and will be used in the next report.

Additional guidance on the methods for calculating new estimates is provided in Box 5.2A (linear interpolation) and Box 5.2B (non-linear interpolation) of the IPCC Refinement report (IPCC 2019).

6.1.3 Reporting the recalculated estimates

Differences in the extent of degradation shown between the previous and new datasets in the baseline and reporting periods should be reported for each sub-indicator and the Indicator using format shown in Table 6-2.

New degradation maps should be produced for the entire duration of the new dataset, or for the entire duration of the previous data (between 1 Jan 2000 to the present date) when there is a change in method only. The recalculation should be conducted at the sub-indicator level and integrated using the 1OAO process to calculate the Indicator.

For the Land Productivity sub-indicator in particular, it will be necessary to calculate annual estimates in order to estimate the change in degraded extent in each reporting period. These annual estimates may provide a richer data series on which to model the relationship between degradation estimates from the previous and new datasets. The relationship between annual productivity estimates can be shown in the report, using Table 6-2 as a template but with the column heading names changed to the years of overlapping data.

Table 6-2. Template for reporting change in degraded area between previous and new iterations of the calculation

Sub-indicator/ Indicator		Baseline (t_0)	Reporting Period (t_n)
Land Cover	Previous Data (ha)		
	New Data (ha)		
	Difference (ha)		
	Change in degraded extent (%)		
Land Productivity	Previous Data (ha)		
	New Data (ha)		
	Difference (ha)		
	Change in degraded extent (%)		
Carbon Stocks	Previous Data (ha)		
	New Data (ha)		
	Difference (ha)		
	Change in degraded extent (%)		
Indicator 15.3.1	Previous Data (ha)		
	New Data (ha)		
	Difference (ha)		
	Change in degraded extent (%)		

- 'Previous Data' is the extent of degradation in ha shown in that year for the previous dataset
- 'New Data' is the extent of degradation in ha shown in that year for the new dataset
- 'Difference' is the signed difference in the extent of degradation shown between the previous and new datasets, calculated as shown in Equation 6-1:

$$Difference\,(ha) = Previous\ Data\,(ha) - Newdata\,(ha)$$

Equation 6-1

- 'Change in degraded extent' is the signed difference in the proportion of land that is degraded in the previous data and the proportion of land that is degraded in the new data, as shown in Equation 6-2:

$$Change\ (\%) = Previous\ Data\ (\%) - Newdata\ (\%)$$

Equation 6-2

Table 6.3 shows a worked example of a completed section of Table 6-2. Note that this example shows information for the Land Cover sub-indicator only, and that a completed Table 6-2 should also include data for the Land Productivity and SOC sub-indicators, and Indicator 15.3.1.

Table 6-3. Worked example of data to be included in the Land Cover section of a completed Table 6-2.

Sub-indicator/ Indicator		Baseline 2000-2015	Reporting Period 2016-2018
Land Cover	Previous Data (ha) e.g., ESA CCI	1,000	500
	New Data (ha), e.g., Copernicus	**1,100**	550
	Difference (ha)	**100**	50
	Change in degraded extent (%)	**+10%**	+10%

Any apparent systematic differences in the extent of degradation shown between the previous and new data, such as might occur from changes in the land cover class definitions, or the spectral, spatial or temporal resolution of the datasets, can be described in the report.

Once the differences between the datasets have been documented in this way the new dataset then becomes the dataset used for all future calculations until another improved dataset becomes available.

7 Assessing the magnitude of degradation

SDG Indicator 15.3.1 reports the extent of land degradation per country as a binary variable - ‘degraded’ or ‘not degraded’. LDN is achieved when the area of ‘losses’ to degradation is balanced by ‘gains’ in the area that improves from a degraded state, within each land type, across land types, at national scale. By failing to consider the magnitude of degradation, there is a risk that losses involving very severe degradation may be considered to be counteracted by a small gain in land-based natural capital on an equal area. Further guidance on how to interpret degradation severity information to address LDN is provided in Chapter 7 of the Scientific Conceptual Framework for LDN (Orr et al. 2017).

The Scientific Conceptual Framework for LDN describes the magnitude of degradation as the total amount of gain or loss in each of the sub-indicators over a given area and time. Calculating the magnitude of degradation is possible using the methods and datasets described in this GPG by measuring change in the extent of a given land cover type, the total mass of SOC or plant biomass between two time periods.

Each of the sub-indicators has a particular confidence level of mapping and measurement accuracy. The level of confidence is related to the sub-indicator’s absolute spatial resolution, the spatial resolution of the map relative to the typical variability of the object of interest in the environment, the measurement accuracy that can be achieved with reasonable effort, and the strength of the quantitative relationship between the sub-indicator model or surrogate and the physical parameter of interest (e.g. the relationship between NDVI as a surrogate for productivity, and weight of plant biomass in the field). The default datasets recommended for each of the sub-indicators are amongst the most accurate global products for assessing each of their respective targets, though a higher level of accuracy would normally be achieved through the production and calibration of a regional, national or local dataset (calibration methods are provided for each sub-indicator in the relevant Chapter above). Calibrating localized maps in sufficient detail and rigor is a highly specialized and expensive task however, and may not be realistically achievable by some countries.

Calculation of the extent of degradation should not consider any alternative or more detailed assessments of degradation magnitude than is described below. In order to prioritize plans of action to prevent or remediate degradation, it may be useful to interrogate the magnitude of degradation in addition to its extent. Consistent with the precautionary principle, it is preferable to potentially overestimate the magnitude of degradation than to erroneously underestimate it. If it is required report degradation magnitude at the Indicator level, then, consistent with the 1OAO process, regions should be labelled with the greatest magnitude of degradation of the sub-indicators.

The following section provides guidance on reporting the magnitude of change of each of the sub-indicators in both absolute and relative terms.

7.1 Land cover and land cover change

For a given land unit and land cover type, the magnitude of degradation is equal to the area (ha) that has exhibited a degrading transition from one land cover type to another in the baseline or reporting period.

Land cover degradation considers the qualitative aspects of transitions from one land cover class to another. Land cover, as a typically categorical description of a complex of biophysical features, can be difficult to rank in terms of change severity. Potential approaches to the quantitative interpretation of the magnitude of land cover change might consider land cover types in terms of factors such as carbon storage, habitat provision, national development goals or a range of other criteria. In the context of Indicator 15.3.1 and LDN, which use a limited range of data sources by default, it is also important that the Land Cover sub-indicator is as independent of the NPP and SOC stocks sub-indicators as possible.

The SEEA land accounts methodology[90] provides guidance on assessing the monetary value of changes in land cover. This may be useful for providing an integrated summary of the 'positive' and 'negative' changes in land cover in terms that are correlated with, but independent of the quantities of land productivity and SOC.

7.2 Land productivity

For a given land unit and land cover type, the magnitude of land productivity degradation is equal to the reduction in NPP (kg or tonnes) per unit area over time.

For the purpose of Indicator 15.3.1, relative change in a vegetation index of plant productivity (such as NDVI or EVI) is used (see Section 4.2.4). Pixel values in most vegetation indices represent differences in green plant biomass, cover and growth vigour, and can be used to indicate differences in the magnitude of productivity degradation within the degraded area. A map showing variations in vegetation index values within the extent of degradation is a simple way to identify the areas of most severe degradation in land productivity at the pixel scale. For most vegetation indices, low positive or increasingly negative index values indicate more severe degradation.

A range of possible functions may be used to aggregate the pixel-scale vegetation index values to reporting units. Vegetation indices often represent productivity in a range of positive and negative values. Using the NDVI as an example, areas of highest productivity and plant cover have a positive value closer to 1, and areas of low productivity or bare areas have a lower value, ranging to -1 for the most barren landscapes. Areas of the severest degradation may therefore be represented by negative vegetation index values, complicating the process of calculating a difference in index values over time using statistical averages such as mean NDVI value. Allocating a percentile value, such as the 50^{th} percentile or median NDVI to a reporting region may provide a reasonable basis for comparison.

It may also be useful to interrogate the metrics used to calculate the land productivity sub-indicator to interpret degradation magnitude. The land productivity sub-indicator interprets degradation

[90] https://seea.un.org/content/land-accounts

from the vegetation index data using three metrics: Trend, State and Performance. This combination of metrics is required to identify degradation in areas where the condition is declining over time (Trend and State), or areas where productivity levels are stable or increasing over time but are low compared to other land units within the LCEU (Performance).

7.2.1 The magnitude of productivity Trend

The assessment of productivity Trend (see Section 4.2.4.2) includes calculation of the positive or negative trend slope and the statistical significance of that slope. Larger slopes (and more significant Mann-Kendall Z scores) indicate a larger magnitude of change in productivity over time, and may be interpreted in terms of level of *change* in land degradation in a given area. Trend may not fully encapsulate the magnitude of degradation at any point in time, such as where productivity may be increasing over time but remain at a relatively low level, or where productivity may be decreasing but remain at a high level.

Section 4.2.4.2.1 recommends interpreting the significance of the Trend slope Z scores in terms of five levels (Degrading, Potentially Degrading, No significant change, Potentially Improving and Improving), which may be interpreted as also indicating the magnitude of Trend change. Teich et al. (2019) present an alternative scale in which changes are expressed as percentages, based on a comparison of the initial and final values during the reporting period.

Table 7-1. Trend intensity groupings recommended by Teich et al. (2019)

Description	Trend Intensity
Strong Negative Trend	Decrease of at least 50%
Moderate Negative Trend	Decrease between 25% and 50%
Light Negative Trend	Decrease of less than 25%
No Trend	No significant slope
Light Positive Trend	Increase of up to 25%
Moderate Positive Trend	Increase between 25% and 50%
Strong Positive Trend	Increase of at least 50%

7.2.2 The magnitude of productivity State

As for Trend, productivity State also determines the significance of change using Z-scores and presents the magnitude of change in five levels (Section 4.2.4.3.1). Productivity State identifies degradation based on the change in condition over time and, as with trend, this may not fully encapsulate the magnitude of degradation.

7.2.3 The magnitude of productivity Performance

Productivity Performance compares the level of productivity within each land unit to the productivity of other pixels within its LCEU. Degraded productivity Performance may indicate areas where unique or point-source pressures are degrading plant productivity locally. Performance is also the key metric for identifying the level of productivity, rather than its change over time, and it can be used to identify areas that have remained at a low productivity level for longer periods of time.

7.3 Carbon Stocks

For a given land unit, the magnitude of degradation in SOC is the sum of the estimated reduction in C stock over all pixels where the estimated reduction in C stock is >10%. A nominal reduction in SOC of 10% or more between the baseline and reporting period reflects the accuracy with which changes in SOC stocks over time can be reasonably assessed using the currently available default datasets and methods, however it is recommended that at higher tiers these thresholds be refined based on available country-specific information.

Within the extent of degradation, locations with a larger reduction in SOC between the baseline and reporting period may indicate a greater magnitude of degradation in SOC stocks.

7.4 A note on measurement thresholds and ecological thresholds

An alternative to measuring absolute change in physical quantities of each sub-indicator is to examine their relative magnitude of degradation. The sub indicators of Indicator 15.3.1 present the sub-indicator values per pixel. Methods to include only areas of degradation that exceed a severity threshold level are incorporated into each of the sub-indicator degradation analyses used to determine the degraded/not-degraded binary state, and so each sub-indicator considers change magnitude in its assessment of degradation.

The definition of land degradation adopted by the UNCCD includes identifying a land unit as degraded solely on the basis of that land unit having exhibited a *reduction* in land productivity: the level of productivity from or to which the reduction occurs is not specified in the definition. However there are a range of opinions in the literature on how to define, identify and measure land degradation (see Prince 2019 for example). The threshold model of vegetation dynamics suggests that substantial alterations to disturbance regime, structure or functioning can cause ecosystems to transition from one 'stable state' of functioning to another (Briske et al. 2005). Crossing these thresholds can modify site characteristics to the extent that it may not be possible to recover the original ecosystem characteristics (Sasaki et al. 2015).

SDG Indicator 15.3.1 measures a range of parameters, mainly using EO data, to identify areas where land degradation is likely to have occurred in the past, and in some cases to identify areas at risk of degradation in the future. It is acknowledged that Indicator 15.3.1 does not capture all facets of degradation, and that there are sources of error in the datasets and methods used. However, Indicator 15.3.1 is designed to be as indicative, consistent and relevant as possible for the majority of terrestrial ecosystems, as required in SDG monitoring. For these reasons, the monitoring approach presented in this GPG includes provisions for assessing anomalies (false positives, false negatives, see Section 2.2.2), and the LDN Framework (Orr et al. 2017) emphasises the importance of reviewing land degradation assessments, and their impacts on ecosystem services and livelihoods, through stakeholder review at national to local levels.

While identifying degradation thresholds in ecosystem functioning is a considerable challenge (Sasaki et al. 2008), and observational measurements such as are used to calculate Indicator 15.3.1

can tell only part of the story of land degradation, it may be possible to achieve some additional insights into ecosystem functioning using the sub-indicators of Indicator 15.3.1, by comparing the changes in productivity with changes in land cover. Land units in which productivity levels have declined significantly or have remained low for a long period of time, and which exhibit a subsequent degrading land cover transition, may warrant further investigation. It should not be presumed that areas undergoing these changes have necessarily exceeded a threshold, and this assessment should always be conducted in the context of local knowledge.

7.5 From regional to local information: Brightspots and Hotspots

Within any land unit, reporting unit or LCEU there will be variations in the condition of each of the sub-indicators, which produces variations in the magnitude of degradation. The quantitative assessments and corresponding mapping at the national level, as required by the Indicator, will help countries to set policy and planning priorities in regions containing a complex of land cover types, productivity levels, SOC stocks, and range of degradation severity magnitudes.

While aggregation to larger regions can simplify the process of comparison between areas with similar land conditions, it is often impractical to implement rehabilitation measures over very large areas. Pixel scale maps indicating the distribution of sub-indicator values, including the magnitude of degradation, should be used to identify the specific location of areas of most significant degradation within the disaggregation zones, which may enable the allocation of resources to address existing severe degradation.

The UNCCD define areas experiencing the most evident and dramatic change'[91], as:

- 'Hotspots', which are highly vulnerable to degradation in the absence of urgent remediation activities
- 'Brightspots', which do not exhibit any signs of degradation, or which have been remediated from a degraded state by implementing appropriate remediation activities, or through land planning processes to prevent degradation (Singh and Ajai, 2019).

Identifying Hotspots may enable the development of plans of action to redress degradation in those areas, including through the conservation, rehabilitation, and restoration and sustainable management of land resources. The location of Hotspots may be known, in which case data from each of the sub-indicators can be used to identify potential drivers of degradation that may be most important to address locally. New Hotspots may also be identified from the sub-indicator data using pixels in which conditions are trending towards, or are close to being degraded, but which have not yet experienced sufficient change to be identified as degraded for the purposes of Indicator 15.3.1. In terms of Land Productivity, for instance, Hotspots might be identified as areas with a negative but non-significant Trend, a reduction in productivity State of 1 decile, and/or a Performance value between the 50th and 60th percentile.

The location of Brightspots may also be known, but new Brightspots might also be located by identifying any areas which have improved from Degraded to Not-Degraded during the baseline or

[91] https://knowledge.unccd.int/lib-unccd-terminology-and-glossary/lib-unccd-terminology-and-glossary-112

reporting period. It may be useful to examine Brightspots as demonstrations of combinations of natural conditions that may prevent degradation, or of the effectiveness of particular remediation or planning actions. In addition, the identification of Brightspots can aid planners and managers seeking to optimize the impact of integrated land use planning and landscape management across much larger areas by systematically capitalizing on the positive influence of more localized success stories. The primary database recommended by the UNCCD for reporting SLM best practices is the World Overview of Conservation Approaches and Technologies (WOCAT) global Sustainable Land Management database[92].

[92] https://www.wocat.net/en/global-slm-database

8 References

Adhikari, K., Hartemink, A.E., Minasny, B., Kheir, R.B., Greve, M.B., Greve, M.H., 2014. Digital mapping of soil organic carbon contents and stocks in Denmark. Plos One 9.8. e105519

Akpa, S.I.C., Odeh, I.O.A., Bishop, T.F.A., Hartemink, A.E., Amapu, I.Y., 2016. Total soil organic carbon and carbon sequestration potential in Nigeria. Geoderma 271. Pp. 202-215.

Angelopoulou, T., Balafoutis, A., Zalidis, G., Bochtis, D., 2020. From laboratory to proximal sensing spectroscopy for soil organic carbon estimation - A review. Sustainability 12(2). pp. 443.

Arrouays, D., Grundy, M.G., Hartemink, A.E., Hempel, J.W., Heuvelink, G.B.M., Hong, S.Y., Lagacherie, P., Lelyk, G., McBratney, A.B., McKenzie, N.J., Mendonca-Santos, M.D.L., Minasny, B., Montanarella, L., Odeh, I.O.A., Sanchez, P.A., Thompson, J.A., Zhang, G.L., 2014a. GlobalSoilMap: Toward a Fine-Resolution Global Grid of Soil Properties. In: Sparks, D.L. (Ed.), Advances in Agronomy, 125. Pp. 93-134.

Arrouays, D., McKenzie, N., Hempel, J., de Forges, A.R., McBratney, A.B., 2014b. GlobalSoilMap: Basis of the global spatial soil information system. Taylor and Francis, London, UK.

Arrouays, D., Marchant, B.P., Saby, N.P.A., Meersmans, J., Jolivet, C., Orton, T.G., Martin, M.P., Bellamy, P.H., Lark, R.M., Louis, B.P., Allard, D., Kibblewhite, M., 2014c. On Soil Carbon Monitoring Networks. In: Hartemink, A.E., McSweeney, K. (Eds.), Soil Carbon. Progress in Soil Science, 59. Springer International Publishing, Switzerland, pp. 59-68.

Arrouays, D., Leenaars, J.G., Richer-de-Forges, A.C., Adhikari, K., Ballabio, C., Greve, M., Grundy, M., Guerrero, E., Hempel, J., Hengl, T. and Heuvelink, G., 2017. Soil legacy data rescue via GlobalSoilMap and other international and national initiatives. GeoResJ 14, pp. 1-19

Asner, G.P., Powell, G.V.N., Mascaro, J., Knapp, D.E., Clark, J.K., Jacobson, J., Kennedy-Bowdoin, T., Balaji, A., Paez-Acosta, G., Victoria, E., Secada, L., Valqui, M., Hughes, R.F., 2010. High resolution forest carbon stocks and emissions in the Amazon. Proceedings of the National Academy of Sciences 107: 16738-16742.

Australian Government, 2014. Carbon Credits (Carbon Farming Initiative) (Sequestering Carbon in Soils in Grazing Systems) Methodology Determination 2014. Available at: https://www.legislation.gov.au/Details/F2015C00582. Australian Government, Canberra, Australia.

Avitabile, V., Herold, M., Henry, M., Schmullius, C., 2011. Mapping biomass with remote sensing: a comparison of methods for the case study of Uganda. Carbon Balance and Management 6 (1). pp. 1-14.

Avitabile, V., Herold, M., Heuvelink, G.B.M., Lewis, S.L., Phillips, O.L., Asner, G.P., Armston, J., Ashton, P.S., Banin, L., Bayol, N., Berry, N.J., Boeckx, P., de Jong, B.H.J., DeVries, B., Girardin, C.A.J., Kearsley, E., Lindsell, J.A., Lopez-Gonzalez, G., Lucas, R., Malhi, Y., Morel, A., Mitchard, E.T.A., Nagy, L., Qie, L., Quinones, M.J., Ryan, C.M., Ferry, S.J.W., Sunderland, T., Laurin, G.V., Gatti, R.C., Valentini, R., Verbeeck, H., Wijaya, A., Willcock, S., 2016. An integrated pan-tropical biomass map using multiple reference datasets. Global Change Biology 22. pp. 1406-1420.

Avtar, R., Suzuki, R., Takeuchi, W., Sawada, H., 2013. PALSAR 50 m Mosaic Data Based National Level Biomass Estimation in Cambodia for Implementation of REDD+ Mechanism. PLOS ONE 8, e74807.

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A., Samanta, S., Houghton, R.A., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nature Climate Change 2: 182-185.

Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., Houghton, R.A., 2017. Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science 358: 230-234.

Bai, Z.G., Dent, D.L., Olsson, L., Schaepman, M.E., 2008. Proxy global assessment of land degradation. Soil use and management 24: 223-234.

Barredo, J.I., San-Miguel-Ayanz, J., Caudullo, G., Busetto, L., 2012. A European Map of Living Forest Biomass and Carbon Stock. EUR–Scientific and Technical Research; Joint Research Centre of the European Commission, Ispra, Italy.

Batjes, N.H., 1996. Total carbon and nitrogen in the soils of the world. European Journal of Soil Science 47: 151-163.

Batjes, N.H., 2011. Soil organic carbon stocks under native vegetation - revised estimates for use with the simple assessment option of the Carbon Benefits Project system. Agriculture, Ecosystems and Environment 142: 365-373.

Batjes, N.H., van Wesemael, B., 2015. Measuring and monitoring soil carbon. In: Banwart, S.A., Noelmeyer, E., Milne, E. (Eds.), Soil Carbon: Science, Management and Policy for Multiple Benefits. CABI, Wallingford, UK, pp. 188-201.

Batjes, N.H., 2016. Harmonized soil property values for broad-scale modelling (WISE30sec) with estimates of global soil carbon stocks. Geoderma 269: 61-68.

Batjes, N.H., Ribeiro, E., van Oostrum, A., 2020. Standardised soil profile data to support global mapping and modelling (WoSIS snapshot 2019). Earth Syst. Sci. Data 12(1). pp. 299-320.

Bellon-Maurel, V., McBratney, A., 2011. Near-infrared (NIR) and mid-infrared (MIR) spectroscopic techniques for assessing the amount of carbon stock in soils – Critical review and research perspectives. Soil Biology and Biochemistry 43: 1398-1410.

Blackard, J.A., Finco, M.V., Helmer, E.H., Holden, G.R., Hoppus, M.L., Jacobs, D.M., Lister, A.J., Moisen, G.G., Nelson, M.D., Riemann, R., Ruefenacht, B., Salajanu, D., Weyermann, D.L., Winterberger, K.C., Brandeis, T.J., Czaplewski, R.L., McRoberts, R.E., Patterson, P.L., Tymcio, R.P., 2008. Mapping U.S. forest biomass using nationwide forest inventory data and moderate resolution information. Remote Sensing of Environment 112: 1658-1677.

Brus, D.J., de Gruijter, J.J., 1997. Random sampling for geostatistical modelling? Choosing between design-based and model-based sampling strategies for soil (with discussion). Geoderma 80: 1-44.

Brus, D.J., Heuvelink, G.B.M., 2007. Optimization of sample patterns for universal kriging of environmental variables. Geoderma 138: 86-95.

Brus, D.J., 2014. Statistical sampling approaches for soil monitoring. European Journal of Soil Science 65: 779-791.

Bartholomé, E., Belward, A.S., 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. International Journal of Remote Sensing, 26(9): 1959–1977.

Bontemps, S., Defourny, P., Radoux, J., 2013. Consistent global land cover maps for climate modelling communities: current achievements of the ESA's land cover CCI. Proceedings of the ESA Living Planet Symposium, Edinburgh.

Bontemps, S., Herold, M., Kooistra, L., Van Groenestijn, A., Hartley, A., Arino, O., Moreau, I. and Defourny, P., 2012. Revisiting land cover observations to address the needs of the climate modeling community. Biogeosciences 9: 2145-2157.

Briske, D.D., Fuhlendorf, S.D., Smeins, F.E., 2005. State-and-Transition Models, Thresholds, and Rangeland Health: A Synthesis of Ecological Concepts and Perspectives. Rangeland Ecology & Management 58: 1-10.

Carlson, T.N., Ripley, D.A., 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sensing of Environment 62: 241-252.

Castro, K.L., Sanchez-Azofeifa, G.A., Rivard, B., 2003. Monitoring secondary tropical forests using space-borne data: implications for Central America. International Journal of Remote Sensing 24: 1853-1894.

Chappell, A., Baldock, J., Viscarra Rossel, R., 2013. Sampling soil organic carbon to detect change over time. Available at: https://publications.csiro.au/rpr/download?pid=csiro:EP136498&dsid=DS4. CSIRO, Australia.

Chappell, A., Baldock, J., Sanderman, J., 2016. The global significance of omitting soil erosion from soil organic carbon cycling schemes. Nature Climate Change 6: 187-191.

Chave, J., Condit, R., Aguilar, S., Herandez, A., Lao, S., Perez, R., 2004. Error propagation and scaling of tropical forest biomass estimates. Philosophical Transactions B. Royal Society London 359: 409-420.

Chotte, J.L., Aynekulu, E., Cowie, A., Campbell, E., Vlek, P., Lal, R., Kapović-Solomun, M., von Maltitz, G., Kust, G., Barger, N., Vargas, R., Gastrow, S., 2019. Realising the Carbon Benefits of Sustainable Land Management Practices: Guidelines for Estimation of Soil Organic Carbon in the Context of Land Degradation Neutrality Planning and Monitoring. A report of the Science-Policy Interface. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany.

Cochran, W.G., 1977. Sampling Techniques. John Wiley & Sons, New York.

Chen, J.M., Black, T., 1992. Defining leaf area index for non-flat leaves. Plant, Cell & Environment 15: 421-429.

Cherlet, M., Hutchinson, C., Reynolds, J., Hill, J., Sommer, S., Von Maltitz, G., 2018 World atlas of desertification: Rethinking land degradation and sustainable land management. Publications Office of the European Union.

Clark, D.A., Brown, S., Kicklighter, D.W., Chambers, J.Q., Thomlinson, J.R., Ni, J., Holland, E.A., 2001. Net primary production in tropical forests: an evaluation and synthesis of existing field data. Ecological applications 11: 371-384.

Claverie, M., Ju, J., Masek, J.G., Dungan, J.L., Vermote, E.F., Roger, J-C., Skakun, S.V., Justice, C., 2018. The Harmonized Landsat and Sentinel-2 surface reflectance data set. Remote Sensing of Environment 219: 145-161.

Cleveland, C.C., Taylor, P., Chadwick, K.D., Dahlin, K., Doughty, C.E., Malhi, Y., Smith, W.K., Sullivan, B.W., Wieder, W.R., Townsend, A.R. (2015) A comparison of plot-based satellite and Earth system model estimates of tropical forest net primary production. Global Biogeochemical Cycles 29: 626-644.

Cleveland, R.B., Cleveland, W.S., McRae, J.E., Terpenning, I. 1990 STL: A Seasonal-Trend Decomposition Procedure Based on Loess. Journal of Official Statistics 6: 3-73.

Congalton, R.G., Gu, J., Yadav, K., Thenkabail, P., Ozdogan, M., 2014. Global land cover mapping: a review and uncertainty analysis. Remote Sensing 6: 12070-12093

Cowie, A.L., Orr, B.J., Castillo Sanchez, V.M., Chasek, P., Crossman, N.D., Erlewein, A., Louwagie, G., Maron, M., Metternicht, G.I., Minelli, S., Tengberg, A.E., Walter, S., Welton, S., 2018. Land in balance: The scientific conceptual framework for Land Degradation Neutrality. Environmental Science and Policy, 79: 25-35

Cruz-Gaistardo, C., Vargas, R., Guevara, M. 2017. National Map of Organic Carbon in the Soils and Mantle of Mexico. Global Symposium on Soil Organic Carbon, 21-23 March 2017, Rome, Italy.

de Brogniez, D., Ballabio, C., Stevens, A., Jones, R.J.A., Montanarella, L., van Wesemael, B., 2015. A map of the topsoil organic carbon content of Europe generated by a generalized additive model. European Journal of Soil Science 66: 121-134.

de Gruijter, J., Brus, D., Bierkens, M., Knotters, M., 2006. Sampling for Natural Resource Monitoring. Springer, Berlin.

de Gruijter, J.J., McBratney, A.B., Minasny, B., Wheeler, I., Malone, B.P., Stockmann, U., 2016. Farm-scale soil carbon auditing. Geoderma 265: 120–130.

Defourny, P., Kirches, G., Brockmann, C., Boettcher, M., Peters, M., Bontemps, S., Lamarche, C., Schlerf, M., Santoro, M. 2012. Land cover CCI. Product User Guide Version 2

Defourny, P., Bontemps, S., 2012. Revisiting land-cover mapping concepts. Remote Sensing of Land Use and Land Cover: Principles and Applications, pp.49-63.

del Barrio G, Puigdefabregas J, Sanjuan ME, Stellmes M, Ruiz A. (2010) Assessment and monitoring of land condition in the Iberian Peninsula, 1989–2000. Remote Sensing of Environment 114: 1817-1832.

de Sousa, L.M., Poggio, L., Batjes, N.H., Heuvelink, G.B.M., Kempen, B., Riberio, E., Rossiter, D., 2020. SoilGrids 2.0: producing quality-assessed soil information for the globe. SOIL Discuss. 2020: 1-37.

DiGregorio, A. and Jansen, L.J.M., 2000. Land cover classification system, concepts and user manual. GCP/RAF/287/ITA Africover. Rome: Food and Agriculture Organization of the United Nations Publishing Service.

DISER, 2020. National Inventory Report 2018 Volume 2. https://www.industry.gov.au/sites/default/files/2020-05/nga-national-inventory-report-2018-volume-2.pdf. Accessed: 4/12/20. Australian Government Department of Industry, Science, Energy and Resources, Canberra.

DotE, 2014a. Carbon Farming Initiative Soil Sampling and Analysis Method and Guidelines. Available at: https://www.environment.gov.au/system/files/pages/b341ae7a-5ddf-4725-a3fe-1b17ead2fa8a/files/cfi-soil-sampling-and-analysis-method-and-guidelines.pdf. The Department of the Environment (DotE), Canberra.

DotE, 2014b. Carbon Farming Initiative Soil Sampling Design Method and Guidelines. Available at: https://www.environment.gov.au/system/files/pages/b341ae7a-5ddf-4725-a3fe-1b17ead2fa8a/files/cfi-soil-sampling-design-method-and-guidelines.pdf. The Department of the Environment (DotE), Canberra.

DotEE, 2018. Carbon Credits (Carbon Farming Initiative – Measurement of Soil Carbon Sequestration in Agricultural Systems) Methodology Determination 2018. Available at: http://www.environment.gov.au/climate-change/government/emissions-reduction-fund/methods/measurement-of-soil-carbon-sequestration-in-agricultural-systems. Department of Environment and Energy, Commonwealth of Australia, Canberra.

DeVries, B., Verbesselt, J., Kooistra, L., Herold, M., 2015. Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series. Remote Sensing of Environment 161: 107-121.

Di Gregorio, A. 2005. Land cover classification system (LCCS): classification concepts and user manual. Food and Agriculture Organization of the United Nations, Rome.

Di Gregorio, A., Jaffrain, G., Weber, J.-L., 2011. Land cover classification for ecosystem accounting, Expert Meeting on Ecosystem Accounts 5 - 7 December 2011, London, UK.

Di Gregorio, A. and O'Brien, D., 2012. Overview of land-cover classifications and their interoperability. Remote sensing of land use and land cover: Principles and applications, pp.37-47.

Diogo, V. and Koomen, E., 2016. Land cover and land use indicators: review of available data. OECD Green Growth Papers, No. 2016/03, OECD Publishing, Paris, https://doi.org/10.1787/5jlr2z86r5xw-en.

ECOSOC, 2016. Report of the inter-agency and expert group on sustainable development goal indicators. Note by the Secretary-General. E/CN.3/2016/2/Rev.1, Statistical Commission 47th Session, 8-11 March 2016. The United Nations Economic and Social Council (ECOSOC), New York.

Eklundh, L., Jönsson, P., 2015a. TIMESAT: A Software Package for Time-Series Processing and Assessment of Vegetation Dynamics. In: Kuenzer, C., Dech, S., Wagner, W. (eds). Remote Sensing Time Series: Revealing Land Surface Dynamics. Springer International Publishing, Cham, pp 141-158.

Eklundh, L., Jönsson, P., 2015b. TIMESAT: A software package for time-series processing and assessment of vegetation dynamics. Remote sensing time series. Springer, pp 141-158.

Ellert, B.H., Janzen, H.H. McConkey, B.G., 2001. Measuring and comparing soil carbon storage. In: Assessment Methods for Soil Carbon (eds Lal, R., Kimble, G., Follet, R., Stewart, B.), pp. 31–146. Lewis Publishers, Boca Raton.

Ene, L.T., Næsset, E., Gobakken, T., Bollandsås, O.M., Mauya, E.W., Zahabu, E., 2017. Large-scale estimation of change in aboveground biomass in miombo woodlands using airborne laser scanning and national forest inventory data. Remote Sensing of Environment 188: 106-117.

England, J.R., Viscarra Rossel, R.A., 2018. Proximal sensing for soil carbon accounting. Soil 4: 101-122.

Englund, O., Sparovek, G., Berndes, G., Freitas, F., Ometto, J.P., Oliveira, P.V.D.C.E., Costa Jr, C., Lapola, D., 2017. A new high-resolution nationwide aboveground carbon map for Brazil. Geo: Geography and Environment 4: e00045.

Evans, J., Geerken, R., 2004. Discrimination between climate and human-induced dryland degradation. Journal of Arid Environments 57: 535-554.

FAO, ISRIC & ISSS, 1998. World Reference Base for Soil Resources. Available at: http://www.fao.org/docrep/W8594E/W8594E00.htm. Food and Agriculture Organisation of the United Nations (FAO), International Soil Reference and Information Centre (ISRIC) and International Society of Soil Science (ISSS), Rome, Italy.

FAO, 2014. Global Land Cover-SHARE of year 2014 - Beta-Release 1.0. Available at: http://www.glcn.org/databases/lc_glcshare_method_en.jsp [Accessed January 25, 2017].

FAO, 2015. Global Forest Resources Assessment 2015. Available at: http://www.fao.org/3/a-i4808e.pdf. FAO, Rome.

FAO & ITPS, 2015. Status of the World's Soil Resources (SWSR) – Main Report. Food and Agriculture Organization (FAO) & Intergovernmental Technical Panel on Soils (ITPS), Rome, Italy.

FAO, 2019. Measuring and modelling soil carbon stocks and stock changes in livestock production systems – Guidelines for assessment. Version 1 – Advanced copy. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy, p. 152.

FAO-GTOS. 2009. Land Cover: Assessment of the status of the development of the standards for the Terrestrial Essential Climate Variables. Global Terrestrial Observing System, Rome.

Fensholt, R., Proud, S.R., 2012. Evaluation of Earth Observation based global long term vegetation trends — Comparing GIMMS and MODIS global NDVI time series. Remote Sensing of Environment 119: 131-147.

Fensholt, R., Rasmussen, K. (2011) Analysis of trends in the Sahelian 'rain-use efficiency'using GIMMS NDVI, RFE and GPCP rainfall data. Remote Sensing of Environment 115: 438-451.

Fensholt, R., Rasmussen, K., Kaspersen, P., Huber, S., Horion, S., Swinnen, E., 2013. Assessing Land Degradation/Recovery in the African Sahel from Long-Term Earth Observation Based Primary Productivity and Precipitation Relationships. Remote Sensing 5: 664.

Fernández-Ugalde, O., Orgiazzi, A., Jones, A., Lugato, E., Panagos, P., 2017. LUCAS 2018 – Soil Component: Sampling Instructions for Surveyors, EUR 28501 EN, doi 10.2760/023673 JRC Technical Report. European Commission, Joint Research Centre, Luxembourg. https://publications.jrc.ec.europa.eu/repository/bitstream/JRC105923/jrc105923_lucas2018_jrctechnicalreport.pdf.

Finegold, Y., Ortmann, A., Lindquist, E., d'Annunzio, R. and Sandker, M., 2016. Map accuracy assessment and area estimation: a practical guide. Rome: Food and Agriculture Organization of the United Nations.

Franklin, S.E., Ahmed, O.S., Wulder, M.A., White, J.C., Hermosilla, T. and Coops, N.C., 2015. Large area mapping of annual land cover dynamics using multitemporal change detection and classification of Landsat time series data. Canadian Journal of Remote Sensing, 41(4), pp.293-314.

Friedl, M.A., McIver, D.K., Hodges, J.C., Zhang, X.Y., Muchoney, D., Strahler, A.H., Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A. and Baccini, A., 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sensing of Environment, 83(1): 287-302.

Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A. and Huang, X., 2010. MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote sensing of Environment, 114(1): 168-182.

Fritz, S., McCallum, I., Schill, C., Perger, C., See, L., Schepaschenko, D., Van der Velde, M., Kraxner, F., Obersteiner, M., 2012. Geo-Wiki: An online platform for improving global land cover. Environmental Modelling & Software, 31: 110-123.

Fuller, R.M., Smith, G.M. and Devereux, B.J., 2003. The characterisation and measurement of land cover change through remote sensing: problems in operational applications?. International Journal of Applied Earth Observation and Geoinformation, 4(3), pp.243-253.

Gao, F., Masek, J., Schwaller, M. and Hall, F., 2006. On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. IEEE Transactions on Geoscience and Remote sensing, 44(8), pp.2207-2218.

GEO-LDN Initiative, 2020. Minimum data quality standards and decision trees for SDG Indicator 15.3.1: Proportion of land that is degraded over total land area. Technical Note. Group on Earth Observation Land Degradation Neutrality (GEO-LDN) Initiative, Geneva, Switzerland. http://earthobservations.org/documents/ldn/20200703_GEOLDN_TechnicalNote_FINAL_SINGLE.pdf

GFOI, 2016. Integration remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observations Initiative. Edition 2.0. (Prerelease). Australian Government, Canberra, Australia.

GFOI, 2020. Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observations Initiative. Edition 3.0. Food and Agriculture Organization of the United Nations, Rome, Italy.

GOFC-GOLD, 2015. A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals associated with deforestation, gains and losses of carbon stocks in forests remaining forests, and forestation. GOFC-GOLD Report version COP21-1. GOFC-GOLD Land Cover Project Office, Wageningen University, Wageningen, The Netherlands.

Gómez, C., White, J.C. and Wulder, M.A., 2016. Optical remotely sensed time series data for land cover classification: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 116, pp.55-72.

Gong, P., Wang, J., Yu, L., Zhao, Y., Zhao, Y., Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S. and Li, C., 2013. Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data. International Journal of Remote Sensing, 34(7), pp.2607-2654.

Gregorio, A. Di, Jansen, L., 2000. Land cover classification system (LCCS): classification concepts and user manual for software version 1.0.

GSP, 2014. Plan of Action for Pillar Four of the Global Soil Partnership. Food and Agriculture Organisation of the United Nations. Available at: http://www.fao.org/3/az921e

Guerschman, J. 2014. Fractional cover—MODIS. CSIRO algorithm. v2. CSIRO, Data Collection. http://hdl. handle. net/102.100, 100, 42094

Guerschman, J.P., Hill, M.J., Renzullo, L.J., Barrett, D.J., Marks, A.S., Botha, E.J., 2009 Estimating fractional cover of photosynthetic vegetation, non-photosynthetic vegetation and bare soil in the Australian tropical savanna region upscaling the EO-1 Hyperion and MODIS sensors. Remote Sensing of Environment 113: 928-945.

Guerschman, J.P., Scarth, P.F., McVicar, T.R., Renzullo, L.J., Malthus, T.J., Stewart, J.B., Rickards, J.E., Trevithick, R. 2015 Assessing the effects of site heterogeneity and soil properties when unmixing photosynthetic vegetation, non-photosynthetic vegetation and bare soil fractions from Landsat and MODIS data. Remote Sensing of Environment 161: 12-26.

Guevara, M., Arroyo, C., Brunsell, N.A., Cruz, C.O., Domke, G., Equihua, J., Etchevers, J., Hayes, D., Hengl, T., Ibelles, A., Johnson, K., de Jong, B., Libohova, Z., Llamas, R.M., Nave, L., Ornelas, J.L., Paz, F., Ressl, R., Schwartz, A., Victoria, A., Wills, S., Vargas, R., 2020. Soil organic carbon across Mexico and the conterminous United States (1991–2010). Global Biogeochemical Cycles, 34, e2019GB006219. https://doi.org/10.1029/2019GB006219.

Guo, L.B., Gifford, R.M., 2002. Soil carbon stocks and land use change: a meta analysis. Global Change Biology 8: 345-360.

Hansen, M.C., Loveland, T.R., 2012. A review of large area monitoring of land cover change using Landsat data. Remote Sensing of Environment, 122: 66–74.

Hein, L., De Ridder, N., Hiernaux, P., Leemans, R., De Wit, A., Schaepman, M., 2011. Desertification in the Sahel: Towards better accounting for ecosystem dynamics in the interpretation of remote sensing images. Journal of Arid Environments 75: 1164-1172.

Helman, D., Mussery, A., Lensky, I.M., Leu, S., 2014. Detecting changes in biomass productivity in a different land management regimes in drylands using satellite-derived vegetation index. Soil Use and Management 30: 32-39.

Hengl, T., de Jesus, J.M., Heuvelink, G.B.M., Ruiperez, M., Gonzalez, M.R., Kilibarda, M., Blagotic, A., Shangguan, W., Wright, M.N., Geng, X., Bauer-Marschallinger, B., Guevara, M.A., Vargas, R., MacMillan, R.A., Batjes, N.H., Leenaars, J.G.B., Ribeiro, E., Wheeler, I., Mantel, S., Kempen, B., 2017. SoilGrids250m: Global Gridded Soil Information Based on Machine Learning. PLoS ONE 12(2): e0169748.

Hengl, T., de Jesus, J.M., MacMillan, R.A., Batjes, N.H., Heuvelink, G.B.M., 2014. SoilGrids1km - Global Soil Information Based on Automated Mapping. PLoS ONE 9: e105992.

Hengl, T., Heuvelink, G.B., Kempen, B., Leenaars, J.G., Walsh, M.G., Shepherd, K.D., Sila, A., MacMillan, R.A., Mendes de Jesus, J., Tamene, L. and Tondoh, J.E., 2015. Mapping soil properties of Africa at 250 m resolution: Random forests significantly improve current predictions. PloS one, 10(6), p.e0125814.

Herold, M., Carter, S., Avitabile, V., Espejo, A.B., Jonckheere, I., Lucas, R., McRoberts, R.E., Næsset, E., Nightingale, J., Petersen, R., Reiche, J., Romijn, E., Rosenqvist, A., Rozendaal, D.M.A., Seifert, F.M., Sanz, M.J., De Sy, V., 2019. The role and need for space-based forest biomass-related measurements in environmental management and policy. Surveys in Geophysics 40: 757-778.

Hengl, T., MacMillan, R.A., 2019. Predictive Soil Mapping with R. OpenGeoHub foundation, Wageningen, the Netherlands, 370 pages, www.soilmapper.org, ISBN: 978-0-359-30635-0.

Heuvelink, G.B.M., 1998. Error Propagation in Environmental Modelling with GIS. Taylor & Francis, London.

Heuvelink, G.B.M., Griffith, D.A., Hengl, T., Melles, S.J., 2012. Sampling design optimization for space-time kriging. In: Mateu, J., Müller, W.G. (Eds.), Spatio-temporal Design: Advances in Efficient Data Acquisition. Wiley, pp. 207-230.

Heuvelink, G.B.M., 2014. Uncertainty quantification of GlobalSoilMap products. In: Arrouays, D., McKenzie, N., Hempel, J., Richer de Forges, A., McBratney, A. (Eds.), GlobalSoilMap. Basis of the Global Spatial Soil Information System. Taylor & Francis Group, London, pp. 335-340.

Higginbottom, T., Symeonakis, E., 2014. Assessing Land Degradation and Desertification Using Vegetation Index Data: Current Frameworks and Future Directions. Remote Sensing 6: 9552.

Hilker, T., Wulder, M.A., Coops, N.C., Seitz, N., White, J.C., Gao, F., Masek, J.G., Stenhouse, G., 2009. Generation of dense time series synthetic Landsat data through data blending with MODIS using a spatial and temporal adaptive reflectance fusion model. Remote Sensing of Environment 113: 1988-1999

Hill, M.J., Guerschman, J.P., 2020. The MODIS Global Vegetation Fractional Cover Product 2001–2018: Characteristics of Vegetation Fractional Cover in Grasslands and Savanna Woodlands. Remote Sensing 12: 406.

Hong, S.Y., Minasny, B., Zhang, Y.S., Kim, Y.H., Jung, K.H., 2010. Digital soil mapping using legacy soil data in Korea. 19th World Congress of Soil Science, Soil Solutions for a Changing World, 1–6 August 2010, Brisbane, Australia.

Huang, X., Xiao, J., Ma, M., 2019. Evaluating the performance of satellite-derived vegetation indices for estimating gross primary productivity using FLUXNET observations across the globe. Remote Sensing 11: 1823.

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment 83: 195-213.

Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment 25: 295-309.

IPCC, 1997. Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories. In: J.T. Houghton, L.G. Meira Filho, B. Lim, K. Treanton, I. Mamaty, Y. Bonduki, D.J. Griggs, Callander, B.A. (Eds.). Meteorological Office, Bracknell, UK.

IPCC, 2003. Penman, J., Gytarsky, M., Hiraishi, T., Krug, T., Kruger, D., Pipatti, R., Buendia, L., Miwa, K., Ngara, T., Tanabe, K., and Wagner, F (Eds). Good Practice Guidance for Land Use, Land-Use Change and Forestry. Intergovernmental Panel on Climate Change (IPCC)/Institute for Global Environmental Strategies (IGES), Hayama, Japan.

Huete, A.R., Didan, K., Shimabukuro, Y.E., Ratana, P., Saleska, S.R., Hutyra, L.R., Yang, W., Nemani, R.R. and Myneni, R., 2006. Amazon rainforests green-up with sunlight in dry season. Geophysical research letters, 33(6).

IPCC, 2006. Eggleston, S., Buendia L., Miwa K., Ngara T., and Tanabe K. (Eds). 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Intergovernmental Panel on Climate Change (IPCC)/Institute for Global Environmental Strategies (IGES), Hayama, Japan.

IPCC, 2013. Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda, M. and Troxler, T.G. (Eds). 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands. Intergovernmental Panel on Climate Change (IPCC), Switzerland.

IPCC. 2019. Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. In: Buendia, E., Tanabe, K., Kranjc, A., Baasansuren, J., Fukuda, M., Ngarize, S., Osako, A., Pyrozhenko, Y., Shermanau, P., Federici, S. (eds). Intergovernmental Panel on Climate Change, Geneva, Switzerland.

Ivits, E., Cherlet, M., 2016. Land productivity dynamics: towards integrated assessment of land degradation at global scales. Joint Research Centre, Luxembourg.

Ivits, E., Horion, S., Erhard, M., Fensholt, R., 2016. Assessing European ecosystem stability to drought in the vegetation growing season. Global Ecology and Biogeography 25: 1131-1143.

Izaurralde, R.C., Rice, C.W., Wielopolski, L., Ebinger, M.H., Reeves, J.B., III, Thomson, A.M., Harris, R., Francis, B., Mitra, S., Rappaport, A.G., Etchevers, J.D., Sayre, K.D., Govaerts, B., McCarty, G.W., 2013. Evaluation of Three Field-Based Methods for Quantifying Soil Carbon. Plos One 8.

Jacquin, A., Sheeren, D., Lacombe, J-P., 2010. Vegetation cover degradation assessment in Madagascar savanna based on trend analysis of MODIS NDVI time series. International Journal of Applied Earth Observation and Geoinformation 12, Supplement 1: S3-S10.

Jiang, Z., Huete, A.R., Didan, K., Miura, T., 2008. Development of a two-band enhanced vegetation index without a blue band. Remote sensing of Environment 112: 3833-3845.

Joint Research Centre of the European Commission. 2017. World Atlas of Desertification, 3rd edition. JRC, Ispra

Joyce, M.J., Erb, J.D., Sampson, B.A., Moen, R.A., 2019. Detection of coarse woody debris using airborne light detection and ranging (LiDAR). Forest Ecology and Management 433: 678-689.

Kates, R.W., 2000. Population and consumption: what we know, what we need to know. Environment: Science and Policy for Sustainable Development, 42(3), pp.10-19.

Kempen, B., Dalsgaard, S., Kaaya, A.K., Chamuya, N., Ruiperez-Gonzalez, M., Pekkarinen, A., Walsh, M.G., 2019. Mapping topsoil organic carbon concentrations and stocks for Tanzania. Geoderma 337: 164-180.

Kennard, M.J., Mackay, S.J., Pusey, B.J., Olden, J.D., Marsh, N., 2010. Quantifying uncertainty in estimation of hydrologic metrics for ecohydrological studies. River Research and Applications 26: 137-156.

Khatami, R., Mountrakis, G., Stehman, S. V., 2016. A meta-analysis of remote sensing research on supervised pixel-based land-cover image classification processes: General guidelines for practitioners and future research. Remote Sensing of Environment, 177: 89–100.

Kumar, L., Rietkerk, M., van Langevelde, F., van de Koppel, J., van Andel, J., Hearne, J., de Ridder, N., Stroosnijder, L., Skidmore, A.K., Prins, H.H., 2002. Relationship between vegetation growth rates at the onset of the wet season and soil type in the Sahel of Burkina Faso: implications for resource utilisation at large scales. Ecological Modelling 149: 143-152.

Lal, R., 2004. Soil carbon sequestration to mitigate climate change. Geoderma 123: 1-22.

Lark, R.M., 2016. Multi-objective optimization of spatial sampling. Spatial Statistics 18: 412-430.

Laso Bayas, J.C., See, L., Fritz, S., Sturn, T., Perger, C., Dürauer, M., Karner, M., Moorthy, I., Schepaschenko, D., Domian, D., McCallum, I., 2016. Crowdsourcing In-Situ Data on Land Cover and Land Use Using Gamification and Mobile Technology. Remote Sensing 8 (11), p.905.

Latham, J., Cumani, R., Rosati, I., Bloise, M., 2014. Global land cover share (GLC-SHARE) database beta-release version 1.0-2014. FAO: Rome, Italy. Available at: http://www.fao.org/uploads/media/glc-share-doc.pdf

Lee, J., Viscarra Rossel, R.A., Luo, Z., Wang, Y.P., 2020. Simulation of soil carbon dynamics in Australia under a framework that better connects spatially explicit data with Rᴏᴛʜ C. Biogeosciences Discuss. 2020, 1-24.

Le Houerou, H.N., 1984. Rain use efficiency: a unifying concept in arid-land ecology. Journal of arid Environments, 7(3), pp.213-247.

Lefsky, M.A., Harding, D., Cohen, W.B., Parker, G., Shugart, H.H., 1999. Surface lidar remote sensing of basal area and biomass in deciduous forests of eastern Maryland, USA. Remote Sensing of Environment 67: 83-98.

Lefsky, M.A., Harding, D.J., Keller, M., Cohen, W.B., Carabajal, C.C., Del Bom Espirito-Santo, F., Hunter, M.O., de Oliveira Jr., R., 2005. Estimates of forest canopy height and aboveground biomass using ICESat. Geophysical Research Letters 32, L22S02.Ließ, M., Schmidt, J., Glaser, B., 2016. Improving the spatial prediction of soil organic carbon stocks in a complex tropical mountain landscape by methodological specifications in machine learning approaches. PLoS One 11: e0153673.

Lobsey, C.R., Viscarra Rossel, R.A., 2016. Sensing of soil bulk density for more accurate carbon accounting. European Journal of Soil Science 67: 504-513.

Loew A, Bell W, Brocca L, Bulgin CE, Burdanowitz J, Calbet X, Donner RV, Ghent D, Gruber A, Kaminski T, Kinzel J, Klepp C, Lambert J-C, Schaepman-Strub G, Schröder M, Verhoelst T. (2017) Validation practices for satellite-based Earth observation data across communities. Reviews of Geophysics 55: 779-817.

Lopes Queiroz, G., McDermid, G.J., Linke, J., Hopkinson, C., Kariyeva, J., 2020. Estimating coarse woody debris volume using image analysis and multispectral LiDAR. Forests 11: 141.

Lorenz, K., Lal, R., 2016. Soil Organic Carbon – An Appropriate Indicator to Monitor Trends of Land and Soil Degradation within the SDG Framework? TEXTE 77/2016. Project No. 55337 Report No. 002413/ENG. Available at: http://www.umweltbundesamt.de/publikationen. Umweltbundesamt, Germany.

Loveland, T.R., Zhu, Z., Ohlen, D.O., Brown, J.F., Reed, B.C., Yang, L., 1999. An analysis of the IGBP global land-cover characterization process. Photogrammetric Engineering and Remote Sensing 65: 1021-1032

Lymburner, L., Tan, P., Mueller, N., Thackway, R., Lewis, A., Thankappan, M., Randall, L., Islam, A., Senarath U., 2011. The National Dynamic Land Cover Dataset. Geoscience Australia, Symonston, Australia

Ma, X., Huete, A., Moran, S., Ponce-Campos, G., Eamus, D. (2015) Abrupt shifts in phenology and vegetation productivity under climate extremes. Journal of Geophysical Research: Biogeosciences 120: 2036-2052.

Maillard, É., McConkey, B.G., Angers, D.A., 2017. Increased uncertainty in soil carbon stock measurement with spatial scale and sampling profile depth in world grasslands: A systematic analysis. Agriculture, Ecosystems & Environment, 236: 268-276.

Malenovský, Z., Rott, H., Cihlar, J., Schaepman, M.E., García-Santos, G., Fernandes, R., Berger, M. 2012. Sentinels for science: Potential of Sentinel-1,-2, and-3 missions for scientific observations of ocean, cryosphere, and land. Remote Sensing of Environment 120: 91-101

Markos, A., Sims, N.C., Giuliani, G. (in press). Comparing Land Productivity Trends using a self-adjusting algorithm: a use case in Santa Cruz, Bolivian Lowland. submitted to International Journal of Applied Earth Observation and Geoinformation.

McKenzie, N., Henderson, B., McDonald, W., 2002. Monitoring Soil Change: Principles and practices for Australian conditions. Report prepared for the National Land and Water Resources Audit. CSIRO Land and Water Technical Report 18/02, May 2002. CSIRO Land and Water, Canberra.

McRoberts, R.E., Næsset, E., Saatchi, S., Liknes, G.C., Walters, B.F., Chen, Q., 2019. Local validation of global biomass maps. International Journal of Applied Earth Observation and Geoinformation 83: 101931.

Milich, L., Weiss, E., 2000. GAC NDVI images: Relationship to rainfall and potential evaporation in the grazing lands of The Gourma (northern Sahel) and in the croplands of the Niger-Nigeria border (southern Sahel). International Journal of Remote Sensing 21: 261-280.

Millennium Ecosystem Assessment., 2005. Ecosystems and human wellbeing: a framework for assessment. Island Press, Washington, DC

Minasny, B., McBratney, A.B., 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. Computers & Geosciences 32: 1378-1388.

Minasny, B., McBratney, A.B., Malone, B.P., Wheeler, I., 2013. Digital mapping of soil carbon. Advances in Agronomy 118: 1-47.

Minasny, B., Malone, B.P., McBratney, A.B., Angers, D.A., Arrouays, D., Chambers, A., Chaplot, V., Chen, Z.S., Cheng, K., Das, B.S. and Field, D.J., 2017. Soil carbon 4 per mille. Geoderma, 292, pp.59-86.

Moran, M.S., Ponce-Campos, G.E., Huete, A., McClaran, M.P., Zhang, Y., Hamerlynck, E.P., Augustine, D.J., Gunter, S.A., Kitchen, S.G., Peters, D.P.C., Starks, P.J., Hernandez, M., 2014. Functional response of U.S. grasslands to the early 21st-century drought. Ecology 95: 2121-2133.

Mücher, S, De Simone, L, Kramer, H, de Wit, A, Roupioz, L, Hazeu, G, Boogaard, H, Schuiling, R, Fritz, S, Latham, J, Cormont, A. (2016) A New Global Agro-Environmental Stratification (GAES). Wageningen Environmental Research, Wageningen.

Mulder, V.L., Lacoste, M., Richer-De-Forges, A.C., Arrouays, D., 2016. GlobalSoilMap France: High-resolution spatial modelling the soils of France up to two meter depth. Science of the Total Environment 573: 1352-1369.

Munn, R., 1988. The design of integrated monitoring systems to provide early indications of environmental/ecological changes. Environmental Monitoring and Assessment 11: 203-217.

Næsset, E., Bollandsås, O.M., Gobakken, T., Gregoire, T.G., Ståhl, G., 2013. Model-assisted estimation of change in forest biomass over an 11 year period in a sample survey supported by airborne LIDAR: A case study with post-stratification to provide activity data. Remote Sensing of Environment 128: 299-314.

Nelson, R., Short, A., Valenti, M., 2004. Measuring biomass and carbon in Delaware using an airborne profiling LIDAR. Scandinavian Journal of Forest Research 19: 500-511.

New Zealand Agricultural Greenhouse Gas Research Centre, 2016. http://www.nzagrc.org.nz/soil-carbon,listing,232,reducing-new-zealands-agricultural-emissions-mapping-soil-organic-carbon-stocks.html

Odgers, N., Libohova, Z., Thompson, J., 2012. Equal-area spline functions applied to a legacy soil database to create weighted-means maps of soil organic carbon at a continental scale. Geoderma 189–190: 153–163.

Oesterwind, D., Rau, A., Zaiko, A. 2016. Drivers and pressures – Untangling the terms commonly used in marine science and policy. Journal of Environmental Management, 181: 8-15

Ogle, S., Breidt, F., Paustian, K., 2005. Agricultural management impacts on soil organic carbon storage under moist and dry climatic conditions of temperate and tropical regions. Biogeochemistry 72: 87–121.

Olsen, J., Miehe, S., Ceccato, P., Fensholt, R., 2015. Does EO NDVI seasonal metrics capture variations in species composition and biomass due to grazing in semi-arid grassland savannas? Biogeosciences 12: 4407-4419.

Olson DM, Dinerstein E, Wikramanayake ED, Burgess ND, Powell GVN, Underwood EC, D'amico JA, Itoua I, Strand HE, Morrison JC, Loucks CJ, Allnutt TF, Ricketts TH, Kura Y, Lamoreux JF, Wettengel WW, Hedao P, Kassem KR. (2001) Terrestrial Ecoregions of the World: A New Map of Life on Earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. BioScience 51: 933-938.

Olsson, L., Barbosa, H., Bhadwal, S., Cowie, A., Delusca, K., Flores-Renteria, D., Hermans, K., Jobbagy, E., Kurz, W., Li, D., 2019. Land Degradation: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse gas fluxes in Terrestrial Ecosystems. IPCC.

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., Wulder, M.A. 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment 148: 42-57

Onyutha, C., Tabari, H., Taye, M.T., Nyandwaro, G.N., Willems, P. (2016) Analyses of rainfall trends in the Nile River Basin. Journal of Hydro-environment Research 13: 36-51.

Orr, B.J., Cowie, A.L., Castillo Sanchez, V.M., Chasek, P., Crossman, N.D., Erlewein, A., Louwagie, G., Maron, M., Metternicht, G.I., Minelli, S., Tengberg, A.E., Walter, S., Welton, S., 2017. Scientific Conceptual Framework for Land Degradation Neutrality. A Report of the Science-Policy Interface. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany. Available at: http://www2.unccd.int/sites/default/files/documents/LDN%20Scientific%20Conceptual%20Framework_FINAL.pdf

Owusu, S., Yigini, Y., Olmedo, G.F., Omuto, C.T., 2020. Spatial prediction of soil organic carbon stocks in Ghana using legacy data. Geoderma 360: pp. 114008.

Padarian, J., Minasny, B., McBratney, A.B., 2017. Chile and the Chilean soil grid: A contribution to GlobalSoilMap. Geoderma Regional 9: 17-28.

Parton, W., Schimel, D., Cole, C., Ojima, D., 1987. Analysis of factors controlling soil organic matter levels in great-plains grasslands. Soil Science Society of America Journal 51: 1173–1179.

Penman, J., Gytarsky, M., Hiraishi, T., Krug, T., Kruger, D., Pipatti, R., Buendia, L., Miwa, K., Ngara, T., Tanabe, K., 2003. Intergovernmental Panel on Climate Change Good Practice Guidance for Land Use, Land-Use Change and Forestry. IPCC National Greenhouse Gas Inventories Programme (http://www.ipcc-nggip.iges.or.jp/public/gpglulucf/gpglulucf.html)

Poeplau, C., Vos, C., Don, A., 2017. Soil organic carbon stocks are systematically overestimated by misuse of the parameters bulk density and rock fragment content. Soil 3: 61–66.

Poggio, L., Gimona, A., 2014. National scale 3D modelling of soil organic carbon stocks with uncertainty propagation - An example from Scotland. Geoderma 232: 284-299.

Ponce-Campos, G.E., Moran, M.S., Huete, A., Zhang, Y., Bresloff, C., Huxman, T.E., Eamus, D., Bosch, D.D., Buda, A.R., Gunter, S.A., 2013. Ecosystem resilience despite large-scale altered hydroclimatic conditions. Nature 494: 349-352.

Prince, S.D., 2019. Challenges for remote sensing of the Sustainable Development Goal SDG 15.3.1 productivity indicator. Remote Sensing of Environment 234: 111428.

Quegan, S., Le Toan, T., Chave, J., Dall, J., Exbrayat, J.-F., Minh, D.H.T., Lomas, M., D'Alessandro, M.M., Paillou, P., Papathanassiou, K., Rocca, F., Saatchi, S., Scipal, K., Shugart, H., Smallman, T.L., Soja, M.J., Tebaldini, S., Ulander, L., Villard, L., Williams, M., 2019. The European Space Agency BIOMASS mission: Measuring forest above-ground biomass from space. Remote Sensing of Environment 227: 44-60.

Ravindranath, N.H., Ostwald, M., 2008. Carbon inventory methods - Handbook for greenhouse gas inventory, carbon mitigation and roundwood production projects. Advances in Global Change Research, Volume 29. Springer, Heidelberg.

Reeves, M.C., Washington-Allen, R.A., Angerer, J., Hunt, E.R., Kulawardhana, R.W., Kumar, L., Loboda, T., Loveland, T., Metternicht, G., Ramsey, R.D., 2015. Global View of Remote Sensing of Rangelands: Evolution, Applications, Future Pathways. Land Resources Monitoring, Modeling, and Mapping with Remote Sensing. CRC Press, pp 237-275.

Reeves, J.B., McCarty, G.W., Calderon, F., Hively, W.D., 2012. Advances in Spectroscopic Methods for Quantifying Soil Carbon. In: Liebig, M., Franzluebbers, A., Follett, R. (Eds.), Managing Agricultural Greenhouse Gases. Elsevier Inc., pp. 345-366.

Rizvi, S.R. and Killough, B., 2018, December. Random Forest Classification of Regions in Colombia and Uruguay using Open Data Cube (ODC) Framework. In AGU Fall Meeting Abstracts (Vol. 2018, pp. H34B-03).

Rodríguez-Veiga, P., Saatchi, S., Tansey, K., Balzter, H., 2016. Magnitude, spatial distribution and uncertainty of forest biomass stocks in Mexico. Remote Sensing of Environment 183: 265-281.

Roxburgh, S.H., Karunaratne, S.B., Paul, K.I., Lucas, R.M., Armston, J.D., Sun, J., 2019. A revised above-ground maximum biomass layer for the Australian continent. Forest Ecology and Management 432: 264-275.

Roy, D.P., Ju, J., Lewis, P., Schaaf, C., Gao, F., Hansen, M., Lindquist, E., 2008. Multi-temporal MODIS–Landsat data fusion for relative radiometric normalization, gap filling, and prediction of Landsat data. Remote Sensing of Environment 112: 3112-3130.

Running, S.W., Baldocchi, D.D., Turner, D.P., Gower, S.T., Bakwin, P.S., Hibbard, K.A., 1999. A global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modelling and EOS satellite data. Remote Sensing the Environment 70: 108-127.

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M., Hashimoto, H., 2004. A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production. BioScience 54: 547-560.

Running, S.W., Zhao, M., 2015. Daily GPP and Annual NPP (MOD17A2/A3) Products NASA Earth Observing System MODIS Land Algorithm. MOD17 Users Guide. MODIS Land Team.

Ruesch, A., Gibbs, H.K., 2008. New IPCC Tier-1 Global Biomass Carbon Map For the Year 2000. Available online from the Carbon Dioxide Information Analysis Center Available at: http://cdiac.ornl.gov, Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., Petrova, S., White, L., Silman, M., Morel, A., 2011. Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the National Academy of Sciences of the United States of America 108, 9899-9904.Santoro, M.C., Cartus, O., 2019. ESA Biomass Climate Change Initiative (Biomass_cci): Global datasets of forest above-ground biomass for the year 2017, v1. Centre for Environmental Data Analysis. DOI:10.5285/bedc59f37c9545c981a839eb552e4084

Sasaki, T., Furukawa, T., Iwasaki, Y., Seto, M., Mori, A.S., 2015. Perspectives for ecosystem management based on ecosystem resilience and ecological thresholds against multiple and stochastic disturbances. Ecological Indicators 57: 395-408.

Sasaki, T., Okayasu, T., Jamsran, U., Takeuchi, K., 2008. Threshold changes in vegetation along a grazing gradient in Mongolian rangelands. Journal of Ecology 96: 145-154.

Sayre, R., Dangermond, J., Frye, C., Vaughan, R., Aniello, P., Breyer, S., Cribbs, D., Hopkins, D., Nauman, R., Derrenbacher, W., 2014. A new map of global ecological land units—an ecophysiographic stratification approach. Washington, DC: Association of American Geographers.

Sayre, R., Karagulle, D., Frye, C., Boucher, T., Wolff, N.H., Breyer, S., Wright, D., Martin, M., Butler, K., Van Graafeiland, K., Touval, J., Sotomayor, L., McGowan, J., Game, E.T., Possingham, H., 2020. An assessment of the representation of ecosystems in global protected areas using new maps of World Climate Regions and World Ecosystems. Global Ecology and Conservation 21: e00860.

Schaaf, C.B., Gao, F., Strahler, A.H., Lucht, W., Li, X., Tsang, T., Strugnell, N.C., Zhang, X., Jin, Y., Muller, J-P., Lewis, P., Barnsley, M., Hobson, P., Disney, M., Roberts, G., Dunderdale, M., Doll, C., d'Entremont, R.P., Hu, B., Liang, S., Privette, J.L., Roy, D. 2002. First operational BRDF, albedo nadir reflectance products from MODIS. Remote Sensing of Environment 83: 135-148. DOI: http://dx.doi.org/10.1016/S0034-4257(02)00091-3

Schlerf, M., Atzberger, C., Hill, J., 2005. Remote sensing of forest biophysical variables using HyMap imaging spectrometer data. Remote Sensing of Environment 95: 177-194.

Shirato, Y., 2017. Calculating changes in soil organic carbon in Japanese agricultural land by IPCC-Tier 3 modeling approach: use of modified Rothamsted carbon model. Global Symposium on Soil Organic Carbon, 21-23 March 2017, Rome, Italy.

Sims, N.C., Green, C., Newnham, G.J., England, J.R., Held, A., Wulder, M.A., Herold, M., Cox, S.J.D., Huete, A.R., Kumar, L., Viscarra Rossel, R.A., Roxburgh, S.H., McKenzie, N.J., 2017. Good Practice Guidance SDG Indicator 15.3.1, Proportion of land that is degraded over total land area. Version 1.0. United Nations Convention to Combat Desertification, Bonn, Germany. http://www2.unccd.int/sites/default/files/relevant-links/2017-10/Good%20Practice%20Guidance_SDG%20Indicator%2015.3.1_Version%201.0.pdf

Sims, N.C., Barger, N., Metternicht, G., England, J.R., 2020. A land degradation interpretation matrix for reporting on UN SDG Indicator 15.3.1 and Land Degradation Neutrality. Environmental Science and Policy 114: 1-6.

Singh, R.B., & Ajai 2019. A composite method to identify desertification ‘hotspots’ and ‘brightspots’. Land Degradation & Development, 30, 1025-1039

Smith, P., 2004. How long before a change in soil organic carbon can be detected? Global Change Biology 10: 1878–1883.

Smith, P., Fang, C., Dawson, J. J., & Moncrieff, J. B. 2008. Impact of global warming on soil organic carbon. Adv. in Agronomy 97: 1-43.

Sims, N.C., Colloff, M.J. (2012) Remote sensing of vegetation responses to flooding of a semi-arid floodplain: Implications for monitoring ecological effects of environmental flows. Ecological Indicators 18: 387-391.

Skakun, S., Justice, C.O., Vermote, E., Roger, J-C., 2018. Transitioning from MODIS to VIIRS: an analysis of inter-consistency of NDVI data sets for agricultural monitoring. International Journal of Remote Sensing 39: 971-992.

Skalsky, R., Tarasovicová, Z., Balkovic, J., Schmid, E., Fuchs, M., Moltchanova, E., Kindermann, G., Scholtz, P., McCallum, I., 2012. Global Homogeneous Response Units. PANGAEA.

Skjemstad, J., Spouncer, L., Cowie, B., Swift, R., 2004. Calibration of the Rothamsted organic carbon turnover model (RothC ver. 26.3), using measurable soil organic carbon pools. Australian Journal of Soil Research 42: 79–88.

SoE, 2011. Australia State of the Environment 2011. Independent report to the Australian Government Minister for Sustainability, Environment, Water, Population and Communities. Department of Sustainability, Environment, Water, Population and Communities (DSEWPaC), Canberra.

Song, X.-D., Wu, H.-Y., Ju, B., Liu, F., Yang, F., Li, D.-C., Zhao, Y.-G., Yang, J.-L., Zhang, G.-L., 2020. Pedoclimatic zone-based three-dimensional soil organic carbon mapping in China. Geoderma 363: 114145.

Sonmez, B., Ozbahce, A., Kececi, S., Akgul, S., Aksoy, E., Madenoglu, S., Karabulut Aloe, A., Incirkus, V., Gorgisen, C., Tuncay, T., Beernaerts, I., Vargas, R. 2017. Turkey's national geospatial soil organic carbon information system. Global Symposium on Soil Organic Carbon, 21-23 March 2017, Rome, Italy.

Spawn, S.A., Sullivan, C.C., Lark, T.J., Gibbs, H.K., 2020. Harmonized global maps of above and belowground biomass carbon density in the year 2010. Scientific Data 7: 112.

Sreenivas, K., Dadhwal, V.K., Kumar, S., Harsha, G.S., Mitran, T., Sujatha, G., Suresh, G.J.R., Fyzee, M.A., Ravisankar, T., 2016. Digital mapping of soil organic and inorganic carbon status in India. Geoderma 269: 160-173.

Stenberg, B., Viscarra Rossel, R.A., Mouazen, A.M., Wetterlind, J., 2010. Visible and near infrared spectroscopy in soil science. In: Sparks, D.L. (Ed.), Advances in Agronomy, pp. 163-215.

Sun, G., Ranson, K.J., Kimes, D.S., Blair, J.B., Kovacs, K., 2008. Forest vertical structure from GLAS: An evaluation using LVIS and SRTM data. Remote Sensing of Environment 112: 107-117.

Teich, I., Gonzalez Roglich, M., Corso, M.L., García, C.L., 2019. Combining Earth Observations, Cloud Computing, and Expert Knowledge to Inform National Level Degradation Assessments in Support of the 2030 Development Agenda. Remote Sensing 11: 2918.

Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment 8: 127-150.

United Nations Statistical Commission, 2012. System of Environmental-Economic Accounting 2012: Central Framework, United Nations, New York. https://unstats.un.org/unsd/envaccounting/seearev/Chapters/SEEA_CentralFramework_Ch5.pdf

UN, 2019. Using the SEEA EEA for Calculating Selected SDG Indicators. Working Document Draft Version: 31 October 2019.

UN Statistics Division, 2020. System of Environmental-Economic Accounting - Ecosystem Accounting. Draft for the Global Consultation on the complete document.

UNCCD, 2018. Default data: methods and interpretation. A guidance document for 2018 UNCCD reporting. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany.

UNHQ, 2015. Expert Group Meeting on the Indicator Framework for the Post-2015 Development Agenda. Available at: https://www.google.com.au/webhp?sourceid=chrome-instant&ion=1&espv=2&ie=UTF-8#q=sdg+spatial+disaggregation.

UN Statistical Commission, 2016. Metadata Goal 15. Available at: http://unstats.un.org/sdgs/files/metadata-compilation/Metadata-Goal-15.pdf.

Van Oost, K., Govers, G., Quine, T.A., Heckrath, G., Olesen, J.E., De Gryze, S., Merckx, R., 2005. Landscape-scale modeling of carbon cycling under the impact of soil redistribution: The role of tillage erosion. Global Biogeochemical Cycles 19.

van Wesemael, B., Paustian, K., Andren, O., Cerri, C.E.P., Dodd, M., Etchevers, J., Goidts, E., Grace, P., Katterer, T., McConkey, B.G., Ogle, S., Pan, G.X., Siebner, C., 2011. How can soil monitoring networks be used to improve predictions of organic carbon pool dynamics and CO2 fluxes in agricultural soils? Plant and Soil 338: 247-259.

Vaughan, H., Brydges, T., Fenech, A., Lumb, A., 2001. Monitoring long-term ecological changes through the Ecological Monitoring and Assessment Network: science-based and policy relevant. Environmental Monitoring and Assessment 67: 3-28.

Viscarra Rossel, R., Adamchuk, V., Sudduth, K., McKenzie, N., Lobsey, C., 2011. Chapter Five – Proximal soil sensing: an effective approach for soil measurements in space and time. Advances in Agronomy 113: 237–282.

Viscarra Rossel, R.A., Webster, R., Bui, E.N., Baldock, J.A., 2014. Baseline map of organic carbon in Australian soil to support national carbon accounting and monitoring under climate change. Global Change Biology 20: 2953-2970.

Viscarra Rossel, R.A., Chen, C., Grundy, M.J., Searle, R., Clifford, D., Campbell, P.H., 2015. The Australian three-dimensional soil grid: Australia's contribution to the GlobalSoilMap project. Soil Research 53: 845-864.

Viscarra Rossel, R.A., Hicks, W.S., 2015. Soil organic carbon and its fractions estimated by visible–near infrared transfer functions. European Journal of Soil Science 66: 438-450.

Viscarra Rossel, R., Brus, D., Lobsey, C., Shi, Z., McLachlan, G., 2016a. Baseline estimates of soil organic carbon by proximal sensing: Comparing design-based, model-assisted and model-based inference. Geoderma 265: 152–163.

Viscarra Rossel, R.A., Behrens, T., Ben-Dor, E., Brown, D., Dematte, J., Shepherd, K., Shi, Z., Stenberg, B., Stevens, A., Adamchuk, V., Aichi, H., Barthes, B., Bartholomeus, H., Bayer, A., Bernoux, M., Bottcher, K., Brodsky, L., Du, C., Chappell, A., Fouad, Y., Genot, V., Gomez, C., Grunwald, S., Gubler, A., Guerrero, C., Hedley, C., Knadel, M., Morras, H., Nocita, M., Ramirez-Lopez, L., Roudier, P., Rufasto Campos, E., Sanborn, P., Sellitto, V., Sudduth, K., Rawlins, B., Walter, C., Winowiecki, L., Hong, S., Ji, W., 2016b. A global spectral library to characterize the world’s soil. Earth-Science Reviews 155: 198–230.

Viscarra Rossel, R., Lobsey, C., Sharman, C., Flick, P., McLachlan, G., 2017. Novel soil profile sensing to monitor organic C stocks and condition. Environmental Science and Technology 51: 5630−5641.

Viscarra Rossel, R.A., Lee, J., Behrens, T., Luo, Z., Baldock, J., Richards, A., 2019. Continental- scale soil carbon composition and vulnerability modulated by regional environmental controls. Nature Geoscience 12: 547–552.

Verbesselt, J., Hyndman, R., Newnham, G., Culvenor, D. 2010. Detecting trend and seasonal changes in satellite image time series. Remote Sensing of Environment 114: 106-115.

Wang, J., Xiong, Z., Kuzyakov, Y., 2016. Biochar stability in soil: meta-analysis of decomposition and priming effects. GCB Bioenergy 8: 512-523.

Webster, R., 2007. Analysis of variance, inference, multiple comparisons and sampling effects in soil research. European Journal of Soil Science 58: 74-82.

Webster, R., Oliver, M.A., 2007. Geostatistics for Environmental Scientists, 2nd Edition. John Wiley & Sons, Ltd., England.

Wehmann, A. & Liu, D., 2015. A spatial–temporal contextual Markovian kernel method for multi-temporal land cover mapping. ISPRS Journal of Photogrammetry and Remote Sensing, 107, pp.77–89.

Weissteiner, C., Böttcher, K., Mehl, W., Sommer, S., Stellmes, M., 2008. Mediterranean-wide Green Vegetation Abundance for Land Degradation Assessment Derived from AVHRR NDVI and Surface Temperature 1989 to 2005. Luxembourg: European Commission-JRC (http://desert jrc ec europa eu/action/documents/CWeissteiner_GVF2008 pdf (Accessed January 2010)).

Wen, L., Yang, X., Saintilan, N. 2012. Local climate determines the NDVI-based primary productivity and flooding creates heterogeneity in semi-arid floodplain ecosystem. Ecological Modelling 242: 116-126.

Wendt, J.W., Hauser, S., 2013. An equivalent soil mass procedure for monitoring soil organic carbon in multiple soil layers. European Journal of Soil Science 64: 58-65.

Wessels, K. 2009. Letter to the editor: Comments on ‘Proxy global assessment of land degradation’by Bai et al.(2008). Soil Use and Management 25: 91-92.

Wessels, K.J., Prince, S.D., Malherbe, J., Small, J., Frost, P.E., VanZyl, D., 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. Journal of Arid Environments 68: 271-297.

Wessels, K.J., van den Bergh, F., Scholes, R.J., 2012. Limits to detectability of land degradation by trend analysis of vegetation index data. Remote Sensing of Environment 125: 10-22.

White, J.C., Wulder, M.A., Hobart, G.W., Luther, J.E., Hermosilla, T., Griffiths, P., Coops, N.C., Hall, R.J., Hostert, P., Dyk, A. and Guindon, L., 2014. Pixel-based image compositing for large-area dense time series applications and science. Canadian Journal of Remote Sensing, 40(3), pp.192-212.

Xie, Y., Sha, Z., Yu, M., 2008. Remote sensing imagery in vegetation mapping: a review. Journal of Plant Ecology, 1(1), pp.9–23.

Xu, L., Saatchi, S.S., Shapiro, A., Meyer, V., Ferraz, A., Yang, Y., Bastin, J.-F., Banks, N., Boeckx, P., Verbeeck, H., Lewis, S.L., Muanza, E.T., Bongwele, E., Kayembe, F., Mbenza, D., Kalau, L., Mukendi, F., Ilunga, F., Ebuta, D., 2017. Spatial Distribution of Carbon Stored in Forests of the Democratic Republic of Congo. Scientific Reports 7, 15030.

Yengoh, G.T., Dent, D., Olsson, L., Tengberg, A.E., Tucker III, C.J., 2015. Use of the Normalized Difference Vegetation Index (NDVI) to Assess Land Degradation at Multiple Scales: Current Status, Future Trends, and Practical Considerations. Springer.

Yin, G., Zhang, Y., Sun, Y., Wang, T., Zeng, Z., Piao, S., 2015. MODIS Based Estimation of Forest Aboveground Biomass in China. PLOS ONE 10, e0130143.

Yokelson, R.J., Susott, R., Ward, D.E., Reardon, J., Griffith, D.W.T., 1997. Emissions from smoldering combustion of biomass measured by open-path Fourier transform infrared spectroscopy. Journal of Geophysical Research 102: 18865–18877.

Yu, L., Wang, J., Gong, P., 2013. Improving 30 m global land-cover map FROM-GLC with time series MODIS and auxiliary data sets: a segmentation-based approach. International Journal of Remote Sensing, 34(16): 5851-5867.

Zhang, L., Dawes, W.R., Walker, G.R. 2001. Response of mean annual evapotranspiration to vegetation changes at catchment scale. Water Resources Research 37: 701-708.

Zhang, Y., Liang, S., Yang, L., 2019. A review of regional and global gridded forest biomass datasets. Remote Sensing 11: 2744.

Zhou, F., Zhong, D., 2020. Kalman filter method for generating time-series synthetic Landsat images and their uncertainty from Landsat and MODIS observations. Remote Sensing of Environment 239: 111628.

Appendices

Appendix A. Land Cover

A.1 Existing Land Cover Products

Land cover products developed and validated by the relevant national authorities will generally provide the most relevant data for the purpose of monitoring key land degradation processes in the context of the SDG 15.3.1 indicator. However, in some instances, the development of a national land cover product may not be possible. In such cases, various regional or global products provide a viable alternative. As stated in the land cover and land cover change sub-indicator chapter, the UNCCD has endorsed the use of the ESA CCI-LC as the global default land cover product, for use where there is no capacity to produce a national product or where more relevant data is not available.

A.1.1 National Land Cover Products

Many countries produce their own land cover mapping products that service both national and international reporting requirements. A number of these have been reviewed by Diogo and Koomen (2015) and are listed in Table A-1. which includes some recent updates. These data are considered to be preferable to global and regional products if they have been designed to include specific land cover types that better capture nationally significant land degradation processes. However, national land cover mapping products vary greatly in terms of the underlying data used, their spatial and temporal resolution, the classification algorithms employed, and the level of validation applied. In order for national land cover mapping approaches to best serve the need for monitoring SDG indicator 15.3.1, care should be taken to incorporate good practice in terms of legend definition, temporal range and frequency, spatial coverage and resolution, and accuracy, as described in the flow chart shown in Figure 3-4.

It may be useful to consider regional land cover products if the development of national land cover products are beyond the resources of an individual country. Two important regional datasets are discussed below and summarized in Table A-2.

- **CORINE Land Cover (CLC)**: The CLC product includes coverage of the European Union member states and other European countries. The product is based primarily on the manual interpretation of satellite imagery including Landsat, SPOT and Sentinel satellite program imagery. National land cover maps are assembled into a seamless European map, resulting in a complete and consistent dataset across Europe. The datasets are available in vector format with minimum spatial unit of 25ha. There are 44 classes defined and organised in three hierarchical levels, combining both land cover and land use concepts. These land cover maps are available for 1990, 2000, 2006, 2012 and 2018.

- **CLC accounting layers**: The CLC accounting layers cover 39 European countries: the 27 European Union member states, the UK and other European countries. The CLC products are based on visual or semi-automated interpretation of high-resolution multispectral satellite imagery by the national teams of the participating countries. National land cover maps are assembled into a seamless European CLC map, resulting in a complete and consistent dataset across Europe. The CLC accounting layers are derived from the CLC layers providing a statistically solid basis for time series analysis of land cover trends. There are 44 classes defined and organised in three hierarchical levels, combining both land cover and land use concepts. The accounting layers are available for 2000, 2006, 2012 and 2018.
- **North American Land Change Monitoring System** (NALCMS): The NALCMS is a 30m spatial resolution land cover product that extends across North America, and is based on MODIS, Landsat-7 and RapidEye satellite imagery. The classification legend includes 19 classes in three hierarchical levels, defined using the FAO's LCCS system. There are currently three time steps available for 2005, 2010 and 2015.

Table A-1. Summary of existing national land cover data available, as reviewed by Diogo and Koomen (2015).

Product	Measurement method	Reported accuracy	Geographical coverage	Spatial resolution	Time periods available	Thematic resolution
PNECO	Based on MODIS TERRA and LANDSAT TM satellite imagery	None	Argentina		2006-2007	Land cover (FAO-LCCS)
National Dynamic Land Cover	Based on MODIS EVI composites	None	Australia	250m	Every two years since 2001	Land cover (FAO-LCCS)
ALUM	AVHRR imagery, land use information and simulation of agricultural crops allocation	None	Australia		1992-1993, 1993-1994, 1996-1997, 1998-1999, 2000-2001, 2001-2002, 2005-2006, 2010-2011, 2015-2016	Land use (ALUMC)
Mapeamento Sitemático do Uso da Terra	Based on Landsat ETM+ satellite imagery	None	Brazil (mosaics, incomplete)		2003 and 2007, but not for all mosaics	Land use (inspired in CORINE)
Land Cover of Canada	Based on AVHRR satellite imagery	None	Canada (merged with Vegetation Map of Alaska dataset)	1km	1998	Land cover (Alaska Interim)
Canada Land Cover circa 2000	Based on Landsat 5 and Landsat 7 satellite imagery	None	Canada	Not reported. Based on data with 30m resolution	2000	Land Cover (EOSD)
Catastro de los Recursos Vegetacionales Nativos de Chile	Initially based on panchromatic aerial photography, currently based on SPOT 5 and FORMOSAT-2 satellite imagery	None	Chile (mosaics of 15 regions)		1997, 2001, 2007 and 2011	Land cover, land use, property rights, forest category, forest establishment and reforestation, biomass, carbon, forest fires, forestry resource extraction
China Land Cover	Based on Landsat TM/ETM satellite imagery	None	China		1990, 1995, 2000, 2005, 2008	Land cover and land use (unknown classification)
National Land Numerical Information	Based on Landsat, TERRA and ALOS satellite imagery	None	Japan (1km mosaics)	100m (1/10) mesh	1976, 1987, 1991, 1997, 2006 and 2009	Land use (classes differ per year)
Uso del Suelo y Vegetacion	1976: aerial photography interpretation. 1993, 2000 and 2007: based on Landsat TM satellite imagery	None	Mexico		1976, 1993, 2000 and 2007	Land cover (IFN2000)
LUCAS LUM	Based on Landsat and SPOT satellite imagery	2012: 95%	New Zealand	Not reported. Based on data with the following resolution: 1990 – 30m 2008 – 10m 2012 – 10m	1990, 2008, 2012, 2016	Land cover (FAO-LCCS)
National Land Use and Cover		-	South Africa		-	Land use (CSDM)
Land Categories Map of the U.S.S.R.	Compilation of different sources from land cadastre inventory	None	Former U.S.S.R.		1991	Land cover (IIASA-LUC Former U.S.S.R.)
National Land Cover Database	Based on Landsat TM satellite imagery	2001:79% 2006: 78%	United States	30m	1992, 2001, 2006, 2011, 2013 and 2016	Land cover (modified Anderson LCCS)

Good Practice Guidance | SDG Indicator 15.3.1 122

Table A-2. Summary of existing regional land cover data available, reviewed by Diogo and Koomen (2015) and updated to current status.

Product	Measurement method	Reported accuracy	Geographical coverage	Spatial resolution	Time periods available	Thematic resolution
CORINE Land Cover	Based on SPOT, Landsat, Sentinel satellite imagery, complemented with ancillary data available at the country level	2000: 87%	EU-28, Albania, Bosnia and Herzegovina, Macedonia, Iceland, Kosovo Liechtenstein, Montenegro, Norway, Serbia, Switzerland, and Turkey	1:100,000 (vector) or 100m (raster)	1990, 2000, 2006. 2012, 2018	CORINE Land Cover
North American LCMS	Based on MODIS, Landsat-7, RapidEye satellite imagery	Canada 2005: 59%-69%	Canada, Mexico and the United States	30m and 250m	2005, 2010 and 2015	Land cover (FAO-LCCS)

A.1.2 Global Land Cover Products

A review of land cover data conducted by Diogo and Koomen (2015) included 27 global, regional and national land cover datasets. It looked at source data, spatial resolution, time periods available, accuracy, geographic extent and the classification system employed. The following conclusions were considered relevant to selecting the most appropriate data for identifying land cover change:

- Land cover data with a reasonable continuity of regular epochs should be preferred as there is more impetus and demonstrated capability to continue generating these into the future.
- Country-specific data benefits from the knowledge of local experts, including the generation of legends which are appropriate at the national scale.
- Higher spatial resolution is generally preferred in order to capture finer scale land cover change such as urban expansion and other landscape fragmentation.

A list of global land cover datasets is shown in Table A-33. Some practical limitations of these products are outlined below:

- **CCI-LC**: The ESA Climate Change Initiative (CCI) Land Cover dataset provides 22 land cover classes defined using the LCML, at 300 m resolution based on 300m MERIS, 1 km Spot vegetation, 1 km Proba-V and 1 km AVHRR data. Annual updates of the CCI-LC product are currently available from 1992 to 2019. Additional years will be made available as soon as they are finalized by ESA.

- **CGLS-LC100**: The Copernicus Global Land Service provides an annual dynamic global Land Cover product at 100 m spatial resolution.[93] The CGLS-LC100 provides 23 land cover classes at three classification levels with class definitions according to the LCCS scheme. The product also includes continuous field layers or "fraction maps" that provide proportional estimates for vegetation/ground cover for the land cover types. The CGLS-LC100 provides yearly change detection and global, regional and national land cover and land cover change statistics can be obtained from the interactive viewer.[94] The data has been produced yearly from 2015 to 2019, with processing based on Proba-V data - and includes per pixel quality layers and reliability of change relative to the previous year. Note that Proba-V will soon be decommissioned, and fully compatible continuation mapping will be based on Sentinel 1 and 2 imagery. CGLS includes a global validation program and the overall accuracy of the CGLS-LC100m V2.0 discrete global land cover map is 80.2% +/-0.7%.

- **GLC-SHARE**: The GLC-SHARE is a 1 km resolution global land cover product created by FAO's Land and Water Division in partnership with various partners and institutions (Latham et al. 2014). The product is derived from a broad set of combined and harmonized products, including national, regional and global land cover datasets. For this reason, it is not attributed to a specific date, but derived from products produced over a date range (2000-2014). Thus, it provides a useful baseline from which land cover change might be measured, as opposed to being a dynamic product that can be used to determine change itself.

- **FROM-GLC**: The Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) dataset is a 30 m resolution global land cover map produced using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imagery, with source data centred around 2006 (Gong et al. 2013). While there is significant value in increasing the spatial resolution of land cover mapping, this can have implications for classification accuracy (Yu et al. 2013). As with GLC-SHARE, the FROM-GLC product is not regularly updated and thus may provide a useful baseline but requires additional product epochs to be generated in order to monitor change.

- **GLC-FCS30**: The GLC-FCS30 is a 30 m resolution global land cover map which used the same 30-class legend as the CCI-LC. with a fine classification system produced by combining time-series of Landsat imagery and high-quality global training data from the GSPECLib (Global Spatial Temporal Spectra Library; Liu et al., 2020). Now, the datasets for 2000 and 2015 are ready for use, and it would be regularly updated.

- **MODIS Land Cover**: The MODIS land cover product is generated using a supervised artificial neural network classification and decision tree classifier, exploiting a global database of training sites interpreted from high-resolution Landsat TM imagery in association with ancillary data (Friedl et al. 2002). The latest collection of the products (Collection 6[95]) includes processes to reduce year-to-year variability not associated with land cover change due to poor spectral–temporal separability in MODIS data (Friedl et al. 2010). MODIS land

[93] https://land.copernicus.eu/global/products/lc
[94] https://lcviewer.vito.be/2015
[95] https://lpdaac.usgs.gov/documents/101/MCD12_User_Guide_V6.pdf

cover products use the International Geosphere–Biosphere Programme (IGBP) classification system[96] and are available for every year from 2001 to the present at 500m spatial resolution.

Table A-3. Summary of existing global land cover data products adapted from Diogo & Koomen (2015).

Product	Measurement method	Reported accuracy	Geographical coverage	Spatial resolution	Time periods available	Thematic resolution
CCI-LC	Based on AVHRR, SPOT, PROBA-V and Sentinel-3 satellite imagery	74%	Global (aggregated dataset)	300m	Every year from 1992 to 2018	Land cover (FAO-LCCS)
CGLS-LC100	Based on Sentinel 1 and 2 satellite imagery	80%	Global (aggregated dataset)	100m	Every year from 2015 to 2019	Land cover (FAO-LCCS)
Global Land Cover Characterization	Based on AVHRR satellite imagery	81%-90% (training data)	Global (aggregated dataset)	10, 8 and 1km	Only available for 1984	Land cover (IGBP)
Global Land Cover Classification (GLCC)	Based on AVHRR satellite imagery	65%-82%	Global (aggregated dataset)	1 km	Only available for 1992-1993	Land cover (IGBP)
GLC 2000	Based on SPOT 4 satellite imagery	66%- 69%	Global and regional (aggregated dataset)	1 km	Only available for 2000	Land cover (FAO-LCCS)
MODIS Land Cover	Based on MODIS satellite imagery	2005: 75%	Global (mosaics and aggregated dataset)	500m, 0.05 degree (aggregated global dataset)	Every year between 2001-present	Land cover (IGBP)
SYNMAP	Merging of GLCC, GLC 2000 and MODIS 2001	-	Global (aggregated dataset)	1km	Only available for (circa) 2000	Land cover (SIMPLE)
GlobCover	Based on MERIS satellite imagery	2005: 73% 2009: 68%	Global (aggregated dataset)	300m	2005 and 2009	Land cover (FAO-LCCS)
Global Land Survey	Satellite imagery collected from Landsat sensors	-	Global (mosaics)	30m	1975, 1990, 2000, 2005 (LTCCF and LFCC only available for 2000 and 2005)	HR satellite imagery, tree cover, forest cover change
FROM-GLC 30m	Based on Landsat TM/ETM+ satellite imagery	64%-66%	Global (mosaics)	30m	Only available for 2006	Land cover (compatible with IGBP and FAO- LCCS)
GlobLand30	Based on Landsat TM/ETM+ and HJ-1 satellite imagery	2010: 79%	Global (mosaics)	30m	2000 and 2010	Land cover (GlobLand30 legend)
GLC-Share	Harmonisation of national, regional and global databases	80%	Global (aggregated dataset)	30 arc-second (~1km)	-	Percentage of each land cover per grid cell and dominant land cover (SEEA)

[96] http://www.igbp.net/

New and emerging data and methods such as the CEOS Open Data Cube (Rizvi & Killough, 2018) algorithms using these global datasets or products are now becoming available. They specifically address the "land cover" sub-indicator by classifying the land type at every pixel (6-class IPCC system) and comparing the change in this classification between two time periods.

Appendix B Land Productivity

B.1 Land productivity indices

A large number of land productivity indices and datasets are available for use by countries, and new ones are emerging as datasets and processing methods evolve. Some of these may be more suitable for use in certain countries than others. This section describes some of the more commonly used alternatives to NDVI.

Note that, ideally, productivity indices should be calculated from image data that have been processed to surface reflectance, which minimises the influence of atmospheric, illumination and detector sensitivity variations on pixel values. Image data that are not calibrated to surface reflectance are more likely to introduce errors into the land productivity assessment within each image by changing the relative brightness of bands in each image, and also over time as the magnitude of these sources of error varies between growing seasons.

B.1.1 Normalised Difference Vegetation Index (NDVI)

The most widely used and best known index which estimates NPP is the NDVI(NDVI; Tucker 1979) which is recommended for use in the WAD method. The NDVI is a normalized ratio of near infra-red (NIR) wavelengths centred around 800 nm (Equation B-1) which are typically strongly reflected by live green vegetation, and red wavelengths centred around 650 nm which are within the photosynthetically active range of the spectrum and typically strongly absorbed by chlorophyll in live green vegetation. The NDVI is the minimum required standard index for countries to use in the absence of evidence to indicate that an alternative index is likely to be more accurate.

The general formula is:

$$NDVI = \frac{NIR \quad red}{NIR + red}$$

Equation B-1

NDVI values are unit-less and range from -1 to +1, with higher values indicating higher levels of green biomass and/or plant growth vigour.

NDVI response is well understood for a wide range of land cover and biomass conditions. It can be calculated from most EO satellite image datasets, including those with the longest archive of imagery such as the Landsat and AVHRR series. By comparing spectral bands within each image, the NDVI minimizes artefacts from a range of sources that typically introduce errors into EO imagery, including topographic shading effects, atmospheric and illumination conditions, which improve the consistency of NDVI data across large areas.

The NDVI is currently recommended as the standard vegetation index to use in assessing SDG Indicator 15.3.1 in the absence of information indicating that an alternative index is likely to be more accurate[97]. The main limitations of the NDVI are that it can be sensitive to variations in soil

[97] http://earthobservations.org/documents/ldn/20200703_GEOLDN_TechnicalNote_FINAL_SINGLE.pdf

background conditions, and that it has a tendency to saturate at high vegetation cover and biomass levels. This can reduce the accuracy of NPP, biomass and cover models in tropical rainforest or arid regions. Several alternative vegetation indexes can be calculated from image data, many of which have been shown to be effective surrogates for fAPAR and highly correlated with NPP in a range of landscapes. Some of these alternative indices may be more suited to productivity assessments in certain countries than the NDVI.

B.1.2 MODIS MOD17A3 Global NPP Model

The MODIS MOD17A3HGF data product (hereafter referred to as MODIS NPP) estimates the annual change in kilograms of carbon per square metre, averaged at 500 m pixel resolution, integrated over each calendar year since 2000 (Running et al. 2004; Running and Zhao 2015). This is the only global, annually updated NPP dataset that is currently available. The use of this dataset simplifies the process of properly quantifying productivity, and this dataset has been used to convert NDVI to NPP units in several studies (Yengoh et al. 2015). However, there are a range of trade-offs with this dataset that make calculating growing season productivity from a time series of vegetation indices images the preferred option.

The MODIS NPP model converts indices of fAPAR to estimated NPP using modelled parameters describing vegetation conversion efficiency (Ɛ) and climatic conditions (Running et al. 2004). This includes a range of indicators and estimated parameters that have been calibrated to match global conditions (Running and Zhao 2015). The uncertainties in each of the parameters accumulate in the model, and the data may not accurately represent local conditions at any particular location.

Several studies have also demonstrated improved accuracy in relation to field validation data when satellite productivity observations are aggregated over all or part of the growing season rather than over the full year (Fensholt et al. 2013; Ma et al. 2015). For instance, the calendar year may split growing seasons in some regions, particularly the summer growing season in the southern hemisphere temperate regions.

B.1.3 Enhanced Vegetation Index (EVI)

One of the potential limitations of the NDVI is that it may be insensitive to changes in biomass or foliar coverage where the leaf area index (LAI), defined as half the total intercepting area per unit ground surface area (Chen and Black 1992), is high. Estimates of the LAI at which loss of sensitivity of NDVI occurs range from two (Carlson and Ripley 1997) to five (Schlerf et al. 2005).

The tendency to saturate in high biomass areas, and the potential sensitivity of NDVI to variations in the brightness of the background material are addressed in the EVI (Equation B-2; Huete et al. 2002; Huete 1988):

$$EVI = G\frac{NIR - red}{NIR + C1 \times red - C2 \times blue + L}$$

Equation B-2

Where **L** is the canopy background adjustment that addresses nonlinear differential NIR and red radiant transfer through a canopy, and $\mathbf{C}_1$, $\mathbf{C}_2$ are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the EVI algorithm are, **L**=1, $\mathbf{C}_1$=6, $\mathbf{C}_2$=7.5, and **G** (gain factor)=2.5 (Huete et al. 2002). The EVI is also provided on the MODIS MOD13Q1 dataset.

While the EVI may have some advantages under certain conditions (Huete et al. 2006), the inclusion of the blue band prevents it being calculated from several global datasets, including the AVHRR which has the longest archive of historical global data coverage. In addition, the low signal to noise ratio of the blue band can increase error in NPP estimates (Jiang et al. 2008). Improvements in atmospheric correction methods, which reduce apparent noise levels in the blue wavelengths, mean that its importance for calibrating EVI measurements is decreasing over time, and a 2-band EVI (known as EVI2, Equation B-3) using only the red and NIR bands has been proposed (Jiang et al. 2008):

$$EVI2 = 2.5\frac{NIR - red}{NIR + 2.4red + 1}$$

Equation B-3

EVI2 is available as an annual 5.6 km resolution product via NASA's Making Earth Science Data Records for Use in Research Environments (MEaSUREs) program.[98] In their review of the comparability between NDVI and EVI for land productivity monitoring, Yengoh et al (2015) suggest that as a surrogate for photosynthetic capacity, as opposed to biomass or LAI, NDVI is preferred over the EVI because it is more directly related to fAPAR and has fewer factors, which simplifies and facilitates calculation from a larger range of satellite image datasets.

A recent unpublished study (Markos et al. in press) demonstrated that the EVI2 responds more rapidly to changes in moisture availability than the NDVI, which makes the EVI2 a more suitable index to use as a basis for climate calibration, particularly for the WUE transformation. A recent study comparing the performance of a range of vegetation Indices to FLUXNET observations (Huang et al. 2019) indicated that the performance of all vegetation indices was improved following BRDF correction, which minimises impacts on apparent pixel values due to differences in sun and sensor position and the reflecting terrain. They concluded that even though the EVI2 contains the same information as NDVI, the EVI2 was less sensitive to soil darkening and had the best performance in estimating GPP at the monthly scale among the traditional vegetation indices (Huang et al. 2019).

B.1.4 Fractional Cover Models

Another alternative to spectral indices are fractional cover products, which are becoming increasingly available at national and global scales (Guerschman et al. 2009; Guerschman et al. 2015; Hill and Guerschman 2020; Weissteiner et al. 2008). These products use the spectra of bare soil, photosynthetic vegetation and non-photosynthetic vegetation to calculate the proportion of these land cover types in each image pixel using an 'unmixing' method. Fractional cover products have an advantage over spectral indices, such as NDVI, in that the fractional cover products can report the proportion of non-photosynthetic vegetation in each pixel, to which the NDVI is not sensitive.

[98] https://lpdaac.usgs.gov/dataset_discovery/measures

Considering both the photosynthetic and non-photosynthetic components of the vegetation cover has proven beneficial for assessing the protection of the soil to erosion processes.

Although a global fractional cover product is available at 500 m resolution from 2000 to present (Guerschman 2014), this product has not yet been properly validated outside of Australia. Potential sources of bias in these products include cover types being defined by spectral models that may not be representative of cover conditions in all regions, and the cover estimates being based on field measurements of the proportion the cover types which may be subject to measurement error.

B.2 Climate calibration

There is considerable debate in the scientific community around whether impacts from climate variability should be considered land degradation, or whether land degradation should be considered only when driven by direct human impacts such as land use and management activities. Some researchers suggest that calibrating for climate impacts is unnecessary, as any significant reduction in productivity, regardless of its driving factors, should be interpreted as degradation. Others feel that minimizing the influence of climatic factors on productivity time series is essential to identify the human factors contributing to productivity degradation. Section 4.1.3 in the IPCC report on Climate Change and Land (Olsson et al. 2019) provides a comprehensive overview of the different arguments in the debate.

Separating the influence of moisture availability in NPP time series datasets is a significant technical challenge, and one of the most contentious areas of research associated with this analysis. The approach taken in this report is that both the calibrated and uncalibrated time series are potentially useful. The climate calibrated time series may highlight areas where land degradation is being driven primarily by 'direct' human impacts such as land clearing or land cover conversion, whereas the uncalibrated time series may highlight responses to climate variability and long-term change. Furthermore, a comparison of calibrated and uncalibrated time series may reveal additional information about the condition of vegetation in degraded areas (see Section B.2.7). We think this information may be of interest for land use planning to avoid future degradation and to optimise response and mitigation actions.

Variations in plant productivity occur over a range of spatial scales and time frames, and from a wide range of drivers. These range from natural disasters (localised and rapid), land use practices (localised and progressive), seasonal phenological cycles (annual and regional) and climate change (global and progressive). The factors influencing long-term productivity levels vary from place to place and over time, and productivity levels in certain regions are more susceptible to influence from some factors than to others.

In many regions, variations in NPP are highly correlated with differences in moisture availability, especially in semi-arid areas where water is the main limiting growth factor (Fensholt and Rasmussen 2011; Ivits et al. 2016; Wen et al. 2012; Wessels et al. 2007). One processing option that may assist with the interpretation of degradation is to calibrate the time series observations to minimize the influence of moisture availability and highlight the direct human-induced changes in NPP. Minimizing the influence of climatic factors on time series measurements of productivity can help to identify the relative importance of climatic versus human factors as drivers of degradation.

However, determining the best methods of climate calibration is a contentious and challenging issue.

Several methods to calibrate time series images to minimize the influence of climatic or seasonal factors are available, each of which may be suitable only in certain vegetation types, climatic regions or for detecting only certain types or magnitudes of degradation. Climate correction methods typically attempt to calibrate NPP in relation to the total amount of rainfall in each growing season. However, NPP outcomes for a given rainfall level may also be influenced by temporal differences in precipitation during the growing season, soil type and topography, amongst other factors (Kumar et al. 2002). These factors vary at different rates and spatial scales, and some are better represented in existing datasets than others. Comprehensive correction for all these factors may require sophisticated modelling approaches that are not described in this document.

Some of the most commonly used and best developed methods are presented below. Datasets showing results from several of these climate calibration processes are available globally, and as national subsets, for the period from 1981 to 2003 from the FAO's Global Assessment of Land Degradation and Improvement website.[99] These may be suitable where it is not possible to calculate these indices at national scales. A detailed review of the application and limitations of additional calibration methods is provided by Higginbottom and Symeonakis (2014).

B.2.1 Rainfall Use Efficiency

Rainfall use efficiency (RUE) is the ratio of annual NPP to precipitation (Le Houerou 1984). Accounting for RUE can improve the comparability of annual NPP measurements between years and between locations where NPP may be limited by variations in local rainfall. RUE correction is only appropriate in water-limited regions where there is a positive correlation between rainfall and NPP (Wessels 2009). Areas that should be masked from this analysis include agriculture and urban areas where productivity is related to management activities (e.g., fertilizer and irrigation) rather than limited by water availability (Bai et al. 2008).

RUE relationships may break down in regions of very high rainfall where factors other than water are growth limiting, in areas with very low cover where evaporation consumes most rainfall (Fensholt et al. 2013), or where the vegetation cover is so low that growth response is insufficient to register a significant change in the chosen productivity index.

B.2.2 Residual Trends (RESTREND)

RESTREND (Evans and Geerken 2004; Wessels et al. 2007) is a development of the RUE method that uses linear regression models to predict an NDVI for a given rainfall amount. RESTREND calculates a linear model between the natural log of annual rainfall and annual NPP estimates based on the observation that vegetation productivity typically reaches a plateau in years with very high rainfall beyond which it does not increase (Hein et al. 2011; Milich and Weiss 2000). Trends in the difference between the predicted NDVI and the observed NDVI (the residual) are interpreted as non-climatically related productivity change (Wessels et al. 2012). This is illustrated in Figure B-1.

[99] http://www.fao.org/geonetwork/srv/en/main.search?any=glada

Subsequent analysis of the sensitivity of RESTREND to land degradation using simulated data (Wessels et al. 2012) indicated that it is difficult to detect degradation using RUE or RESTREND where there is a positive trend in precipitation. RESTREND is best suited to detecting extreme and rapid degradation resulting in differences between the predicted and observed sum of the growing season NDVI (∑NDVI) of around 20-40%. RESTREND was also determined to be unreliable when ∑NDVI is reduced by 20% or more because the relationship between ∑NDVI and rainfall breaks down as a result of significantly reduced vegetation cover (Wessels et al. 2012). Additionally, both RUE and RESTREND can fail to detect land degradation where rainfall is variable over time (Wessels et al. 2012).

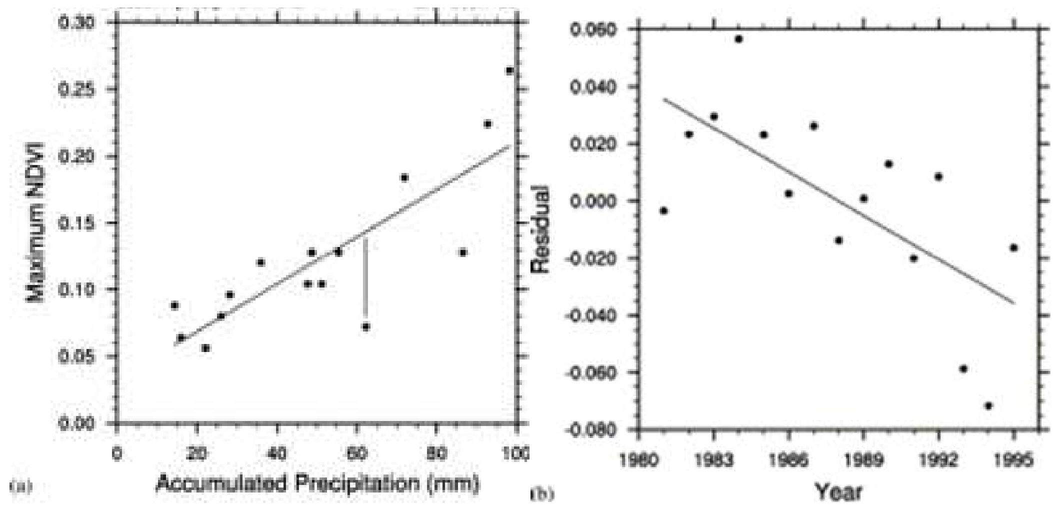


Figure B-1. Linear regressions between (a) accumulated precipitation and the maximum NDVI – the residual is illustrated by the line, and (b) the temporal trend of associated residuals (source Evans and Geerken 2004).

B.2.3 Relative RUE

Relative RUE (rRUE; del Barrio et al. 2010) increases the applicability of RUE to a wider range of climatic zones. This method involves rescaling NDVI observations to match the historical range of NDVI values within climatic aridity zones (Equation B-4).

$$rRUE_{me} = \frac{RUE_{OBS\_me} - RUE_{EXP\_me\_P05}}{RUE_{EXP\_me\_P05} - RUE_{EXP\_me\_P95}}$$

Equation B-4

rRUE reports the position of the observed RUE-corrected NDVI within the range of NDVI values observed across the full time series within each climatic zone. *rRUE* can be implemented with a freely available R package (r2dRue).[100]

The *rRUE* method simplifies the application of RUE methods across large areas which may have varying climatic conditions, yet is sensitive to changes in the range of observations in the time series. The addition of new data may cause a rescaling of the potential data range. In addition, the

[100] https://r-forge.r-project.org/R/?group_id=752

occurrence within land units of locations receiving extra water, such as irrigated crops, will inflate the range of values indicating maximum vegetation performance within that region, which may lead to an underestimation of the productivity in other similar regions. This is likely to occur more frequently in developing countries where conversion of lands to irrigation is generally higher.

B.2.4 Calibration against a Reference Site

Helman et al. (2014) compared RESTREND results over three dryland sites with known land use and degradation conditions, and similar climatic, topographic, edaphic and vegetation characteristics using MODIS NDVI data. There was a significant negative trend in RUE for all sites but no significant trends were identified using RESTREND. While each site had a unique RUE characteristic, they concluded that a decreasing trend of RUE in the assessment sites was only revealed by comparison of NDVI trends against the control site.

The use of control or 'reference' sites to aid interpretation of conditions at test sites may require normalization and rescaling of NPP time series to correctly identify trends in productivity over time (Sims and Colloff 2012). Ideally, control sites should contain identical vegetation communities and occur in the same bioclimatic region as the test sites, with the prime difference between the control and test sites being the land use type or intensity. In practice, ideal control sites do not exist, and the sensitivity of this method is usually limited by differences in vegetation characteristics, or by slight differences in the timing and magnitude of rainfall between the reference and test sites.

B.2.5 Time Series Decomposition

Seasonal Decomposition of a Time Series by Loess (STL): Time series decomposition is a statistical method that deconstructs a time series into the underlying categories of patterns. STL[101] (Cleveland et al. 1990), available in R, decomposes time series into three components:

1. Seasonal, which is the underlying cycle of variation occurring over a certain period within the time series, such as annual phenological cycles;
2. Trend, which is revealed by subtracting the seasonal component from the original time series;
3. Remainder, which shows the proportion of variation in the original time series that is truncated by the Loess smoothing process.

Jacquin et al. (2010) applied STL to non-smoothed and non-filtered MODIS NDVI time series data and a dataset of NDVI values accumulated over the growing season data over the Madagascar savannah. STL was found to be useful for identifying the start and end of the growing season, and for indicating the overall trend of NDVI decline over their study period. They interpreted their results in the context of local rainfall information rather than by transforming the data to minimise climatic influences *per se*.

Breaks for Additive Seasonal and Trend (BFAST): BFAST (Verbesselt et al. 2010) is based on STL and includes tools to indicate departures from the long term trend. BFAST uses an ordinary least squares, residuals-based moving sum (MOSUM) test to identify whether one or more breakpoints are

[101] http://stat.ethz.ch/R-manual/R-devel/library/stats/html/stl.html

occurring in a time series. At broad scales, the breaks identified in BFAST analysis tend to occur in grasslands rather than forests because of the more pronounced and rapid growth responses of grasses compared to deep rooted tree species. BFAST can also be sensitive to changes in the time series provided, e.g., reanalysing a time series with the addition of a few recent data points can result in a repositioning of the breaks identified throughout the time series. While BFAST has been explored for degradation assessment (DeVries et al. 2015), its suitability for this application requires further investigation.

B.2.6 Water Use Efficiency (WUE)

The method that appears to provide the most consistent representation of productivity responses to moisture availability across the widest range of land cover types is Water Use Efficiency (WUE: Ponce-Campos et al. 2013). One of the assumptions in many RUE-based methods is that all of the rainfall in a given region is available for assimilation by plants. The hydrological cycle includes significant losses, however, including surface runoff of excess water, groundwater recharge and evaporation which influences the proportion of rainfall that is available for use by plants. WUE incorporates these losses by calculating the ratio of NPP to evapotranspiration (ET), defined as precipitation minus the water lost to surface runoff, recharge to groundwater and changes to soil water storage.

ET observations should be integrated from the time series data over the same period as the productivity observations each year (iET). Ponce-Campos et al. (2013) integrated their measurements over the calendar year, which may be appropriate for regions where plant productivity exhibits a unimodal and mid-year maximum.

The method for calculating WUE corrected NPP (NPP_w) per year is:

$$iNPP_w = \frac{iNPP}{iET}$$

Equation B-5

Ponce-Campos et al. (2013) demonstrate a near linear relationship between NPP and ET across grassland and forest biomes in the United States, Puerto Rico and Australia. The main limitation on the accuracy of WUE calibration is likely to be the availability and accuracy of the evapotranspiration data. Ponce-Campos et al. estimated ET using a model developed by Zhang et al., (2001) which computes mean annual evapotranspiration from changes in annual precipitation and the percentage of forest cover. However, a range of alternative global ET datasets are available including:

1. Global 8-day evapotranspiration data from MODIS, based on the Penman-Monteith equation[102]
2. The GLEAM datasets[103] which are based on microwave remote sensing and calculate evapotranspiration using the Priestly and Taylor model
3. Global annual and monthly potential evapotranspiration,[104] which is modelled using the WorldClim database[105] at approximately 1km spatial resolution.

[102] http://www.ntsg.umt.edu/project/mod16
[103] http://www.gleam.eu/

A recent unpublished study (Markos et al. in press) has demonstrated that Peak NDVI typically lags peak EVI by about one month, and the faster response of EVI to water availability compared to NDVI improves the correlation between EVI-derived NPP and evapotranspiration for the purpose of water use efficiency calculation.

B.2.7 Comparing NPP and WUE time series

The definition of land degradation for SDG Indicator 15.3.1 does not distinguish between anthropogenic, climatic or biotic drivers of degradation. The NPP time series retains the influence of drought and the effects of climate change, whereas these impacts are reduced in the WUE time series which highlights more direct anthropogenic impacts such as changes in land use activities. The view of this GPG is that calculating both the NPP and WUE time series may provide the ability to apportion land degradation impacts from these different drivers, which may help to identify the appropriate remediation activities and their success (see Sims et al. 2020).

In general, an increase in NPP may be interpreted as an improvement in plant condition, provided the increase is not associated with a negative transition in land cover type. Similarly, an increase in WUE indicates an increased efficiency of converting available water to biomass which may be interpreted as improved physiological functioning. A positive correlation between increasing WUE and NPP might indicate efficient agricultural practices, for instance, whereas concordant negative trends might indicate inefficient land management, or be an early indicator of a reduction in ecosystem functional integrity. A loss of NPP accompanied by an increase in WUE may reveal a process of adaptation to a drying climate, or as an increase in ecosystem resilience despite large-scale altered hydroclimatic conditions (Ponce-Campos et al. 2013).

For the purposes of the GPG, the NPP time series integrates greater impacts from climatic variations, whereas these effects are less prominent in the WUE time series, which may respond more to impacts from land use and management practices. The relative magnitude of change in both the NPP and WUE time series may therefore indicate the relative significance of climatic versus anthropogenic drivers of changes in land productivity. In practice, the correlation between WUE and NPP is highly variable and often low and/or negative. The interpretation of the correlation between these time series requires further investigation, and must always be interpreted in the context of other information describing the main drivers of changes in land productivity for a given area.

B.3 Image datasets and selection considerations

The NDVI and EVI2 indices can be calculated from any Earth observing satellite sensors that include a red and near Infrared band, and many datasets that are available for free or at very low cost are well-suited to assessing land productivity at local, national and global scales (Table B-1). While sensors such as Landsat 8 Operational Land Imager (OLI) and Sentinel 2 Multi Spectral Imager (MSI) are ideal for productivity assessment at national scales, their relatively recent launch means that their archive of historical images is limited and may not be suitable for calculating baseline conditions. Some guiding principles for selecting image datasets are provided in Table B-2.

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[104] http://www.cgiar-csi.org/data/global-aridity-and-pet-database
[105] http://worldclim.org/

Table -B-1. Low or no-cost satellite sensors and data streams utilized for land surface phenology studies (modified from [106]).

Sensor	Satellite	Revisit period	Data Source	Data Record	Spatial Resolution(s)	Time Step
AVHRR	NOAA series	Daily	USGS/EROS	1989-present	1 km	1-week, 2-weeks
AVHRR	NOAA series	Daily	GIMMS 3g http://ecocast.arc.nasa.gov/data/pub/gimms/3g.v0/	1982-2015	8 km	Twice monthly
AVHRR/ MODIS	-	Daily	VIP30 (EVI2)	1981-2014	5.6 km	Monthly
Vegetation	SPOT 4 & 5	1-2 days	Copernicus Global Land Service http://land.copernicus.eu/global/products/ndvi	1999-2014	1.15 km	10-day
PROBA-V	PROBA-V	1-2 days	Copernicus Global Land Service http://land.copernicus.eu/global/products/ndvi	2014-2020	333m and 1km	10-day
MODIS	Terra	1-2 days	MOD17 (NPP and GPP)	2000 - present	500 m	Annual
MODIS	Terra/ Aqua	1-2 days	MOD13 vegetation indices (NDVI and EVI)	2000-present	250 m, 500 m, 1 km	8-day, 16-day
VIIRS	Suomi NPP	Daily	NOAA CLASS VIIRS Land Team (nasa.gov)	October 2011-present	375-750m	Daily to yearly composites
MSS	Landsat 1-5	18 days	USGS/EROS	1972-1992	79 m	Distributed by scene
PanMux/ MUXCAM	CBERS 3 & 4	>3 days	http://www.dgi.inpe.br/CDSR/	Oct 1999 - present	5-20 m	Distributed by scene
TM	Landsat 4-5	16 days	USGS/EROS	1982-2011	30 m	Distributed by scene
ETM+	Landsat 7	16 days	USGS/EROS	1999-present	30 m	Distributed by scene
OLI*	Landsat 8	16 days	USGS/EROS	Feb 2013-present	30 m	Distributed by scene
Sentinel 2	Sentinel 2A and 2B	5 days (from March 2017)	https://sentinel.esa.int/web/sentinel/home	Jun 2015-present	10 m – 20 m (VIS, NIR & SWIR)	Distributed by scene
Sentinel 3	Sentinel 3	1-2 days	https://sentinel.esa.int/web/sentinel/technical-guides/sentinel-3-olci	Oct 2016 - present	300 m	Distributed by Scene

*Due to the relatively recent launch of these satellites their archive of historical images may not be sufficient to calculate baseline conditions.

[106] https://phenology.cr.usgs.gov/ndvi_avhrr.php

Table B-2. Guiding principles for image dataset selection

Attribute	Recommendation
Revisit period and time series length	Image datasets that observe the same location over time are required to assess the change in land productivity over time. The revisit period is the frequency at which the sensor observes the same location on earth. A shorter revisit period provides a greater opportunity to capture transient features such as peak biomass, the onset of increased growth and the rates of productivity change at the commencement and cessation of the growing period. More frequent observations also increase the opportunity of collecting cloud-free images of the Earth's surface. The length of the time series is another key parameter. Image datasets with long archives of frequently collected and well calibrated imagery provide the most consistent basis to assess change over time.
Coverage and spatial resolution	Pixels integrate the spectral characteristics of the target area over a spatial extent. Large pixels (coarse spatial resolution) represent average conditions over a larger land area, which may not be desirable in landscapes with very complex or heterogeneous structures. Smaller pixels (finer spatial resolution) can represent objects in more detail to show the distribution of features of interest, which can improve the accuracy and representativeness of area measurements, especially in spatially complex landscapes. Smaller pixels can present some additional challenges, however. Significantly higher image registration and GPS accuracy is required to correctly locate field sample locations in higher resolution imagery. Accurately locating your position in an image requires that the sum of the spatial errors in image registration and position location devices (GPS) should be less than 1 pixel. For a given spatial extent on the ground, large pixels also result in a smaller dataset than the same area imaged at finer spatial resolution.
Spectral resolution	The number of wavelength bands, their centre wavelengths, and band width influence the sensitivity of a dataset to changes in productivity as well as the range of productivity indexes that can be calculated from it. It is essential that datasets contain all the spectral wavelengths required to calculate the preferred productivity index.
Cost	A wide range of datasets that present data at varying spatial, spectral and temporal resolutions are freely available, many of which are well-suited for assessing land productivity at global to national scales. Very high-resolution images including pixels smaller than 10m x 10m in size, which may be suitable in spatially complex or smaller landscapes, are also available commercially for purchase. While few high resolution datasets have an archive of repeat coverage historical images which is essential to assess change over time, high resolution images are becoming increasingly available through systems such as Google Earth and Bing maps.
Ease of use	Many image datasets are now provided in 'analysis ready' condition, which have been processed to minimise image artefacts associated with changes in illumination and atmospheric conditions, image detector sensitivity and/or topographic relief. These datasets provide the most accurate representation of changes in land surface conditions over time. Pre-processed vegetation index products are also provided from a range of sensors, and these are the simplest to use and interpret in terms of changes in land productivity.

B.4 Harmonizing datasets from different sources

Given the short historical archive of some of the datasets identified in Table B-1, and the continual emergence of new image datasets suitable for assessing productivity, methods to calibrate between datasets from different sensors may be required to provide continuity through time.

Harmonization should account for:

a) Differences in the sensor spectral responses;
b) Differences in the radiometric calibration of the sensors;
c) Differences in the processing level (e.g., if BRDF correction was applied);
d) Differences in sensor geometric resolutions and map projections;

e) Differences in temporal resolution of time composites (e.g., weekly, 16-day or monthly composites).

Usually, data providers ensure that all aspects of calibration of the instrument itself and the processing system is complete before making the data available for use, especially if the data is made compliant with the CEOS Analysis Ready Data (ARD) guidelines. In particular, the generation of Spectral Band Adjustment Factors accounting for the spectral aspect (a), the proper and traceable radiometric calibration (b), and a comparable processing to ortho-rectified Level 2A Bottom of Atmosphere (BOA) reflectance (c). Whenever possible, the end user should take advantage of harmonized multi-mission datasets, such as the existing NASA and ESA Sentinel-2 and Landsat 8 harmonization initiatives.

For geometric aspects (d), pixels in the highest resolution image (i.e., smaller pixels) should be aggregated to match the resolution of the larger pixels before comparison. A linear regression between images captured from both sensors over the same location at the same time can indicate the function required to translate one dataset to match the other. This method can be applied to compare vegetation indices, such as the NDVI, or between wavelength bands in the source imagery used to create the indices.

Pixels in the less-well calibrated image should be transformed to match the values in the better calibrated dataset where possible. The MODIS MOD13 vegetation index datasets are regarded as being amongst the best calibrated (Yengoh et al. 2015). Alternatively, any two other datasets could be transformed to match the MOD13 values. It may also be useful to interpolate the time series to daily values before comparison to achieve temporal consistency (e). More detail on the application and validation of the linear regression calibration method can be found in Reeves et al. (2015).

It is also possible to adjust the wavelengths from which the indices are created using Spectral Band Adjustment Factors. For instance, the Visible Infrared Imaging Radiometer Suite (VIIRS) is proposed as a replacement for the MODIS sensors in future. Skakun et al. (2018) derived spectral response functions in the red and NIR spectral domain from the calibration parameters for MODIS Aqua[107] and VIIRS[108]. Although these sensors image the Earth's surface at approximately the same time of day, the day of the year within an 8-day period over which the best pixel composites are created may differ between these two datasets. To minimise these impacts, Skakun et al. (2018) compared only observations captured on the same day of the year, and images that were captured close to nadir (view zenith angle less than 7.5°) to reduce the effects of different spatial resolution and BRDF between datasets.

For information on harmonising higher resolution datasets such as Landsat and Sentinel 2 images see Roy et al. (2008). To harmonize Landsat 8 and Sentinel-2 optical see Claverie et al. (2018), and for information on the fusion of coarser and finer resolution data such as MODIS and Landsat using the Kalman filter methods see Zhou and Zhong (2020).

[107] https://mcst.gsfc.nasa.gov/calibration/parameters
[108] https://ncc.nesdis.noaa.gov/VIIRS/VIIRSSpectralResponseFunctions.php

B.5 Validating productivity measurements

Field validation of remotely sensed maps is a highly specialised area, and a detailed discussion of all aspects of this process is beyond the scope of this report. Loew et al. (2017) provides a comprehensive review of validation practices for satellite-based EO data, and Cleveland et al. (2015) provide detailed guidance on NPP validation in tropical forest environments. Also, the CEOS Land Validation subgroup (of the Working Group Calibration and Validation) provides a hierarchy of validation stages which are used for assessing the data products developed from Earth Observation[109].

In the absence of, or to supplement quantitative validation data, expert opinion can be used to determine the validity of productivity assessment methods and metrics. Teich et al. (2019) developed a software survey tool to harness expert opinion to identify the best representation of productivity Trend in Argentina. While this process can be time consuming, the expert's opinions also yielded additional information on the drivers of productivity change, and established a network which may increase the likelihood of adoption of new methods in future.

Below, we briefly describe some of the data options available for validating estimates of NPP.

B.5.1 Flux Tower Data

Flux towers measure the exchange of carbon dioxide between plant canopies and the atmosphere and are a direct correlate with NPP at local scales (Running et al. 1999). Fluxnet[110] maintains a global network of flux towers (Figure B-2) many of which are aligned with national flux monitoring programs. Some examples of National flux tower programs include:

- Australia: TERN[111] and OzFlux[112]
- Korea: KLTER[113]
- USA: NEON[114]

[109] https://lpvs.gsfc.nasa.gov/
[110] https://fluxnet.ornl.gov/
[111] http://www.tern.org.au/NASA-partners-with-TERN-to-map-global-carbon-bgp3623.html
[112] http://www.ozflux.org.au/
[113] http://www.klter.org/emain.htm
[114] http://www.neonscience.org/science-design/collection-methods/flux-tower-measurements

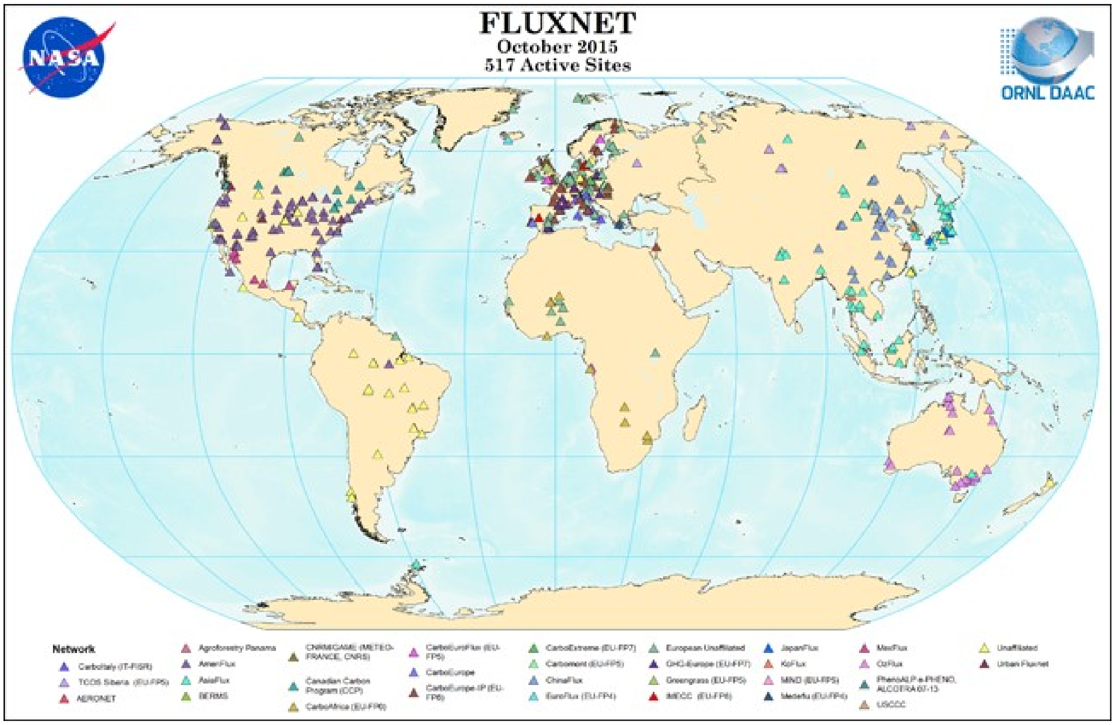

Figure B-2. Fluxnet carbon flux tower locations in October 2015[115]

Limitations on the suitability of flux towers for productivity validation include the limited distribution of the towers and the cost of establishing a network of flux towers, which is not likely to be reasonable for countries that are developing their capacity to report on SDG 15.3.1. The sparse distribution of the towers can also complicate the spatial interpolation of productivity assessments. Another limitation is that flux towers actually measure Net Ecosystem Exchange (NEE), the balance between CO_2 uptake by photosynthesis and the CO_2 returned back to the atmosphere by respiration and decomposition, including not only the vegetation but also the microorganisms and soil organic carbon. Estimating NPP using flux towers requires a whole range of additional assumptions and ancillary measurements (see for example Clark et al (2001) for a discussion of NPP measurements in forests).

Gross and Net Primary productivity measured through eddy covariance flux towers has been the main methodology to validate the MODIS NPP/GPP product (Section B.1.2). This was done thoroughly, and the MODIS product achieved a general accuracy of stage 3[116], meaning that:

"Uncertainties in the product and its associated structure are well quantified over a significant (typically > 30) set of locations and time periods representing global conditions by comparison with reference in situ or other suitable reference data. Validation procedures follow community-agreed-upon good practices."

[115] https://fluxnet.ornl.gov/maps-graphics
[116] https://lpvs.gsfc.nasa.gov/

B.5.2 Destructive biomass sample collection

Validation of NPP estimates using destructive samples collected in the field is possible, but the specific methodology depends on the vegetation type. The difficulty relies on the fact that NPP is a flux variable (carbon being incorporated to plant tissues via photosynthesis) but biomass is a state variable (amount of carbon in plant tissues at any given time).

In annual systems (e.g. annual crops, highly seasonal pastures) harvesting the green biomass (i.e. produced in the growing season) can be used as a surrogate for the annual NPP. In perennial systems and other systems with slow turnover, biomass harvesting has to be complemented with estimates of litterfall and decomposition and samples taken repeated times during the growing season. Sala and Austin (2000) provide a comprehensive description of methods for estimating aboveground NPP. Roxburgh et al (2005) also explains the fundamental concepts of NPP and the frequent confusion with other carbon fluxes and stocks in the ecosystem.

Appendix C Soil Organic Carbon

C.1 Global SOC data sources

IPCC defaults exist for the minimum six land cover classes 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 available defaults are summarised for mineral and organic soils in Table C-1 and Table C-2, respectively. They are also provided in the IPCC Emission Factor Data Base which is regularly updated.[117]

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. For example, in the absence of a national SOC database, use of the SOC 0-30 cm product derived from SoilGrids250m v.2 as a stand-in for baseline SOC stock has been recommended for Land Degradation Neutrality target setting, noting this first requires derivation of stock SOC from SOC concentration, proportion of coarse fragments and bulk density.

International organizations such as FAO, ISRIC World Soil Information, OpenLandMap.org[118] and others have compiled and harmonized national soil information in several global datasets and continue with active compilation.[119] These have different spatial resolutions but have potential for estimating reference SOC stocks. A summary of existing freely available sources is provided in Table C-3. Countries with little data may be able to use information from other countries to produce maps provided they share similar characteristics (e.g. climate, soils, management, and so on).

Table C-1. 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	IPCC 2019
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	Table 2.3 (updated)
Relative stock change factors	Table 3.3.4 Table 3.4.5	Table 5.5 Table 5.10 Table 6.2	Table 5.3	Table 5.5 (updated) Table 5.5A (new) Table 6.2 (updated)

[117] http://www.ipcc-nggip.iges.or.jp/EFDB/main.php
[118] https://openlandmap.org/#/?base=Stamen (OpenStreetMap)&center=45.5312,26.2112&zoom=3&opacity=80&layer=sol_organic.carbon_usda.6a1c_m&depth=0
[119] https://gitlab.com/openlandmap/compiled-ess-point-data-sets

Table C-2. Source of defaults in IPCC guidance documents for 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	Table 2.7
CH_4 emission factors for reservoirs older than 20 years (> 20 years) – *Flooded Land Remaining Flooded Land*	IPCC 2019	Ch. 7	Table 7.9
CO_2-C emission factors for reservoirs ≤ 20 years old – *Land converted to Flooded Land*	IPCC 2019	Ch. 7	Table 7.13

Table C-3. Examples of existing freely available global soil organic carbon datasets/maps.

Global product	Description
Harmonized World Soil Database (HWSD)[120]	• Version 1.2 is the latest update. • Spatial resolution is 30 arc seconds (about 1 km). • Includes soil organic carbon (%), 0-30 cm depth. • ISRIC has updated the HWSD (Batjes 2016) resulting in a database (**WISE30sec**)[121] with more depth intervals and more parameters quantified, and an estimate of uncertainty (SD). • There is no assessment of accuracy.
SoilGrids250m version 2.0 (de Sousa et al. 2020)	• Version 2 released in May 2020. • Spatial resolution is 250 m. • 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 (and to a greater depth) and uncertainties.
GSOC map[122]	• Released in 2017; current 2019 version 1.5.0. • Spatial resolution is 1 km soil grids. • Soil organic C stock covering a depth of 0-30 cm. • Based on data from 110 countries, consists of national SOC maps. • There is no assessment of uncertainty. • A Soil Organic Carbon Mapping Cookbook[123] was developed to provide technical support.
Open Land Map [124]	• Released 2018, update pending. • Spatial resolution being revised to 100m with per pixel uncertainty • 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 (and to a greater depth). • Reproducible methods outlined[125].

C.2 National and regional SOC datasets

At the broadest level, the use of national datasets might include national stratification of land cover categories/sub-categories 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 (see Table C-4) they should use these in accordance with Tier 2 methods. Ground-based data

[120] http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/
[121] https://data.isric.org/geonetwork/srv/eng/catalog.search#/metadata/dc7b283a-8f19-45e1-aaed-e9bd515119bc
[122] http://www.fao.org/global-soil-partnership/pillars-action/4-information-and-data-new/global-soil-organic-carbon-gsoc-map/en/
[123] http://www.fao.org/documents/card/en/c/I8895EN
[124] www.openlandmap.org
[125] www.soilmapper.org (Hengl & MacMillan, 2019)

can be used to estimate SOC values and to derive stock change factors for mineral soils, as well as to estimate emissions and removal factors for organic soils.

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

Country/continent	Reference
Africa	2020[126]
Australia	Viscarra Rossel et al. (2014)
Belgium	2017[127]
Chile	Padarian et al. (2017)
China	Song et al. (2020)
Denmark	Adhikari et al. (2014)
Europe	de Brogniez et al. (2015)
France	Mulder et al. (2016)
Ghana	Owusu et al. (2020)
Mexico	Cruz-Gaistardo et al. (2017)
New Zealand	New Zealand Agricultural Greenhouse Gas Research Centre (2016)
Nigeria	Akpa et al. (2016)
Scotland	Poggio and Gimona (2014)
South Korea	Hong et al. (2010)
Tanzania	Kempen et al. (2019)
Turkey	Sonmez et al. (2017)
USA	Odgers et al. (2012)
USA and Mexico	Guevara et al. (2020)

[126] https://www.isda-africa.com/isdasoil/
[127] http://www.geopunt.be/catalogus/datasetfolder/037427b6-d9ad-43ec-9c1e-b423396266d6

C.3 Tier 2 Steady State Method for mineral soils of Cropland Remaining Cropland

IPCC 2019 includes an optional alternative Tier 2 steady-state method for mineral soils of Cropland Remaining Cropland (see Ch. 5, Vol. 4, Section 5.2.3.1). The method addresses additional complexity in soil C dynamics than Tier 1 or Tier 2 methods using default equations by subdividing SOC into three separate sub-pools with fast (Active sub-pool), intermediate (Slow sub-pool), and long (Passive sub-pool) turnover times. The turnover time of C within each sub-pool determines the length of time that C remains in the soil. The new method estimates C stock changes by incorporating spatial and temporal variation in climate, organic carbon inputs to soils, soil properties and management practices, but is not appropriate for irrigated rice cultivation and is not parameterised to estimate the change in soil organic C stocks due to biochar C amendments. The change in SOC stock is calculated using Equation 5.0a (Ch. 5, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines) and reproduced here (Equation C-1):

$$\Delta C_{mineral} = \sum_i \left(F_{SOC_i} \times A_i \right)$$

$$F_{SOC_i} = SOC_{yi} - SOC_{(y-1)_i}$$

$$SOC_{yi} = ACTIVE_{yi} + SLOW_{yi} + PASSIVE_{yi}$$

Equation C-1

Where:

$\Delta C_{mineral}$ = annual SOC stock change factor for mineral soil, summed across all grid cells or regions, t C

F_{SOC_i} = annual stock change factor for mineral soils in grid cell or region *i*, t C ha^{-1}

A_i = Area of grid cell or region *i*, ha

SOC_{yi} = SOC stock at the end of the current year *y* for grid cell or region *i*, t C ha^{-1}

$SOC_{(y-1)_i}$ = SOC stock at the end of the previous year for grid cell or region, t C ha^{-1}

$ACTIVE_{yi}$ = active sub-pool SOC stock in year *y* for grid cell or region *i*, t C ha^{-1} (see Equation 5.0b, Ch. 5, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines)

$SLOW_{yi}$ = slow sub-pool SOC stock in year y for grid cell or region, t C ha^{-1} (see Equation 5.0c, Ch. 5, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines)

$PASSIVE_{yi}$ = passive sub-pool SOC stock in year *y* for grid cell or region *i*, t C ha^{-1} (see Equation 5.0d, Ch. 5, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines).

Equations associated with the steady state method (Equations 5.0b – 5.0g) in PCC 2019 (Vol. 4, Ch. 5) are completed separately using data derived for each grid cell or region. Default parameters are provided in Table 5.5a for the three-pool steady-state C pool equations and in Tables 5.5b and 5.5c for the average lignin and nitrogen contents of the C input required to estimate the size of the three C pools (IPCC 2019). Note: The Tier 2 steady-state method developed here for Croplands may be applicable to other land uses, but this will require further development and parameterisation.

C.4 Tier 2/3 Method for Biochar Amendments to Mineral soils

As part of the refinements to Tier 2 (and Tier 3) methods (IPCC 2019), countries can now estimate the change in mineral soil organic C stock due to biochar amendments to mineral soils. Tier 2 methods for biochar amendments utilize a top-down approach in which the total amount of biochar generated and added to mineral soil is used to estimate the change in soil organic C stocks with country-specific factors. The impact of biochar C amendments on mineral soils can be estimated using Equation 2.25A (Ch. 2, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines) and reproduced here (Equation C-2), and adding this estimate to the result from Equation C-1 above:

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

Equation C-2

Where:

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

BC_{TOT_p} = the mass of biochar incorporated into mineral soil during the inventory year for each biochar production type *p*, t biochar d.m. yr^{-1}

F_{C_p} = the organic carbon content of biochar for each production type *p*, t C t^{-1} biochar d.m

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

n = the number of different production types of biochar.

Note: Since the impact of biochar amendments is a separate calculation and summed with the result from Equation 5-3, it is essential that biochar C is not included as an organic amendment in the estimates of $SOC_{mineral}$ in Equation C-2.

Country-specific values for the C content of the forms of biochar can be measured directly from representative samples of biochar, or may also be based on published data on carbon content of biochar produced using the same feedstock and process conditions as the biochar that is applied to soils in the country. It is not possible to measure directly the fraction of biochar C remaining after 100 years due to the time scales involved. Thus, this parameter is estimated from other data including the elemental composition of biochar either measured directly from representative samples or derived using published equations relating composition to mean residence time or half-life, or from published data for biochar produced using similar process conditions as the biochar that is applied to soils in the country (for details see p. 2.41, Ch. 2, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines). Justification is required if a permanence timeframe other than 100 years is used.

The additional activity data required to support a Tier 3 method for biochar C amendments will depend on the processes represented and the environmental variables required as inputs to the model (IPCC 2019). Because responses to biochar amendments including priming effects, soil greenhouse gas emissions, and plant production all vary with biochar type, climate, and soil type, and in some cases, with vegetation type and management (e.g. Wang et al. 2016), Tier 3 methods may require environmental data on climate zones, soil types, vegetation types and management systems, in addition to the amount of biochar amendments in each of the individual combinations of strata for the environmental variables. More detailed activity data specifying the process conditions for biochar production or the physical and chemical characteristics of the biochar may also be required.

C.5 Examples using default calculations

Example 1: Reporting unit 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 SOC stock change within a reporting unit over a 5-year reporting period. The reporting unit in a warm temperate moist climate on Mollisols (classified as high activity clay (HAC) mineral soil in the IPCC (2006) guidelines) is made up of 10,000 ha of permanent annual cropland. Using the IPCC defaults (Table 2.3, Ch. 2, Vol. 4, IPCC 2019), native reference carbon stock (SOC_{REF}) for the region is 64 t C ha^{-1}.

At the beginning of the calculation period, the distribution of cropland systems was 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, Ch. 5, Vol. 4, IPCC 2019. Using Eqn 5-3[128], initial soil carbon stocks (SOC_0) for the area were:

4,000 ha × (64 t C ha^{-1} × 0.69 × 1 × 0.92) + 6,000 ha × (64 t C ha^{-1} × 0.69 × 1 × 1) = 427,469 t C.

With parameters:

	Low C input Full till	Medium C input Full till
Area (A; ha)	4000	6000
Reference carbon stock (SOC_{REF}; t C ha^{-1})	64	64
Land use stock change factor (F_{LU})	0.69	0.69
Management regime stock change factor (F_{MG})	1.0	1.0
Organic matter input stock change factor (F_I)	0.92	1.0

[128] 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.

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 reporting period ($SOC_{0\text{-}T}$) are:

2,000 ha × (64 t C ha^{-1} × 0.69 × 1 × 0.92) + 7,000 ha × (64 t C ha^{-1} × 0.69 × 1.05 × 1) + 1,000 ha × (64 t C ha^{-1} × 0.69 × 1.10 × 1) = 454,406 t C.

With parameters:

	Low C input Full till	Medium C input Reduced till	Medium C input No till
Area (A; ha)	2000	7000	1000
Reference carbon stock (SOC_{REF}; t C ha^{-1})	64	64	64
Land use stock change factor (F_{LU})	0.69	0.69	0.69
Management regime stock change factor (F_{MG})	1.0	1.05	1.10
Organic matter input stock change factor (F_I)	0.92	1.0	1.0

The average annual stock change over the period for the entire area is: (454,406 – 427,469) t C / 20 yr = 26,938 t C/ 20 yr = 1,347 t C yr^{-1} increase.

Using Eqn 5-2, over our reporting unit area of 10,000 ha and reporting period of 5 years this is equivalent to 1,347 / 10,000 ha = 0.135 t ha^{-1} yr^{-1} = 0.135 × 5 = 0.67 t ha^{-1} increase. There are no organic soils in this reporting unit.

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

SOC_{REF}: 64±5%;

F_{LU}: long-term cultivated 0.69±16%;

F_{MG}: full tillage 1.0±50% (no estimate available, assumed error); reduced tillage 1.05±4%; no-till 1.10±4%;

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

A: Area (no uncertainty assumed).

Using Eqn. 5-8, 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:

$$= (0.4 \times \sqrt{5^2 + 16^2 + 50^2 + 14^2}\,) + (0.6 \times \sqrt{5^2 + 16^2 + 4^2 + 50^2}\,) = 65\%$$

And for t_n is:

$$= (0.2 \times \sqrt{5^2 + 16^2 + 50^2 + 14^2}\,) + (0.7 \times \sqrt{5^2 + 16^2 + 4^2 + 50^2} + (0.1 \times \sqrt{5^2 + 16^2 + 4^2 + 50^2}\,) = 53\%$$

To calculate relative change (r_{SOC}) from Eqn 5-8 for this reporting unit, where SOC_{t0} is 427,469 t C / 10,000 ha = 42.7 t ha^{-1} and SOC_{tn} is 454,406 t C / 10,000 ha = 45.4 t ha^{-1}:

r_{SOC} = (45.4-42.7) / 42.7 × 100 = 6.3%

Based on an increase in carbon stocks of 6.3%, this reporting unit has not degraded over the reporting period.

Example 2: Reporting unit 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 reporting unit over a 10-year reporting period. The reporting unit 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, Ch. 2, Vol. 4, 2019 Refinement to the IPCC 2006 Guidelines, the native reference carbon stock (SOC_{REF}) is 19 t C ha^{-1} for the LAC soils and 24 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 reporting unit, with the ordering of parameters within the equation as per Example 1:

<u>LAC soils</u>

t_0 3,000 ha × 19 t C ha^{-1} = 57,000 t C

t_n 2,000 ha × (19 t C ha^{-1} × 0.69 × 1 × 0.92) + 1,000 ha × 19 t C ha^{-1} = 43,122 t C

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

SOC_{REF}: 19±16%;

F_{LU}: long-term cultivated 0.69±16%;

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

F_I: low input 0.92±14%.

A: Area (no uncertainty assumed).

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:

$$= (0.67 \times \sqrt{16^2 + 16^2 + 50^2 + 14^2}) + (0.33 \times 16) = 43\%$$

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

SOC_{t0} is 57,000 t C / 3,000 ha = 19 t C ha^{-1} and SOC_{tn} is 43,122 t C / 3,000 ha = 14.37 t C ha^{-1}:

r_{SOC} = (-14.37-19) / 19 × 100 = -24.4%

Area LAC soils degraded = 2,000 ha

<u>HAC soils</u>

t_0 7,000 ha × 24 t C ha^{-1} = 168,000 t C

t_n 5,000 ha × (24 t C ha^{-1} × 0.69 × 1 × 0.92) + 2,000 ha × 24 t C ha^{-1} = 124,176 t C

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

SOC_{REF}: 24±5%F_{LU}: long-term cultivated 0.69±16%;

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

F_I: low input 0.92±14%.

$= (0.71 \times \sqrt{5^2 + 16^2 + 50^2 + 14^2}) + (0.29 \times 5) = 40\%$

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

SOC_{t0} is 168,000 t C / 3,000 ha = 24 t C ha^{-1} and SOC_{tn} is 124,176 t C / 7,000 ha = 17.74 t C ha^{-1}:

r_{SOC} = (17.74-24) / 24 × 100 = -26.1%

Area LAC degraded = 5,000 ha

The total area degraded in the reporting unit is 2,000 ha + 5,000 ha = 7,000 ha

C.6 National monitoring

Because estimates from default values and maps have wide associated uncertainties, more sensitive methods are recommended to detect SOC stock 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;

ii) Detect and interpret any changes detected, assess their causes, and identify management interventions that improve SOC stocks.

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.

Judicious soil monitoring networks at (supra-) national scale can provide information on direct changes in SOC stocks relative to the defined baseline through repeated measurements (e.g., decadal) at a given site to provide a set of point observations that represent the variation in climate, soil, land use and management at the national scale. The recommended approach for this (i.e., model-based or design-based) must be determined at an early stage (Brus and de Gruijter 1997; Brus and de Gruijter et al. 2006; Webster and Oliver 2007).

The determination of SOC stock requires measurements of SOC concentration, soil bulk density and gravel content. 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 changes in SOC stock. 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 the measurement and monitoring of SOC stocks include:

- Spatial sampling strategies (site selection, sampling locations, number of samples, compositing, and so on).
- Temporal sampling strategies (timing, frequency).
- Measurement (consistency, accuracy, cost, method (direct or sensors), and so on).
- Scaling of point measurements to areal estimates.

Specific guidance on these aspects is context-specific, and is not provided here, but is covered elsewhere (e.g. de Gruijter et al. 2006; Chappell et al. 2013; DotE 2014b; Batjes and van Wesemael, 2015). For example, within monitoring networks, sites can be organised according to different sampling schemes, such as regular grid, stratified approach or randomized; different statistical methods should be associated with each of these sampling designs. Further monitoring methods must consider the minimum detectable difference (Batjes and van Wesemael, 2015). Different protocols for field sampling, measurement and SOC stock calculation (e.g., fixed depth versus equivalent mass) are used across the world. Direct measurement of bulk density and proportion of coarse fragments[129] (>2 mm, by mass) is necessary. Cost-effective, proximal and airborne sensing techniques, such as soil spectroscopy, may be used (Viscarra Rossel and Hicks 2015; Viscarra Rossel et al. 2016b) while recognizing the continued need for conventionally-measured SOC content (e.g., dry combustion) in reference laboratories to calibrate such values. Benchmark sites and 'round-robin' tests will be needed to allow for worldwide inter-calibration of soil analytical methods.

Ideally, soil samples from soil monitoring networks should be archived to allow re-analysis as new or updated techniques are developed, implying additional costs for data storage and handling. Further, the range of soil and ancillary data (e.g., climate and land use history) collated through soil monitoring networks and other field sampling programs should be stored in freely-accessible global information systems, with the main socio-economic and biophysical driving variables at relevant scales, to support global SOC mapping using either geo-statistical or ecosystem modelling approaches. In many countries there are no national systems in place for statistically-based sampling of SOC, while in others they are in the planning or early stages of implementation. Few systems are located in developing countries where most deforestation and land use change is occurring (van Wesemael et al. 2011; Batjes and van Wesemael 2015). For example, see Box C-1. Further examples of soil monitoring networks and sample designs in selected countries are provided in Table C-5.

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 5-2). 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 reviews on the use of soil sensing for measuring SOC concentration which highlight the usefulness of visible-near infrared and mid-infrared spectroscopy (Stenberg et al., 2010; Bellon-Maurel and McBratney, 2011; Viscarra Rossel et

[129] Regional differences e.g. where "< 1mm" is used as the limit, mainly former Soviet Union and satellite countries.

al., 2011; Reeves et al., 2012; Izaurralde et al., 2013), although further work is required, for example, in terms of selecting the proper spectral range of the sensor, the pre-processing methods, and the calibration techniques (Angelopolou et al. 2020). 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 (Lobsey and Viscarra Rossel 2016). The calculation of SOC stock requires measures of bulk density and gravel content, and new systems that integrate different soil sensors (e.g., visible-near infrared; 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 (Viscarra Rossel et al. 2017). Furthermore, there is recent work demonstrating the use of soil sensors for SOC stock base-lining (Viscarra Rossel et al. 2016a). A recent review assessing the potential of proximal soil sensing techniques for carbon accounting (England and Viscarra Rossel 2018) concluded that proximal sensing can be used for soil organic C accounting, but methods need to be standardized and procedural guidelines developed to ensure proficient measurement and accurate reporting and verification. Accounting frameworks should allow for efficient updating with new measurements, data and models as they become available.

Table C-5. Examples of soil monitoring networks and sampling design in selected countries[1].

Country	Objective	Coverage[2]	Soil sampling				
			Timing	Design	Sub-samples	Depth (cm)	Frequency
Belgium	National SOC monitoring	CL, GL; Belgium	1950-1970; resampled 2004-2007	Stratified	Composite	0-30, 0-100	Once, resampling funding-dependent
Germany	National SOC monitoring	CL, GL	2010	Grid	Composite	10 cm slices to 100 cm	Every 10 years
Mexico	National SOC monitoring	FL, d non-FL (GL and shrubs)	2003; each year 20% sites resampled	Grid	Composite	0-30, 30-60	Every 5 years
New Zealand	National SOC monitoring	All regions and land uses	1996	Stratified	Single	Variable, sampled by horizon	Resampling ongoing
Sweden	National SOC monitoring	~3 Mha CL	1995 (some 1988)	Grid	Composite	0-20, 40-60	1995, 2005, 2015; every 10 years
Australia	Baseline SOC sampling, land use × soil class	CL, GL	2009	Stratified	Composite	0-10, 10-20, 20-30	Once, resampling funding-dependent

Brazil	SOC response to land use/ mgmt change	Rodonia and Matto Grosso	~2007	Stratified	Composite	0-10, 10-20, 20-30, 30-40	Once
China	Regional SOC monitoring	NE, N, E, S, NW, SW	1985-1996	Stratified	Composite	0-20	Annual sampling from 2010

[1] Adapted from van Wesamael et al. 2011; Batjes and van Wesamael 2015; [2] CL cropland; GL grassland; FL forestland.

Box C-1: Example of statistically based sampling of soil using LUCAS

The European project LUCAS (Land Use/Cover Area Frame Statistical Survey)[130] 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 25 (and later 28) Member States of the European Union (EU)[131] in order to derive policy-relevant statistics on the effect of land management on soil characteristics. 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. Soil samples have been collected from approximately 20,000 points at three time-periods: 2009–2012, 2015 and 2018. Details of the dataset from the first two samplings (2009-2012, 2015) is provided in Origiazzi et al. (2018). 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, and 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 were modified in the 2018 sampling to collect samples for the assessment of new properties including bulk density and thickness of the organic horizon in peat soils (Fernández-Ugalde et al. 2017; Origiazzi et al. 2018).

[130] http://esdac.jrc.ec.europa.eu/projects/lucas
[131] http://esdac.jrc.ec.europa.eu/ESDB_Archive/eusoils_docs/other/EUR26102EN.pdf

Box C-2: 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 carbon and not possible to analyse them for bulk density. This same approach has now been used elsewhere in the United States of America and China.

C.7 Global biomass and debris data sources

Where country-specific data are not available, it is good practice to apply the best available defaults for biomass carbon stocks and debris carbon stocks to national land cover maps obtained by EO data. For biomass, IPCC defaults exist for the minimum six land cover classes and are stratified further into combinations based on climate, ecology, disturbance or management. For debris, IPCC defaults exist for Forest land and mangroves (Wetlands) and are stratified further into combinations based on climate and forest type. Spatial stratification based on these defaults would further improve the quality of the results at the national level. The sources of available IPCC defaults for above ground biomass stocks and root to shoot ratios (for estimating below ground biomass from above ground biomass), and litter and dead wood carbon stocks in forests and mangroves, are summarised in Table C-6 and Table C-7 respectively. They are also provided in the IPCC Emission Factor Data Base which is regularly updated.[132]

Where available and considered robust and representative, it is good practice to use global spatial datasets for biomass carbon stocks as an alternative to using defaults. Several global datasets have been compiled and regional maps for tropical areas have also been produced. With few tropical countries having national above ground biomass maps or reliable statistics on forest carbon stocks, regional maps may provide advantages compared to the use of default mean values. The majority of current global products map forest biomass only. Zhang et al. (2019) recently reviewed available regional and global gridded forest biomass products. Further, a biomass change map is now available (Santoro and Cartus 2019) and global biomass density maps at multiple points in time using data from dedicated space-based sensors are expected (Herold et al. 2019).

Some examples of current global and regional biomass map products are provided in Table C-8. These cover a range of different spatial resolutions (100 m to 1 km) and have potential for estimating biomass carbon stocks. It should be noted that many products provide biomass in terms of dry matter rather than biomass carbon, so in these cases values would need to be converted to biomass carbon. It is likely that the predictions of biomass stocks derived from global or regional maps at a specified location will typically have very wide confidence intervals. In general, the use of datasets with the highest spatial resolution is recommended.

[132] http://www.ipcc-nggip.iges.or.jp/EFDB/main.php

Table C-6. 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	IPCC 2019
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		Table 4.4 (updated)
Above ground biomass stocks in natural and plantation forests	Tables 3A.1.2 & 3A.1.3	Tables 4.7, 4.8		Tables 4.7, 4.8 (updated)
Above ground net biomass growth in natural forests		Tables 4.9, 4.10		Tables 4.9, 4.10 (updated)
Above ground volume growth in plantations		Table 4.11A (excl. 11B)		Table 4.11 (updated)
Above ground biomass for various types of perennial croplands	Table 3.3.2	Table 5.3		Table 5.3 (updated)
Biomass carbon stocks present on Land Converted to Cropland in the year following conversion	Table 3.3.8	Table 5.9		Table 5.9 (updated)
Above ground biomass for various types of grasslands	Table 3.4.2			
Ratio of below-ground biomass to aboveground biomass for the major grassland and 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 C-7. 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	IPCC 2019
Forest litter and dead wood carbon stocks	Table 3.2.1 & 3.2.2	Table 2.2		Table 2.2 (updated)
Litter and dead wood stocks in mangroves			Table 4.7	

Table C-8. Examples of existing freely available global or regional biomass/biomass carbon maps

Scale	Map product	Description
Global	**Harmonized global maps of above and below ground biomass carbon density in the year 2010[133]**	• Harmonized global maps of above and below ground biomass in 2010 at 300 m resolution. • Biomass carbon density estimates with quantified uncertainty. • The harmonization approach used existing independent, landcover-specific biomass maps and ancillary layers. A predictive model was used to gap fill where existing maps were not available for particular epochs of interest.
Global	**CCI Biomass[134]**	• Map products currently being developed. Aim to provide global maps of above ground biomass for four epochs (mid 1990s, 2010, 2017 and 2018) to support quantification of biomass change. • The mapping aims to achieve 500 m to 1 km spatial resolution with a relative error of less than 20% where AGB exceeds 50 Mg ha^{-1}. • 2017 dataset (AGB and AGB standard error) has been completed as part of Climate Research Data Package v.1[135].
Global	**GlobBiomass project[136,137]**	• Map product currently being developed. • Will have specified requirements to spatial resolution (150-500 m) and 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 as well as established algorithms for the retrieval of forest variables at regional to continental scale. • One product already available: Global, remotely sensed map of woody AGB in living trees with DBH greater than 10 cm[26] and masked to pixels containing Landsat-identified tree cover in 2010. Native resolution of 100 m. Includes accompanying standard error of predictions layer.
Global	**New IPCC Tier-1 Global**	• Global map of biomass carbon stored in above and

[133] Spawn, SA, Sullivan, CC, Lark, Tyler J, Gibbs, H (2020) Harmonized global maps of above and belowground biomass carbon density in the year 2010. figshare. Collection. https://doi.org/10.6084/m9.figshare.c.4561940
[134] http://cci.esa.int/biomass
[135] http://cci.esa.int/sites/default/files/biomass_D4.2_Climate_Research_Data_Package_V1.0.pdf
[136] http://globbiomass.org/products/global-mapping/
[137] Santoro, M. et al. (2018): GlobBiomass - global datasets of forest biomass. PANGAEA, https://doi.org/10.1594/PANGAEA.894711

	Biomass Map for the Year 2000[138]	below ground living vegetation at 1 km resolution. • In conjunction with GLC2000 land cover data. • Accuracy/uncertainty not reported.
Regional	**Integrated pan-tropical biomass map**[139]	• Product combines two existing datasets of vegetation above ground 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 up-scaled to 14,477 1-km estimates.
Regional	**National Level Carbon Stock Dataset (Tropics)**[140]	• Maps of above ground live woody biomass at 500 m resolution for the tropics in 2007-2008. • Used 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.
Regional	**Above ground biomass map of African savannahs and woodlands**[141]	• Continental map of AGB of African savannahs and woodlands at a resolution of 25 m. • A value of AGB and its uncertainty has been assigned to each pixel. • Map built from the 2010L-band PALSAR mosaic produced by JAXA, with stratification into wet/dry season areas to account for seasonal effects and development of a direct model relating the PALSAR backscatter to AGB, with the help of in situ and ancillary data.
Regional	**European Map of Living Forest Biomass and Carbon Stock**[142]	• Map of living forest biomass and carbon stock at 1 km resolution. • IPCC Tier 1 method (FRA data, CORINE Land Cover data).

[138] http://cdiac.ornl.gov/epubs/ndp/global_carbon/carbon_documentation.html
[139] 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
[140] http://whrc.org/publications-data/datasets/pantropical-national-level-carbon-stock/
[141] Bouvet et al. 2018. An above-ground biomass map of African savannahs and woodlands at 25m resolution derived from ALOS PALSAR. Remote Sensing of Environment 206, 156-173. https://doi.org/10.1016/j.rse.2017.12.030
[142] Barredo et al. 2012. A European Map of Living Forest Biomass and Carbon Stock. EUR–Scientific and Technical Research; Joint Research Centre of the European Commission, Ispra, Italy. https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/european-map-living-forest-biomass-and-carbon-stock-executive-report

C.8 National biomass and litter datasets

National and regional products are based on Earth Observation data at finer resolutions than for global products. Typically, remote sensing techniques do not derive biomass directly, but use parameters that are related to biomass (i.e., model drivers/covariates), for example height, leaf area index, or net primary production. These parameters are widely incorporated into the mapping of above ground biomass, based on established relationships with above ground biomass. Available remote sensing data sources for producing biomass density maps currently include active sensors such as Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR) sensors (IPCC 2019; GFOI 2020). Passive sensors are classified based on the spatial resolution of data as coarse resolution (pixel size >250 m, e.g. MODIS), medium resolution (pixel size 10-80 m, e.g. Landsat, Sentinel 2), and fine resolution (pixel size <10 m, e.g. Rapideye, SPOT and ALOS-2). From 2019, a series of targeted space-based missions will improve the capabilities for forest biomass predictions from LiDAR (e.g. GEDI, ICESAT-2) and SAR (e.g. BIOMASS, NISAR), and may be useful for national purposes (Herold et al. 2019; Quegan et al. 2019). Adequate field data are critical to biomass mapping from remotely sensed data, regardless of which methods are chosen (e.g. Lu et al. 2016). Apart from mapping biomass density, there are evolving approaches that monitor changes in biomass density through time directly from remotely sensed data (see Baccini et al. 2017). However, these approaches require consistent measurements and estimates, and this can be challenging when different satellite data sources and different ways of data processing and analysis are used. In addition to spaceborne LiDAR, 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). Airborne LiDAR has a long history of operational use in forestry applications in developed countries (e.g. Næsset 2002; Wulder et al. 2012) but is less common in tropical forests (but see for examples Xu et al. 2017; Ene et al. 2017) for several reasons including a higher diversity of tree species, the complexity involved in analysing the data, and the cost of routine collection of measurements (GFOI 2020).

Examples of current national and sub-national biomass/biomass carbon map products are provided in Table C-9. Although country-specific data are desirable, countries with little data may able to use biomass information from other countries to produce maps as long as they share similar characteristics (e.g. climate, soils, managements, forest types, and so on). Although there has been some recent research around remote sensing of forest debris using LiDAR (e.g. Joyce et al. 2019; Lopes Quieroz et al. 2020), there are no mapped products. Thus, national estimates will rely on field measurement and monitoring.

Table C-9. Examples of biomass/biomass carbon maps at national or sub-national scales. AGB above-ground biomass

Scale	Country	Product & Resolution	Reference
National	Canada	AGB; 250 m	Beaudoin et al. 2017
National	China	AGB, forest; 1 km	Yin et al. 2015
Sub-national	Northeast China	AGB; 500 m	Zhang et al. 2014
National	Brazil	AGB C; 50 m	Englund et al. 2017
National	Mexico	AGB, forest; 250 m	Rodriguez-Veiga et al. 2016
National	USA	AGB, forest; 250 m	Blackard et al. 2008
National	Australia	Maximum AGB; 1 km	Roxburgh et al. 2019
National	Cambodia	AGB; 50 m	Avtar et al. 2013
National	Poland	AGB; 50-150 m	https://globbiomass.org/products/regional-mapping/regional-biomass-mapping-poland/
National	Sweden	AGB; 50-150 m	https://globbiomass.org/products/regional-mapping/regional-biomass-mapping-sweden/
Sub-national	Kalimantan (Indonesia)	AGB; 50-150 m	https://globbiomass.org/products/regional-mapping/regional-biomass-mapping-indonesiakalimantan/
Sub-national	Eastern South Africa	AGB; 50-150 m	https://globbiomass.org/products/regional-mapping/regional-biomass-mapping-south-africa/