# Good Practice Guidance

## SDG Indicator 15.3.1

### Proportion of land that is degraded over total land area

**Version 1.0**
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# Acknowledgements

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## Inter-Agency Advisory Group on SDG Indicator 15.3.1

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# Introduction: Good Practice Guidance for SDG Indicator 15.3.1

In the last decade, there have been a number of global/regional targets and initiatives to halt and reverse land degradation and restore degraded land. Starting in 2010, these include the CBD's Aichi Biodiversity Targets, one of which aims to restore at least 15% of degraded ecosystems; the Bonn Challenge and its regional initiatives to restore more than 150 million hectares; and most recently the 2030 Agenda for Sustainable Development and the Sustainable Development Goals (SDGs).

The SDGs provide 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 SDGs came into effect in January 2016 and are expected to guide social, economic and environmental policy and investment over the next 15 years. SDG 15 promotes "Life on Land" and SDG target 15.3 states:

> **'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.'**

The United Nations Convention to Combat Desertification (UNCCD) is the custodian agency for SDG indicator 15.3.1 ("**Proportion of land that is degraded over total land area**") which was proposed by the Inter-Agency and Expert Group on SDG indicators (IAEG-SDGs) and adopted by the United Nations Statistical Commission (UNSC) in March 2017 to monitor progress towards achieving SDG target 15.3.

The UNCCD and its key partner, the Food and Agriculture Organization of the United Nations (FAO), have convened an inter-agency advisory group to develop and refine the methodology and data options contained in this Good Practice Guidance (GPG) for SDG indicator 15.3.1. The group also includes the United Nations Framework Convention on Climate Change (UNFCCC), Convention on Biological Diversity (CBD), United Nations Environment (UNEP) and the United Nations Statistics Division (UNSD).

SDG indicator 15.3.1 will be reported as a binary (i.e., degraded/not degraded) quantification based primarily, and to the largest extent possible, on comparable and standardized national official data sources. This GPG aims to assist countries in implementing the methodology for deriving SDG indicator 15.3.1 ("the indicator") by calculating and assessing changes in i) land cover, ii) land productivity and iii) carbon stocks ("the sub-indicators") in concert.

The methodology is intended to be universal, allowing countries to select the most appropriate datasets for the sub-indicators and determine the most suitable pathway for deriving the indicator. This GPG also recognizes that any significant negative change in the sub-indicators pointing to land degradation is context specific and to be determined by national authorities based on a convergence of evidence, i.e, complemented with other indicators, data and information.

This GPG describes the methods to process and interpret data from available sources that can be used to support countries in their assessment and quantification of land degradation. While it difficult for a single indicator to fully capture the state or condition of the land, the sub-indicators are proxies to monitor the key factors and driving variables that reflect the capacity of the land to

deliver ecosystem services. In this regard, this GPG assists countries in accessing and interpreting a wide range of data sources for the sub-indicators, including Earth observation and geospatial information, while at the same time ensuring national ownership. The UNCCD reporting template includes the indicator and sub-indicators. 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.[1]

The quantitative assessments and corresponding mapping at the national level, as required by the indicator, will help countries to set policy and planning priorities among diverse land resource areas, in particular to (1) identify hotspots and plan actions of redress, including through the conservation, rehabilitation, restoration and sustainable management of land resources, and (2) address emerging pressures in order to help avoid future land degradation.

In 2014-2015, 14 countries participated in the UNCCD's land degradation neutrality (LDN) pilot project[2] to implement the LDN target setting approach, including the use of the methodology and data options for reporting on the three sub-indicators. All of the countries established baselines based on these sub-indicators, either by using national data and/or global default data provided by the UNCCD and its partners. This pilot project demonstrated the importance of upfront technical assistance and country-tailored advisory services for overcoming data analysis challenges and barriers.

As of September 2017, there were 113 countries participating in the land degradation neutrality target setting programme (LDN-TSP),[3] of which 64 countries have established and validated a baseline for the indicator. With the support of the Global Environment Facility (GEF), multilateral and country donors, the UNCCD and its partners are leading a massive capacity building initiative that includes defining national baselines, targets and the associated implementation measures and monitoring approaches for achieving the SDG target 15.3.

The sources of global default data provided to LDN-TSP countries are: i) land cover and land cover change from the European Space Agency's Climate Change Initiative on Land Cover; ii) land productivity from the Joint Research Centre of the European Commission initiative on Land Productivity Dynamics; and iii) soil organic carbon from the International Soil Reference and Information Center's SoilGrids250m dataset. These and other open-access datasets are described in detail in this GPG. 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.

National teams, which include National Statistical Office (NSO) representatives, established in all LDN-TSP countries are using the methodology and selecting the most suitable datasets as described in this GPG. Furthermore, collaboration with the Group on Earth Observations (GEO) is expected to provide space-based information and *in situ* measurements to assist countries in fulfilling the

[1] 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.

[2] http://knowledge.unccd.int/knowledge-products-and-pillars/ldn-target-setting-building-blocks/lessons-learned-14-pilot-4

[3] http://www2.unccd.int/actions/ldn-target-setting-programme

reporting requirements for the indicator, and to help foster data access, national data capacity-building and the development of standards and protocols.[4]

As SDG indicator 15.3.1 relies on geospatial information and digital data from national, regional and global sources, this GPG follows ISO 19115-1:2014[5] which defines the schema required for describing geographic information and services by means of metadata. This international standard provides information about the identification, the extent, the quality, the spatial and temporal aspects, the content, the spatial reference, the portrayal, distribution, and other properties of digital geographic data and services.

An international standard for the sub-indicator on land cover exists (ISO 19144-2:2012).[6] This includes the Land Cover Meta Language (LCML) which provides a common reference structure for the comparison and integration of data for any generic land cover classification system. LCML is also used for defining land cover and ecosystem functional units used in the System of Environmental-Economic Accounting (SEEA).

The other two sub-indicators will require new international standards to be approved by the appropriate governing body. For land productivity, ISO 19115-1:2014 will guide the development of a new international standard. For carbon stocks, IPCC (2006) contains the most relevant definitions, especially with regard to reference values usable for Tier 2 and 3 GHG reporting.[7] In this regard, the technical soil infrastructure, data transfer and provision of national reporting data will be standards-based (ISO and OGC for the exchange of digital spatial data sets). An extended ISO 28258:2013 (Soil quality - Digital exchange of soil-related data)[8] will be the core model for exchanging soil data.

Chapter 1 summarizes the method of computation for the indicator using the "One Out, All Out" principle based on the assessment and quantification of the three sub-indicators. Chapters 2, 3, and 4 feature good practice guidance for implementing the methodology and using available data sources for each of the sub-indicators.

[4] http://www2.unccd.int/sites/default/files/sessions/documents/2017-09/ICCD_COP%2813%29_L.21-1716102E.pdf
[5] https://www.iso.org/standard/53798.html
[6] https://www.iso.org/standard/44342.html
[7] IPCC. 2006. IPCC Guidelines for National Greenhouse Gas Inventories: Agriculture, Forestry and other Land Use. Prepared by the National Greenhouse Gas Inventories Programme: Eggleston H.S., Buendia L., Miwa K., Ngara T. and Tanabe K. (eds). IGES, Japan.
[8] https://www.iso.org/standard/44595.html

# 1. SDG Indicator 15.3.1: Proportion of land that is degraded over total land area

## 1.1 Definitions and Concepts

**Land degradation** 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. This definition was adopted by and is used by the 196 countries that are Party to the UNCCD.[9]

**Total land area** is the total surface area of a country excluding the area covered by inland waters, like major rivers and lakes.[10]

**SDG indicator 15.3.1** is 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.[11]

**The method of computation** for this indicator follows the "One Out, All Out" statistical principle and is based on the baseline assessment and evaluation of change in the sub-indicators to determine the extent of land that is degraded over total land area.

**The One Out, All Out (1OAO)**[12] principle is applied taking into account 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 monitoring year) for a particular land unit, then it would be considered as degraded subject to validation by national authorities.

**The measurement unit** for this indicator is the spatial extent (hectares or $km^2$) expressed as the proportion (percentage or %) of land that is degraded over total land area.

As proxies to monitor the key factors and driving 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 systematic observation under both the Global Climate Observation System (GCOS)[13] and the integrated measurement framework of the System of Environmental Economic Accounting (SEEA).[14] The

[9] 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

[10] Food and Agriculture Organization of the United Nations

[11] 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

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

[13] https://library.wmo.int/opac/doc_num.php?explnum_id=3854

[14] https://seea.un.org/

ultimate determination of the extent of degraded land made by national authorities should be contextualized with other indicators, data and ground-based information.

While necessary but not sufficient, the three sub-indicators provide good coverage and together can assess the quantity and quality of land-based natural capital and its associated ecosystem services. They address changes in different yet highly relevant ways: for example, land productivity trends can capture relatively fast changes while changes in carbon stocks reflect slower changes that suggest a trajectory or proximity to thresholds.[15]

**1) Land cover** refers to the observed physical cover of the Earth's surface which describes the distribution of vegetation types, water bodies and human-made infrastructure.[16] It also reflects the use of land resources (i.e., soil, water and biodiversity) for agriculture, forestry, human settlements and other purposes.[17] It 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, thus increasing the indicator's policy relevance. This sub-indicator is expected to be used for SDG indicators 6.6.1, 11.3.1, and 15.1.1

There is an international standard for the sub-indicator on land cover (ISO 19144-2:2012)[18] which includes the Land Cover Meta Language (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 land cover and ecosystem functional units used in the SEEA, and closely linked to the Intergovernmental Panel on Climate Change (IPCC) classification on land cover/land use.

**2) Land productivity** refers to the total above-ground net primary productivity defined as the energy fixed by plants minus their respiration which translates into the rate of biomass accumulation that delivers a suite of ecosystem services.[19] This sub-indicator points to 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, where declining trends are often a defining characteristic of land degradation.[20] For land productivity, ISO 19115-1:2014 will guide the development of a new international standard.

**3) Carbon stock** is the quantity of carbon in a "pool": a reservoir which has the capacity to accumulate or release carbon and comprised of above- and below-ground biomass, dead organic matter, and soil organic carbon.[21] In UNCCD decision 22/COP.11, *soil organic carbon (SOC) stock* was adopted as the metric to be used with the understanding that this metric will be replaced by *total*

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[15] Orr, B.J., A.L. Cowie, V.M. Castillo Sanchez, P. Chasek, N.D. Crossman, A. Erlewein, G. Louwagie, M. Maron, G.I. Metternicht, S. Minelli, A.E. Tengberg, S. Walter, and S. Welton. 2017. Scientific Conceptual Framework for Land Degradation Neutrality. A Report of the Science-Policy Interface. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany.
[16] Di Gregorio, A. 2005. Land cover classification system (LCCS): classification concepts and user manual. Food and Agriculture Organization of the United Nations, Rome.
[17] 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.
[18] https://www.iso.org/standard/44342.html
[19] Millennium Ecosystem Assessment. 2005. Ecosystems and human wellbeing: a framework for assessment. Island Press, Washington, DC.
[20] Joint Research Centre of the European Commission. 2017. World Atlas of Desertification, 3rd edition. JRC, Ispra.
[21] IPCC. 2006. IPCC Guidelines for National Greenhouse Gas Inventories: Agriculture, Forestry and other Land Use. Prepared by the National Greenhouse Gas Inventories Programme: Eggleston H.S., Buendia L., Miwa K., Ngara T. and Tanabe K. (eds). IGES, Japan.

*terrestrial system carbon stocks*, once operational. SOC is an indicator of overall soil quality associated with nutrient cycling and its aggregate stability and structure with direct implications for water infiltration, soil biodiversity, vulnerability to erosion, and ultimately the productivity of vegetation, and in agricultural contexts, yields. SOC stocks reflect the balance between organic matter gains, dependent on plant productivity and management practices, and losses due to decomposition through the action of soil organisms and physical export through leaching and erosion.[22]

For carbon stocks, IPCC (2006) contains the most relevant definitions, especially with regard to reference values usable for Tier 2 and 3 GHG reporting.[23] In this regard, the technical soil infrastructure, data transfer and provision of national reporting data will be standards-based (ISO and OGC for the exchange of digital spatial data sets). An extended ISO 28258:2013 (Soil quality - Digital exchange of soil-related data)[24] will be the core model for exchanging soil data.

## 1.2 Methodology

**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 determine which land units are to be classified as degraded, sum the total, and report on the indicator. The methodology for the indicator is universal, allowing countries to select the most appropriate datasets for the sub-indicators and determine national methods for estimating the indicator.**

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, Earth observation and geospatial information from regional and global data sources can play an important role in its derivation, subject to validation by national authorities.

Quantifying the indicator is based on the evaluation of changes in the sub-indicators in order to determine the extent of land that is degraded over total land area. The sub-indicators are few in number, complementary and non-additive components of land-based natural capital and sensitive to different degradation factors. 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. If one of the sub-indicators is negative (or stable when degraded in the baseline or previous monitoring year) for a particular land unit, then normally it would be considered as degraded subject to validation by national authorities.

The baseline year for the indicator is 2015 and its value ($t_0$) is derived from an initial quantification and assessment of time series data for the sub-indicators for each land unit during the period 2000-2015. Subsequent values for the indicator during each monitoring period ($t_{1-n}$) are derived from the quantification and assessment of changes in the sub-indicators as to whether there are has been positive, negative or no change for each land unit relative to the baseline value. Although the indicator will be reported as a single figure quantifying the area of land that is degraded as a

[22] 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.
[23] IPCC. 2006. ibid
[24] https://www.iso.org/standard/44595.html

proportion of land area, it can be spatially disaggregated by land cover class or other policy-relevant units.

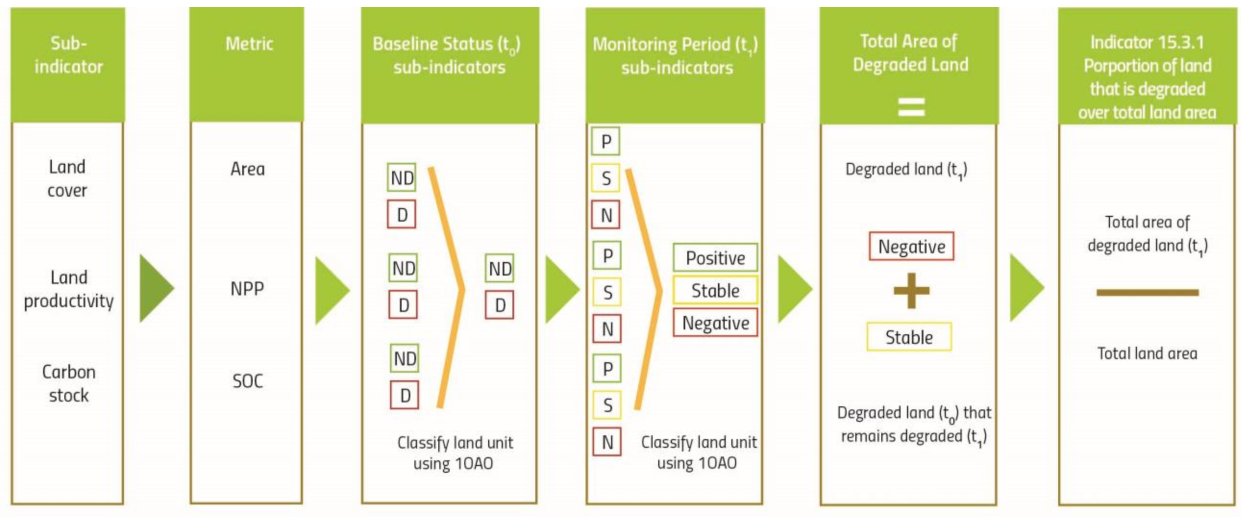
Deriving the indicator for the baseline and subsequent monitoring years is done by summing all those areas where any changes in the sub-indicators are considered negative (or stable when degraded in the baseline or previous monitoring year) by national authorities. This involves the:

(1) assessment and evaluation of **land cover and land cover changes**;
(2) analysis of **land productivity** status and trends based on net primary productivity; and
(3) determination of **carbon stock** values and changes, with an initial assessment of soil organic carbon as the proxy.

It is good practice to assess change for interim and final reporting years in relation to the baseline year for each sub-indicator and then the indicator. This facilitates the spatial aggregation of the results from the sub-indicators for each land unit to determine the proportion of land that is degraded for the baseline and each monitoring year. Furthermore, it ensures that land classified as degraded will retain that status unless it has improved relative to the baseline or previous monitoring year.

Land degradation (or improvement) as compared to the baseline may be identified with reference to parameters describing the slope and confidence limits around the trends in the sub-indicators, or to the level or distribution of conditions in space and/or time as shown during the baseline period. The evaluation of changes in the sub-indicators may be determined using statistical significance tests or by interpretation of results in the context of local indicators, data and information. The method of computation for SDG indicator 15.3.1 is illustrated in Figure 1.

**Figure 1.1: Steps to derive the indicator from the sub-indicators where ND is not degraded and D is degraded.**




The area degraded in the monitoring period $t_n$ within land cover class *i* is estimated by summing all the area units within the land cover class determined to be degraded plus all area units that had previously been defined as degraded and that remain degraded:

$$A(Degraded)_{i,n} = \sum_{j=1}^{n} Arecent_{i,n} + Apersistent_{i,n} \qquad (1)$$

Where:

$A(Degraded)_{i,n}$ is the total area degraded in the land cover class *i* in the year of monitoring *n* (ha);

$Arecent_{i,n}$ is the area defined as degraded in the current monitoring year following 1OAO assessment of the sub-indicators (ha);

$Apersistent_{i,n}$ is the area previously defined as degraded which remains degraded in the monitoring year following the 1OAO assessment of the sub-indicators (ha).

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

$$P_{i,n} = \frac{A(degraded)_{i,\mathrm{n}}}{A(total)_{i,\mathrm{n}}} \qquad (2)$$

Where

$P_{i,\mathrm{n}}$ is the proportion of degraded land in that land cover type *i* in the monitoring period *n*;

$A(Degraded)_{i,\mathrm{n}}$ is the total area degraded in the land cover type *i* in the year of monitoring *n* (ha);

$A(total)_{i,\mathrm{n}}$ is the total area of land cover type *i* within the national boundary (ha).

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

$$A(Degraded)_{\mathrm{n}} = \sum_{i}^{m} A(Degraded)_{i,\mathrm{n}} \qquad (3)$$

Where

$A(Degraded)_{\mathrm{n}}$ is the total area degraded in the year of monitoring *n* (ha);

$A(Degraded)_{i,\mathrm{n}}$ is the total area degraded in the land cover type *i* in the year of monitoring *n*.

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

$$P_{\mathrm{n}} = \frac{A(Degraded)_{\mathrm{n}}}{\sum_{i}^{m} \mathrm{A(Total)}} \qquad (4)$$

Where

$P_{\mathrm{n}}$ is the proportion of land that is degraded over total land area;

$A(Degraded)_{\mathrm{n}}$ is the total area degraded in the year of monitoring *n* (ha);

$\mathrm{A(Total)}$ is the total area within the national boundary (ha).

The proportion is converted to a percentage value by multiplying by 100.

## 1.3 Data Sources and Collection

National data on the three sub-indicators is and can be collected through existing sources (e.g., databases, maps, reports), including participatory inventories on land management systems as well as remote sensing data collected at the national level. Datasets that complement and support existing national indicators, data and information are likely to come from multiple sources, including statistics and estimated data for administrative or national boundaries, ground measurements, Earth observation and geospatial information. A comprehensive inventory of all data sources available for

each sub-indicator is contained in the Good Practice Guidance for SDG Indicator 15.3.1. The most accessible and widely used regional and global data sources for each of the sub-indicators are briefly described below.

**1) Land cover and land cover change data** are available in the:

> **(1) ESA-CCI-LC,**[25] containing annual land cover area data for the period 1992-2015, produced by the Catholic University of Louvain Geomatics as part of the Climate Change Initiative of the European Spatial Agency (ESA); or
>
> **(2) SEEA-MODIS,**[26] containing annual land cover area data for the period 2001-2012, derived from the International Geosphere-Biosphere Programme (IGBP) type of the MODIS land cover dataset (MCD12Q1).

**2) Land productivity data** represented as vegetation indices (i.e., direct observations), and their derived products are considered the most independent and robust option for the analyses of land productivity, offering the longest consolidated time series and a broad range of operational data sets at different spatial scales. The most accurate and reliable datasets are available in the:

> **(1) MODIS data products,**[27] averaged at 1 km pixel resolution, integrated over each calendar year since 2000; and
>
> **(2) Copernicus Global Land Service products,**[28] averaged at 1 km pixel resolution and integrated over each calendar year since 1998.

**3) Soil organic carbon stock data** are available in the:

> **(1) Harmonized World Soil Database (HWSD), Version 1.2,**[29] the latest update being the current de facto standard soil grid with a spatial resolution of about 1 km; and
>
> **(2) SoilGrids250m,**[30] a global 3D soil information system at 250m resolution containing spatial predictions for a selection of soil properties (at six standard depths) including SOC stock (t $ha^{-1}$).

In the absence of, to enhance, or as a complement to national data sources, good practice suggests that the data and information derived from global and regional data sets should be interpreted and validated by national authorities. The most common 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.

[25] https://www.esa-landcover-cci.org/
[26] https://modis.gsfc.nasa.gov/data/dataprod/mod12.php
[27] https://modis.gsfc.nasa.gov/data/dataprod/mod13.php
[28] http://land.copernicus.eu/global/
[29] http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/
[30] https://www.soilgrids.org/

**Data Collection:** Data on the indicator and sub-indicators will be collected by national authorities ("main reporting entity") to the UNCCD in their national reports following a standard format every four years beginning in 2018 or through other national data platforms and mechanisms endorsed by the UN Statistical Commission. This will include the original data and reference sources, and descriptions of how these have been used to derive the indicator and sub-indicators. Eligible countries will receive financial and technical assistance in preparing their national reports from the UNCCD and its partners.

Once received, national reports will undergo a review process by the UNCCD and its partners to ensure the correct use of definitions and methodology as well as internal consistency. A comparison can be made with past assessments and other existing data sources. Regular contacts between the main reporting entity and UNCCD secretariat via a help desk system, and through regional/sub-regional/national workshops, will form part of this review process, enable data adjustments when needed, and contribute to building national capacities. The data will then be aggregated at sub-regional, regional and global levels by the UNCCD and its partners.

## 1.4 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 key factors and driving variables that reflect the 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. As regards slow changing variables, such as soil organic carbon stocks, reporting every four years may not be practical or offer reliable change detection for many countries. Nevertheless, this sub-indicator captures important data and information that will become more available in the future via improved measurements at the national level, such as those being facilitated by the FAO's Global Soil Partnership and others.

While access to remote sensing imagery has improved dramatically in recent years, there is still a need for essential historical time series that is currently only available at coarse to medium resolution. The expectation is that the availability of high-resolution, locally-calibrated datasets will increase rapidly in the near future. National capacities to process, interpret and validate geospatial data still need to be enhanced in many countries; good practice guidance for the monitoring and the reporting of the sub-indicators in other processes will assist in this regard. To this end, the UNCCD's governing body has invited the Group on Earth Observation (GEO) to provide space-based information and *in situ* measurements to assist countries in fulfilling the reporting requirements for Sustainable Development Goal indicator 15.3.1, and to help foster data access, national data capacity-building and the development of standards and protocols.[31]

[31] http://www2.unccd.int/sites/default/files/sessions/documents/2017-09/ICCD_COP%2813%29_L.21-1716102E.pdf

# 2. Sub-Indicator on Land Cover and Land Cover Change

## 2.1 Executive Summary

Chapter 2 of this Good Practice Guidance (GPG) describes the methodology and data sources for establishing baselines and evaluating change in the sub-indicator on land cover. It is one of the three sub-indicators being used to derive Sustainable Development Goal (SDG) indicator 15.3.1 (“Proportion of degraded land over total land area”). It outlines the general principles for how countries can access land cover data to monitor change in the context of quantifying their area of degraded land, drawing on well-accepted methodologies and international standards.

Land cover and land cover change address the state and transitions in the structure and composition of the landscape due to natural events and human activities. There are a wide range of national, regional and global datasets that specify the distribution and composition of land cover classes. Using these datasets, countries can develop national land cover maps and context-specific estimations of the extent of degradation from land cover changes drawing on the recommendations contained in this GPG.

For these reasons, countries are best placed to make their own decisions regarding the best methods to assess land cover and land cover change. National methods should, as far as possible, exploit existing data and take advantage of accepted practices so as not to increase the overall reporting burden. It is also recognised that to be an effective tool, land cover data must be relevant in the context of implementing policies that encourage the prevention, mitigation and restoration of land degradation.

In terms of the development of a national method it is *good practice* to:

1. Adopt or formulate a land cover map legend with classes that are unambiguous, exhaustive and complete;
2. Generate a land cover class transition matrix that identifies land cover changes that could potentially be classified as degradation;
3. Define a spatial disaggregation scheme that is policy relevant and actionable;
4. Specify the product and method for generating a national land cover map including the source data, pre-processing, the classification approach and the accuracy assessment procedure;
5. Evaluate the performance of any new classification algorithm or existing product to be used in terms of the:
    a. availability of complete and temporally consistent national coverage;
    b. ability to capture the thematic detail defined in the legend;
    c. ability to capture classes at a high level of thematic accuracy;
    d. spatial resolution that is as high as possible (ideally 300 m or finer);
    e. ability to generate, or availability of, a land cover baseline extending back to at least the year 2000, which corresponds to the baseline period.
6. Specify when interim reporting will occur.

With respect to reporting on the land cover and land cover change sub-indicator, it is *good practice* to:

1. Provide two national land cover datasets, one which defines the baseline state ($t_0$) and one that defines the land cover state for the reporting date.
2. Generate land cover change data including:
    a. Gridded change data which identify the flows for each grid cell
    b. A table that identifies the total area for each major land cover flow
    c. Data specifying if change is degradation or not degradation for each grid cell in the source land cover data
    d. A map that indicates the probability of degradation, based on the land cover sub-indicator, for each spatial feature defined by the national disaggregation approach
3. Perform and report on validation of the land cover flows for any areas identified as degraded since the previous reporting period.
4. Explain why any spatial features identified as degraded in the land cover change data should not to be included as such in the overall indicator calculation.
5. Explain why any spatial features not identified as degraded in the land cover change data should be included as degraded in the overall indicator calculation.
6. Assess change for all interim and final reporting periods with respect to the land cover baseline ($t_0$).

No dataset is expected to be the ideal single source for rigorous land cover change detection and monitoring. However, the development of national methods for quantitative and repeatable land cover mapping provides the basis for the objective assessment of the sub-indicator in the context of the indicator. This is particularly true when the methods are combined with extensive, calibrated and validated data.

While there is general consensus regarding good practice for monitoring land cover and land cover change, decisions made at the national level will always take precedence as they are more likely to account for specific land cover types and change processes relevant to their situation. It is also recognised that data availability, the level of expertise and the resources available for reporting will vary immensely between countries and that this GPG should help reduce the reporting burden on national authorities. While the intention of this chapter is to describe how land cover and land cover change can be measured, monitored and reported in the context of SDG indicator 15.3.1, it is recognised that land cover assessment has applications within other SDG indicators (e.g., 6.6.1, 11.3.1, and 15.1.1) and for fulfilling the requirements of other international and national level reporting obligations.

## 2.2 Definitions and Concepts

**Land cover** refers to the observed physical cover of the Earth's surface which describes the distribution of vegetation types, water bodies and human-made infrastructure (Di Gregorio 2005). It also reflects the use of land resources (i.e., soil, water and biodiversity) for agriculture, forestry, human settlements and other purposes (FAO-GTOS. 2009). This sub-indicator 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, thus increasing the indicator's policy relevance.

To some extent, land cover is one of the most easily detectable properties of the earth's surface and has been used as an important indicator of change that is both human induced and natural. However, at the fine scale, land cover can be a complex arrangement of different vegetation and abiotic components. For example, a given land unit may include vegetation with a soil substrate. The vegetation may include a selection of woody and non-woody species arranged in a complex way both horizontally and vertically. Land cover, in this sense, is the description of these components in a way that has some logical meaning at the spatial unit of interest and in the thematic context being considered.

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

The **Land Cover Meta Language** (LCML) (ISO 19144-2: 2012)[32] is an ontological tool for land cover classification expressed as a Unified Modelling Language (UML) that allows different land cover classification systems to be described based on the physiognomic aspects. While UML has traditionally been used in software engineering to define object-oriented software, in this application the UML classes represent concepts: specifically 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.

A **spatial feature**, in the context of a classified landscape represented as a thematic map, is an individual landscape element which is labelled as a member of a class from the classification system or map legend. Features may be abstract regions defined by a grid (pixels) or a polygon, or may be a logical unit defined by a political or natural boundary. Within a landscape, the set of features should be spatially exhaustive, such that the entire region of interest (e.g., country) can be classified according to the legend in use. A feature is often a contiguous unit that is assigned to a single class. However, a feature may be considered heterogeneous and information may be recorded about the proportions of all land cover types present. The degree of homogeneity of features depends on the classification system in use. Given uncertainty in the data, features may be labelled using the most probable class, with one or more other likely classes also recorded.

**Land cover elements** are the basic components in the landscape that make up a given land cover class. Elements may be abiotic (e.g., water, soil, rock and man-made surfaces) or vegetation (e.g., grasses, shrubs, bushes and woody plants). A particular land cover class may include one or more elements, depending on the complexity of the land cover and on the spatial unit being considered.

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

A **land cover class** is a single category or type of land cover within a broader set of classes defined within a classification system. Its specification will generally describe the properties of the elements that constitute a particular class. For example, the definition of a forest class may include woody and non-woody vegetation, while some criteria for the canopy cover and height of the woody elements may also be specified. At its most basic, a land cover class is defined using a unique identifier (class name) and description. This is sufficient for land cover classes that are simple to describe, but may be inadequate for those that are complex, requiring a definition that includes multiple elements and properties. Simple textual definitions also tend to lead to more cognitive than logical descriptions (Di Gregorio & O'Brien 2012) that are not necessarily well understood across different regions or different disciplines.

For more rigorous and scalable class definitions, a schema written in a mark-up language (e.g., xml, json or rdf) may be used. These languages are designed to be both human and machine readable which can assist in automated comparison of land cover classes, even if different legends are used. Such languages can be used to fully describe the criteria for the presence and arrangement of land cover class elements as well as the range of acceptable properties for each and can be used to produce such a metadata classification schema that exactly specifies the criteria for classes in a machine readable format.

A **land cover legend** is the set of classes which have been defined using the classification system and incorporated into a given measurement, mapping, monitoring or reporting exercise. The classes constituting a suitable legend should be:

1. **unambiguous**: being mutually exclusive and unique;
2. **complete:** in terms of spatial coverage for the region of interest;
3. **exhaustive**: providing complete thematic coverage of 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. 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). At the national scale, it is important to consider the level of detail required from a legend to ensure that important changes in land cover can be identified. The appropriate legend, or level of detail, varies and should be based on the national reporting and planning requirements within a country.

**Land cover changes** describe the transition from one land cover class to another (Di Gregorio et al. 2011), which can be either rapid of gradual. For example, changes can occur rapidly as a result of significant environmental disturbances, natural disasters or human interference, but there may also be gradual processes of decline such as changes in soil fertility, vegetation or climate. In theory, a transition can occur between any two classes though some may be improbable or go through intermediate states. For example, a transition from a forest class to pasture may be referred to as

deforestation, while a transition from a grassland to a water body may be defined as inundation. It is good practice to define a matrix of flows changes that include all classes in the national legend.

## 2.3 Methodology

The method of computation used for this sub-indicator is a national decision and this chapter merely sets out guidance and other considerations for national authorities when implementing their own measurement, validation and reporting approaches. It can be is described in two phases: i) the development of the national method for establishing baselines, and ii) the interim and final reporting of the sub-indicator. It is important to ensure that the national method conforms to good practice and provides an objective assessment of land cover change.

### 2.3.1 National Method

The national method identified to map land cover change should be described in detail, including the determination of a baseline land cover map from which subsequent change can be assessed. Any subsequent changes in the national method due to the availability of additional expertise, resources and data should be reported in the next interim report, including the reprocessing and resubmission of the revised baseline land cover data. The following are good practice principles to guide the development of a national method of computation for the sub-indicator.

- **It is good practice to define and justify a spatial disaggregation scheme**. This scheme will specify the spatial features within which land cover and land cover change will be reported. It will also be used to stratify the assessment and for reporting on the other sub-indicators.
- **It is good practice to define a land cover map legend with classes that are unambiguous, exhaustive (mapping total land area) and complete (whereby all major changes can be identified).** The capacity of a given country to utilize existing expertise and available data to support accurate mapping and validation of classes across the country must also be considered.
- **It is good practice to generate a land cover class change matrix that describes the processes of transition between land cover classes.** This will assist in determining if the most appropriate classes have been used in the legend and that all major land cover change processes have been captured. The major flows identified in the matrix should be listed and identified as degraded, not degraded or stable.
- **It is good practice to clearly specify the method selected for generating a national land cover map.** This should include the source data, any pre-processing, the classification algorithm and the accuracy assessment procedure. A number of global and regional land cover products are available which can be used to generate a national land cover map.
- **It is good practice to evaluate (quantitatively where possible) the performance of any new classification algorithm or existing product** in terms of:
    - The availability of complete and temporally consistent national coverage;
    - The use of time series data to assess when changes in land cover occur and to identify these transitions through the analysis of spectral change;
    - Their ability to capture the thematic detail defined in the legend;
    - Ability to capture classes at a high level of thematic accuracy;
    - A spatial resolution that is at least as detailed as the global default data (300 $m^2$)

- The availability of or ability to generate a baseline map for 2015

- **It is good practice to define a baseline ($t_0$) from which changes in land cover will be assessed.** Baseline values for land cover classes should be fixed to reflect their extent for the baseline year 2015. This serves to disaggregate the trends in the other two sub-indicators at the baseline year and estimate land cover changes in subsequent monitoring periods. Countries may wish to assess land cover changes during the baseline period (2000-2015) in order to contribute to their estimation of the extent of land that is degraded in 2015.
- **It is good practice to ensure that the method of generating the land cover products for future reporting is the same as the one for the baseline, and to specify the reporting frequency.** While it may be possible to assess land cover and land cover change annually, this will need to be synchronized with the other sub-indicators for each monitoring period.

### 2.3.2 National Reporting

Reporting on land cover and land cover change is nominally is every four years, consistent with the recommended UNCCD reporting cycles.[33] Reporting on the sub-indicator in the monitoring period ($t_1$) will help identify areas where land cover has changed significantly relative to the baseline ($t_0$).

Defining a national land cover and land cover change assessment method is a necessary first step in the reporting process. Reporting should be detailed enough so that national stakeholders are able to determine the location, type and level of change that has occurred. In this regard, the following good practice principles should be considered.

- **It is good practice to provide two gridded national land cover datasets, one for $t_0$ and one for the reporting date.** These should be generated at the same grid spacing (spatial resolution) using the same land cover classification scheme and accompanied by an accuracy assessment for each map, including a confusion (error) matrix with accuracy and confidence intervals.
- **It is good practice to generate land cover change information based on the reporting date ($t_1$) and baseline ($t_0$).** This will include:
    - Gridded change data which identify any changes for each grid cell in the land cover data.
    - A table that identifies the total area of land that is associated with each major land cover change.
    - Gridded data that specifies if change is degradation or not degradation for each grid cell in the land cover data.
    - A map that indicates the probability of degradation within spatial features that are based on the national disaggregation approach. Significant negative change or degradation can be identified according to the equations in the next section.
- **It is good practice to perform qualitative assessments of areas identified as degraded.** This assessment should specify the dominant land cover changes occurring within a country.
- **It is good practice to justify why any spatial features identified as degraded in the land cover change data should not be included in the overall indicator calculation.** This should

[33] http://sdg.iisd.org/news/cric-15-discusses-future-of-reporting-unccd-strategic-framework/

be based on the identification of false positives, where change in the land cover data is due to stable or improved land condition.

- **It is good practice to justify why any spatial features not identified as degraded in the land cover change data should be included in the overall indicator calculation.** This should include a proposed improvement to the land cover classification approach or legend so that such degradation processes become more apparent in future assessment periods.
- **It is good practice to assess change for interim and final reporting periods with respect to the baseline land cover data product ($t_0$).** This will ensure that land defined as degraded, from a land cover change perspective, will remain in the degraded category unless it is improved relative to the land cover baseline.

## 2.4 Rationale and Interpretation

### 2.4.1 Establishing the Baseline

Baseline values for land cover classes should be fixed to reflect their extent for the baseline year 2015. Countries may wish to assess land cover changes during the baseline period (2000-2015) in order to contribute to their estimation of the extent of land that is degraded in 2015. Nevertheless, national authorities should consider the specific period for assessing the baseline in the context of the rate of land cover change in their country. For example, a shorter baseline period could be used to ensure the baseline better reflects land cover classes in 2015.

The specific target date for the final reporting on SDG indicator 15.3.1 is specified as 2030, and is a special case for reporting that is referred to below as $t_n$. The baseline is referred to as $t_0$ and interim assessment dates are referred to as $t_1$->$t_n$. It is the change between the land cover classes at $t_0$ and $t_n$ that will help national authorities determine if land degradation has occurred.

### 2.4.2 Defining the Legend

Land cover classes should be exhaustive, such that all of a country's land area can be attributed to a specific class at $t_0$ and monitored over the period to $t_n$. National authorities are best placed to determine the exact classes to include in a land cover legend. While the six classes included in the IPCC land use change legend (Penman et al. 2003) should be considered a minimum set, national authorities are encouraged to expand this legend set in order to enhance their ability to identify and map potential land degradation processes occurring in their country.

The UN Statistical Commission's System of Environmental and Economic Accounting (SEEA) defines 14 land cover classes that are considered to best describe the state of natural capital in a country. The FAO GLC-SHARE land cover dataset adopts 11 of these classes by aggregating SEEA cropland classes (Latham et al. 2014). The European Space Agency's Climate Change Initiative on Land Cover (ESA CCI-LC) provides a typology of 22 land cover classes based on the UN Land Cover Classification System and its classifiers to support the further conversion into Plant Functional Types distribution required by the Earth System Models.

Tools that form part of the LCCS allow users to take land cover classes and store them in a hierarchical structure that groups the classes according to the main land cover type. Individual countries should endeavour to harmonise their national land cover classes with existing LCML-based

classifications wherever possible. While the FAO provides software tools to help in harmonising non-LCML classes, these tools require some prior understanding of the object-based structure of the meta-language. A mapping between land cover classes used in various legends is shown in Table 2.1.

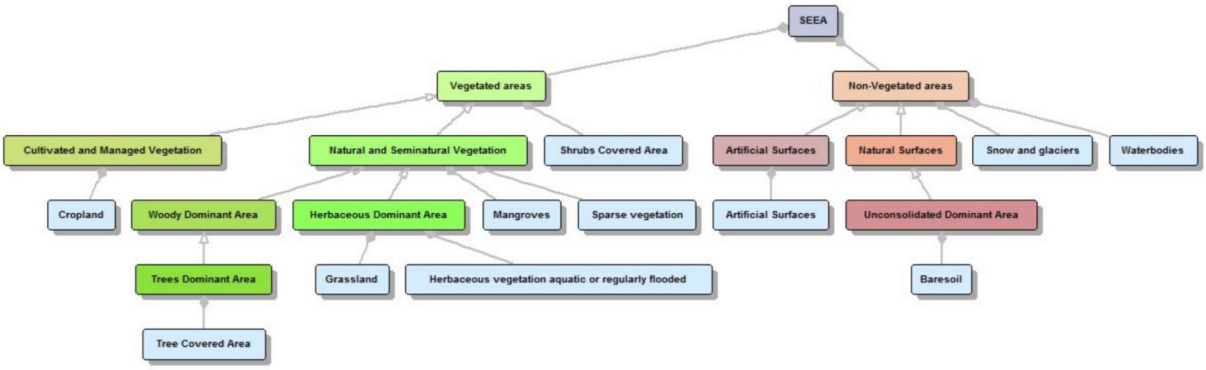
**Table 2.1: Mapping between land cover classes used in various legends.**

| IPCC | GLC-Share | SEEA CF Land cover classification (interim) | ESA CCI-LC classes |
|---|---|---|---|
| **Forest Land** | Tree Covered Areas | Tree-covered areas | Tree cover, broadleaved, evergreen, closed to open (>15%)<br>Tree cover, broadleaved, deciduous, closed to open (>15%)<br>Tree cover, needleleaved, evergreen, closed to open (>15%)<br>Tree cover, needleleaved, deciduous, closed to open (>15%)<br>Tree cover, mixed leaf type, closed to open (>15%)<br>Mosaic tree and shrub (>50%)/herbaceous cover (<50%) |
| **Grassland** | Grassland<br>Shrub Covered Areas<br>Sparse Vegetation | Grassland<br>Shrub-covered areas<br>Sparsely natural vegetated areas<br>Natural vegetation associations and mosaics | Mosaic natural vegetation, tree, shrub, herbaceous cover (>50%)/cropland (<50%)<br>Scrubland<br>Grassland<br>Lichens and mosses<br>Sparse vegetation, tree, shrub, herbaceous cover (<15%) |
| **Cropland** | Cropland | Herbaceous crops<br>Woody crops<br>Multiple or layered crops | Cropland, rainfed:<br>- Herbaceous cover<br>- Tree or shrub cover<br>Cropland, irrigated or post-flooding<br>Mosaic cropland (>50%)/natural vegetation, tree, shrub, herbaceous cover (<50%)<br>Mosaic herbaceous cover (>50%)/tree and shrub (<50%) |
| **Wetlands** | Herbaceous Vegetation, aquatic and regularly flooded<br>Mangroves | Shrubs and/or herbaceous vegetation, aquatic or regularly flooded<br>Mangroves | Tree cover, flooded, saline water*<br>Tree cover, flooded, fresh or brackish water*<br>Shrub or herbaceous cover, flooded, fresh/saline/brackish water |
| **Settlements** | Artificial Surfaces | Artificial surfaces (including urban and associated areas) | Urban areas |
| **Other Land** | Bare Soil<br>Snow and Glaciers | Terrestrial barren land<br>Permanent snow and glaciers | Bare areas<br>Permanent snow and ice |
| | Water Bodies | Inland water bodies<br>Coastal water bodies and intertidal areas | Water bodies |

* Université catholique de Louvain includes these ESA CCI-LC classes under Forest Land (Tree Covered Areas)

In order to illustrate the relationship among land cover classes in a particular legend, the hierarchical structure of the GLC-SHARE legend is shown in Figure 2.1.

**Figure 2.1: The SEEA based legend used by GLC-SHARE and defined using the LCML (Latham et al. 2014).**




A clear and unambiguous definition of land cover classes is imperative in order to ensure that changes can be identified to provide a better understanding of degradation processes. While LCML provides the most structured approach to class definition, Gregorio & Jansen (2000) do provide guidance on how to translate from conventional descriptive class definitions to a LCML-based schema.

### 2.4.3 Assessing Land Cover Changes

Land degradation is context-specific depending on the characteristics of the environment and the values of those assessing it. Some of the ways in which degradation can be considered include:

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 nutrients
2. A reduction in the land's capacity to provide resources for human livelihoods
3. A loss of biodiversity or ecosystem complexity
4. Increased vulnerability of populations or habitats to destruction or crisis

In the context of SDG indicator 15.3.1, land cover refers to the naturally stable aspects of the land such as its constituent elements, their structure and homogeneity, rather than the transient aspects such as vegetation phenology, snow and flood water cover or burned area. National authorities must determine what changes and their underlying processes are considered to be degrading. This may include the identification of specific class transitions that are of national concern such as deforestation, desertification or urbanization. The identification of specific flows will help to ensure a complete set of land cover classes required to monitor and stratify land degradation at the national scale.

It is good practice to define a matrix of changes that include all classes in the national legend. Using the relatively simple IPCC legend (Penman et al. 2003) as an example, the 6 classes can be used to define 6 x 5 (30) possible land cover class changes. An example of how these class changes might be

classified according to major change processes is shown in Figure 2.2 and includes 11 unique land cover changes. Guidance on how to assess these changes is provided in Table 2.2.

**Figure 2.2: Graphical summary of the land cover/land use change matrix for the 6 IPCC classes (30 possible transitions). Unlikely transitions are highlighted in red text. Major land cover processes (flows) are identified and boxes are colour coded as improvement (green), stable (blue) or degradation (red).**

**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 |

**Table 2.2: Descriptions of major land cover change processes identified as flows in Figure 2.2.**

| FLOW ID | FLOW PROCESS DESCRIPTION | DEGRADATION |
|---|---|---|
| **LCF1** | Deforestation | Yes |
| **LCF2** | Urban Expansion | Yes |
| **LCF3** | Vegetation Loss | Yes |
| **LCF4** | Inundation | Yes |
| **LCF5** | Wetland drainage | Yes |
| **LCF6** | Withdrawal of agriculture | Yes |
| **LCF7** | Stable | No |
| **LCF8** | Afforestation | No |
| **LCF9** | Agricultural Expansion | No |
| **LCF10** | Vegetation establishment | No |
| **LCF11** | Wetland Establishment | No |

Not all possible transitions between classes will be logical or plausible (Gómez et al. 2016; Wehmann & Liu 2015). The identification of illogical or unlikely flows in the transition matrix will assist in validation of land cover change maps. A comprehensive approach would be to specify the probability of all transitions in the matrix and could be incorporated into automated classifications

schemes (e.g., using Bayesian prior probabilities) to improve the accuracy of subsequent land cover maps.

It should be noted that it may be extremely difficult to attribute specific causal factors to land cover changes. For example, Lambin et al., (2001) challenge the attribution of land cover change to factors such as population, affluence or technology, which have gained acceptance in some disciplines (Kates 2000), and call for recognition of the more complex socio-economic and biophysical drivers of change. For this reason, it is good practice in the identification and labelling of flows to avoid attribution of cause, and to instead use change descriptions, rather than why land cover has changed.

The attribution of change for a reporting period can only be done using annual land cover changes from 2000-2015 of corresponding classified features recognizing the need fora thorough assessment of intra-annual variability in order to decouple stable and dynamic land cover components (Defourny and Bontemps et al., 2012). In the case of land cover, features will generally be a spatial unit, and the attribution of flows to these spatial units will result in a new spatial dataset. In the case of SDG 15.3.1, this spatial dataset is used to stratify and aggregate the area of land that is determined to be degraded.

### 2.4.4 Earth Observation Data

Land cover mapping is often based on surface reflectance products derived from Earth observation (EO) data. These products attempt to minimise, normalise or remove some or all of the following:

- Sensor-to-sensor spectral radiometric variations;
- Atmospheric attenuation and obscuration by cloud; and
- Surface bi-directional reflectance distribution function (BRDF) variations.

In addition, the identification of land cover change requires consecutive epochs of land cover to be overlayed precisely. The removal of geometric distortions, such as by projecting native swath data to an established spatial or coordinate reference system (ISO 19111: 2007)[34] and the removal of topographic distortions are important steps for ensuring that land cover change is identified correctly. The choice of projection and datum to which these data are registered should also consider the spatial registration of data used to report on the other two sub-indicators. Ideally, all datasets used to estimate SDG indicator 15.3.1 will be registered to the same reference system.

Products such as the MODIS Nadir BRDF Adjusted Reflectance (Schaaf et al. 2002) and MERIS surface reflectance (Defourny et al. 2012) provide good examples of the required pre-processing of EO data prior to attribution of land cover classes. Further refinement of these products using compositing, including best available pixel approaches (White et al. 2014) from Landsat, have resulted in the availability of annual global cloud-free surface reflectance composites that provide a sound basis for generating land cover maps. Information on the timing of any measurement is important for understanding change, however, and it is good practice to record, interrogate and understand pixel observation dates in any composite product before land cover is attributed.

[34] https://www.iso.org/standard/41126.html

While the spectral properties of some classes within a legend may be quite distinct (e.g., vegetation, water, urban), other classes may be less easy to distinguish using conventional spectral methods at a given spatial resolution (e.g., deciduous and evergreen forests), particularly when using annual image composites. In such cases, the assessment of spectral change metrics is required and may provide a means of increasing classification accuracy (Gómez et al. 2016; Fuller et al. 2003).

The spatial and temporal resolution of EO source data are key factors which can determine the usefulness of derived land cover products. A survey of the user community conducted as part of the implementation of the ESA CCI-LC (Herold et al. 2010) suggests there is a need to move towards finer spatial resolution (e.g., from 1 km to 30 m) and towards finer temporal coverage (from 1 year to seasonal or monthly) in order to better detect land cover change.

While high-quality cloud free imagery are an important basis for land cover classification, the native spatial resolution of the observation also has a significant impact on the type of land cover and the change processes that can be detected. Sub-pixel change processes are less likely to be identified where the pixels are large compared to the extent of land cover change within the pixels. This has led to a call for increased spatial resolution in land cover products (Herold et al. 2010) and is an emerging opportunity for moderate resolution sensors on board the Landsat (Franklin et al. 2015) and Sentinel (Malenovský et al. 2012) satellites.

Since trade-offs between spatial and temporal resolution are required to achieve an acceptable signal to noise ratio for satellite observations, data fusion algorithms (e.g., Gao et al. 2006; Hilker et al. 2009) may assist in the development of the required data to underpin accurate and timely land cover classification.

### 2.4.5 Land Cover Datasets

While national and regional initiatives to monitor and map land cover have existed for decades, the first global land cover product, DISCover based on AVHRR data, was not released until the early 1990s (Loveland et al. 1999). Increased spectral information available via the MODIS and SPOT-VEGETATION instruments allowed for more detailed legends (Bartholomé & Belward 2005; Friedl et al. 2002). Recently, medium resolution sensors, MERIS and SPOT-VGT, have allowed for an increase in the spatial resolution achievable for global land cover maps like the ESA CCI-LC (Bontemps et al. 2013; Defourny et al. 2012).

Many countries have systems in place that regularly collect quantitative data to assist in mapping land cover. Occasionally multiple land cover mapping systems exist within the one country, often developed by different departments and agencies, serving different land management and reporting purposes. For reporting on SDG indicator 15.3.1, a land cover dataset approved by all relevant national agencies is preferred. Furthermore, this nationally agreed product should use a legend that is appropriate to monitor land cover changes that may indicate land degradation.

Some national land cover mapping systems rely solely on data collated, calibrated and validated locally, while others rely on regional or global land cover datasets. Ideally, a nationally agreed, calibrated and validated land cover product is considered preferable. However, in cases where there is little or no capacity to produce a national dataset, regional or global land cover data may be

useful. These data should be customised to local conditions such that an appropriate legend is used, and some form of local validation is conducted.

National, regional and global land cover products should not be considered mutually exclusive, rather that each product can be used to cross-validate others and to achieve greater confidence at the national level. For the selection of the most appropriate product, thematic detail, temporal range and frequency, and spatial resolution should be considered at the national level. Specifically, national subsets that span the entire baseline period and are generated frequently at high spatial resolution are preferred.

Both automated and semi-automated classification methods have been developed for the generation of land cover maps based on EO data. 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. Khatami et al. (2016) present a list of most accurate 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 raw spectral data) can yield improvements in classification accuracy (see Table 2.3). Specifically, the inclusion of spatial, directional and temporal context information, along with other orthogonal variables such as topography and geology, generally improve classification accuracy.

**Table 2.3: 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% |

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

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. It is important to recognize that changes in the stable components that indicate land cover change in the context of SDG indicator 15.3.1, and the challenge is to identify these 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).

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 over time to determine what the final state of land cover is likely to be. This method will help to identify transient, as well as illogical or improbable changes (Gómez et al. 2016) to support the final land cover class specification.

### 2.4.6 Training and Validation Data

Good practice for collecting training and validation data as well as assessing map accuracy are described in a recent FAO publication (Finegold et al. 2016). Optimum training and validation data depend on the classification legend and method employed. The most common non-parametric methods of land cover classification require training data that best describe class boundaries as opposed to parametric methods which require the location and spread in the input data space (Gómez et al. 2016).

The size of the training dataset will depend on the thematic detail of the legend and on the spatial variability of the land cover class. It is difficult to specify an appropriate number of field samples since this depends on information that is not known *a priori* (Finegold et al. 2016). However, it was estimated that around 1000 samples were required for adequate training and validation of the GLC-Share global land cover product (FAO 2014), while the CCI-LC product made use of 2600 sampling points (Defourny et al. 2012). For the Australian Dynamic Land Cover Map, more than 25,000 field validation sites were used (Lymburner et al. 2011). It is good practice to define a spatial stratification approach to help guide the selection of samples. Crowd-sourced data, such as those available through the Geo-Wiki (Laso Bayas et al. 2016; Fritz et al. 2012), are also gaining acceptance for validation of land cover.

Ideally the distribution of each variable for each land cover class needs to be captured. 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)
- High temporal resolution data (e.g., NDVI time series for a feature of interest)

Expert knowledge and training may be required to ensure that such data accurately captures the spatial and thematic variability. Methods for calculating and reporting error statistics in land cover classification are well established and generally begin with a confusion (or error) matrix, which is a cross-tabulation of map classes (rows) and validation classes (columns) (see Table 2.4). The number of samples that appear along the diagonal show those samples that are correctly classified while those that appear off the diagonal are errors. Confidence intervals should be reported for each of the accuracy measures in the confusion matrix (Olofsson et al. 2014).

**Table 2.4: 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** | $p_{11} / \sum p_{i1}$ | $p_{12} / \sum p_{i2}$ | $p_{13} / \sum p_{i3}$ | $\sum p_{ii}$ |

### 2.4.7 Reporting Change

For any features that are identified as being degraded at $t_1$, it is good practice to provide some ground truth to validate that changes indicated by the data are realistic and that they actually represent land degradation. Some discussion of significant changes at the scale of individual features will be useful for understanding national trends and planning policy responses. Justification should also be provided for not including any areas that have been identified as degraded in the data but are considered not degraded based on more detailed validation studies.

It is good practice to report on the degraded area for each land cover type in addition to the total proportion of land degraded at the national level. If all spatial features are considered homogeneous at $t_0$ and at $t_1$, then the baseline land cover specific area is calculated by:

$$A_{i,0} = \sum_{j=1}^{n} a_j X_{i,0} \qquad (1)$$

where $a_j$ is the area of the jth feature (e.g., pixel or polygon) and $X_{i,0}$ -> {0,1} is an indicator function that takes the value one if features are of land cover type *i* at time $t_0$. At $t_1$ the area of land cover class *i* that is degraded is:

$$A_{i,1} = \sum_{j=1}^{n} a_j X_{i,1} \qquad (2)$$

where $X_{i,1}$ -> {0,1} is the indicator function taking the value one when features are originally of land cover class *i* and have transitioned to a degraded class before $t_1$. The proportion of land cover type *i* that is degraded is then given by:

$$P_{i,1} = \frac{A_{i,1}}{A_{i,0}} \qquad (3)$$

The total area of degraded land at the national scale is the accumulation across the *m* land cover classes defined within the legend:

$$A_1 = \sum_{i=1}^{m} A_{i,1} \qquad (4)$$

and the total proportion of degraded land over total land area is given by:

$$P_1 = \frac{A_1}{\sum_{i=1}^{m} A_{i,0}} \qquad (5)$$

If features are not considered homogeneous at either $t_0$ or $t_1$, then significant change can be specified when p > $\alpha$ when p is calculated using the equation:

$$p = \sum_{i=1}^{m} \left| P_{i,0} - P_{i,1} \right| \quad (6)$$

Nominally $\alpha$=0.10 (indicating that significant change occurs where 10% or more of the feature area has changed classes), while $P_{i,0}$ and $P_{i,1}$ are the initial and final proportions of each of the *m* land cover types. The baseline land cover specific area at $t_0$ is these proportions as follows:

$$A_{i,0} = \sum_{j=1}^{n} a_j \, P_{i,0} \quad (7)$$

At $t_1$ the area of land cover class *i* that is degraded is only accumulated over those features where change has been shown to be significant:

$$A_{i,1} = \sum_{j=1}^{n} a_j \, P_{i,1} X_{i,1} \quad (8)$$

where the indicator function $X_{i,1}$ -> {0,1} takes the value one for features where p indicates significant change. The proportion degraded for land cover type, the total area degraded and the total proportion of land degraded are again based on equations 3-5. A template for reporting land cover change is shown in Table 4.5.

**Table 2.5: Template for reporting degraded area and proportion by land cover class**

| Class | Class Area at $t_0$ | Area Degraded at $t_1$ | Proportion Degraded at $t_1$ |
|---|---|---|---|
| $C_1$ | $A_{1,0}$ | $A_{1,1}$ | $P_{1,1}$ |
| $C_2$ | $A_{2,0}$ | $A_{2,1}$ | $P_{2,1}$ |
| … | … | … | … |
| $C_m$ | $A_{m,0}$ | $A_{m,1}$ | $P_{m,1}$ |
| Total | | | $P_1$ |

## 2.5 Data Sources and Collection

The land cover sub-indicator is used to detect land cover change but also as a means of stratifying the analysis of the other sub-indicators (productivity and carbon stocks). Land cover products developed and validated by the relevant national authorities will generally provide a more relevant summary for the purpose of monitoring changes over time. However, in some instances, the development of a national land cover product may not be possible. In such cases, various regional or global products can provide a viable alternative.

### 2.5.1 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 & Koomen (2015) and are listed in Table 8. These data are considered to be preferable to global and regional products for monitoring land cover change because class legends can be designed to include specific land cover types, and to better capture nationally significant land cover change 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 class definition, legend design, classification approaches and the extent and approach to validation as described in this GPG.

**Table 2.6: Summary of existing national land cover data available, as reviewed by Diogo & 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 | 2000-2008 Time series with a dataset for each year between 2000 and 2010 is expected to be released | Land cover (FAO-LCCS) |
| **ALUMP** | 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 | 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 and 2012 | 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 and 2011 | Land cover (modified Anderson LCCS) |

### 2.5.2 Regional Land Cover Products

Regional land cover products may have advantages at the individual country scale in terms of better characterizing important land cover classes specific to that region. Two important regional datsets are discussed and summarized in Table 2.7.

- **CORINE Land Cover**: The CORINE Land Cover product includes coverage of the 28 European Union member states and other European countries. The prodiuct is based primarily on the manual interpretation of Landsat ETM+. National land cover maps are assembled into a seamless European map, resulting in a complete and consistent dataset across Europe. The datasets are distributed in at a 100 m pixel resolution, including 44 classes organised in three hierarchical levels, combining both land cover and land use concepts. Land cover maps are available for 1990, 2000, 2006 and 2012.
- **North American Land Change Monitoring System** (NALCMS): The NALCMS is a harmonised land cover product based on MODIS data, which can be applied across North America at 250 m spatial resolution. The classification legend is designed in three hierarchical levels using the FAO-LCCS system. There are currently two series available for the year 2005 and 2010.

**Table 2.7: Summary of existing regional land cover data available, as reviewed by Diogo & Koomen (2015).**

| Product | Measurement method | Reported accuracy | Geographical coverage | Spatial resolution | Time periods available | Thematic resolution |
|---|---|---|---|---|---|---|
| **CORINE Land Cover** | Based on SPOT, Landsat TM and MSS 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 foreseen) | Land cover and land use (CORINE, based on FAO-LCCS) |
| **North American LCMS** | Based on MODIS satellite imagery | Canada 2005: 59%-69% | Canada, Mexico and the United States | 250m | 2005 and 2010 | Land cover (FAO-LCCS) |

### 2.5.3 Global Land Cover Products

A recent review of land cover data conducted by Diogo & 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 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 sprawl and other landscape fragmentation.

A list of global land cover datasets is shown in Table 2.8. 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 moderate resolution satellite data (ENVISAT MERIS, MODIS, SPOT VGT and PROBA-V). Annual updates of the CCI-LC product are currently available from 1992 to 2015. Additional years will be made available as soon as they are finalized by ESA.
- **GLC-SHARE**: The Global Land Cover-SHARE (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 bassline 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 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.
- **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 5) 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 cover products use the International Geosphere–Biosphere Programme (IGBP) classification system[35] and are available for every year in the period 2000 to 2014 at 500m spatial resolution.

New and emerging data and methods are coming online, and the most appropriate integration of EO data, manual interpretation of high resolution imagery and ground based surveys should be determined. This will vary depending on the land cover classes and the degradation processes present at the national scale.

[35] http://www.igbp.net/

**Table 2.8: Summary of existing global land cover data available as reviewed by Diogo & Koomen (2015).**

| Product | Measurement method | Reported accuracy | Geographical coverage | Spatial resolution | Time periods available | Thematic resolution |
|---|---|---|---|---|---|---|
| **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 (mosaics) or 5' and 0.5o (aggregated global dataset) | Every year between 2001-2012 | 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) |
| **CCI-LC** | Based on MERIS and SPOT-Vegetation satellite imagery | 2008-2012: 74% | Global (aggregated dataset) | 300m | 1998-2002, 2003-2007 and 2008- 2012 | 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) |

## 2.6 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 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. 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.

By following good practice, decisions made by individual 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. It should also be recognised that 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 obligations.

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# 3. Sub-Indicator on Land Productivity

## 3.1 Executive Summary

Chapter 3 of this Good Practice Guidance (GPG) describes the methodology and data sources for establishing baselines and evaluating changes in the sub-indicator on land productivity. It is one of the three sub-indicators being used to derive Sustainable Development Goal (SDG) indicator 15.3.1 ("Proportion of degraded land over total land area"). This chapter outlines the general principles for how countries can access land productivity data to monitor changes in the context of quantifying the area of degraded land, drawing on well-accepted methodologies and international standards.

Land productivity is the biological productive capacity of the land, the principle 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 Annual Net Primary Production (ANPP) of vegetation.

Consistent with the Intergovernmental Panel on Climate Change (IPCC 2006) guidelines, a range of datasets and processing options are presented with the level of accuracy, detail and processing complexity increasing from Tier 1 (simple methods with default values) to Tier 2 (additional use of country-specific data) to Tier 3 (more complex methods involving ground measurements and modelling) with the level of accuracy, detail and processing complexity increasing at each level. Tier 1 uses global datasets and is intended for use where data availability or processing capacity is limited. Tier 2 includes the use of national datasets and models, which may include high-resolution image data and Tier 3 validates productivity predictions against additional sources of information including field samples, to further improve the accuracy of the assessment and facilitate the conversion of productivity estimates into biomass units such as kg/ha/year.

Countries should ultimately strive to report changes in land productivity at the highest level of detail and rigour (Tier 3). 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. Estimates of relative change in productivity levels, such as those provided by the Normalised Difference Vegetation Index (NDVI), are sufficient to assess and evaluate trends in land degradation in accordance with the methodology presented in this GPG.

This chapter provides guidance on the methods that countries can use to determine land productivity baselines and monitor land productivity trends over time. Improving, declining or stable land productivity is calculated at the pixel scale based on three metrics calculated from the image data:

1. **Trend**, which represents the trajectory of productivity over time,
2. **State**, which compares the current productivity level in a given area to historical observations of productivity in that same area, and

3. **Performance**, which measures local productivity relative to other similar vegetation types in similar land cover types and bioclimatic regions.

These three metrics help determine if land is degraded in areas where productivity may be increasing but remains low relative to other areas with similar land cover characteristics and climatic conditions. In this assessment, changes in productivity are considered negative when there is a statistically significant negative trend over time, or when both the Performance and State assessments indicate potential degradation, including in areas where the trend is not significantly negative.

Guidance on dataset and productivity index selection, options for calibrating land productivity time series data to minimise the influence of inter-annual differences in moisture availability, and reporting recommendations are also provided in this chapter.

## 3.2 Definitions and Concepts

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

Land productivity can be measured across large areas from Earth observations of Net Primary Productivity (NPP). NPP is the net amount of carbon assimilated after photosynthesis and autotrophic respiration over a given period of time (Clark et al. 2001) and is typically represented in units such as kg/ha/year (annual NPP or ANPP). Remote sensing is the most effective way to measure ANPP in fine detail at national scales, but it is not directly measured by Earth observation sensors. ANPP is estimated from known correlations between the fraction of absorbed photosynthetically active radiation (fAPAR) and plant growth vigour and biomass.

**Productivity index** is the algorithm used to measure 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 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 biomass units of ANPP, 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 unitless index, such as the NDVI, is often sufficient to determine land degradation. This also reduces the sampling effort required by countries to convert index values into finite biomass units for ANPP assessments.

Note however that an increase in NPP or productivity index values does not necessarily indicate improvements in land condition. However, Orr et al. 2017 provides the example of shrub or bush encroachment, which may increase NPP levels in native, formerly sparsely-vegetated areas and might be

interpreted as degradation in terms of land cover change. The interpretation of changes in productivity levels should always be conducted in the context of additional local data and information.

## 3.3 Methodology

### 3.3.1 Overview

One of the earliest proposed methods for mapping land degradation globally (Bai et al. 2008) calculated trends in the trajectory of land productivity using coarse resolution image data, and calibrated climate influences using a Rainfall Use Efficiency (RUE) analysis (Le Houerou 1984). Amongst the limitations of this method are that it is tailored to regions where rainfall is the primary driver of productivity, making it less well suited to tropical or very sparsely vegetated regions (Wessels 2009). There are a range of other assumptions about the assimilation of rainfall by plants that may also influence the accuracy of these calibration methods (see Section 3.5.3).

Other aspects of productivity have also been considered in similar analyses. Wessels et al. (2008) used a 'local scaling' method (Prince 2004) to assess the productivity performance of vegetation relative to other vegetation in similar land capability units (areas of similar topographic, edaphic and climatic conditions). Similar assessments can be conducted for a given location over time, as an indicator of the current state of vegetation productivity.

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

1. **Trend**, which represents the trajectory of productivity over time,
2. **State**, which compares the current productivity level in a given area to historical observations of productivity in that same area, and
3. **Performance**, which measures local productivity relative to other similar vegetation types in similar land cover types and bioclimatic regions.

The methodology presented in this chapter is comprised of five main processing steps (see Table 3.1). Countries may differ considerably in their access to high-quality productivity data, and in their capacity to collect and analyse these datasets.

**Table 3.1: Processing steps, recommendations and options for assessing the sub-indicator on land productivity**

| Chapter Section | Processing Step | Recommendations | Options |
|---|---|---|---|
| **3.3.2** | Select image dataset | Global data products (Tier 1) | High resolution and/or national datasets where available (Tiers 2 & 3) |
| **3.3.3** | Select a productivity index | The most widely used and best known index of plant productivity is the Normalized Difference Vegetation Index | A large number of alternative vegetation indexes can be calculated from image data (see Section 3.5.2) |
| **3.3.4** | Calculate growing season metrics | Use TIMESAT or similar to retrieve data from time series measurements over all of part of the growing season each year | Calibrate for moisture availability using Water Use Efficiency (WUE) or alternative (see Section **Error! eference source not found.**). This may be important in areas with very high or very low |

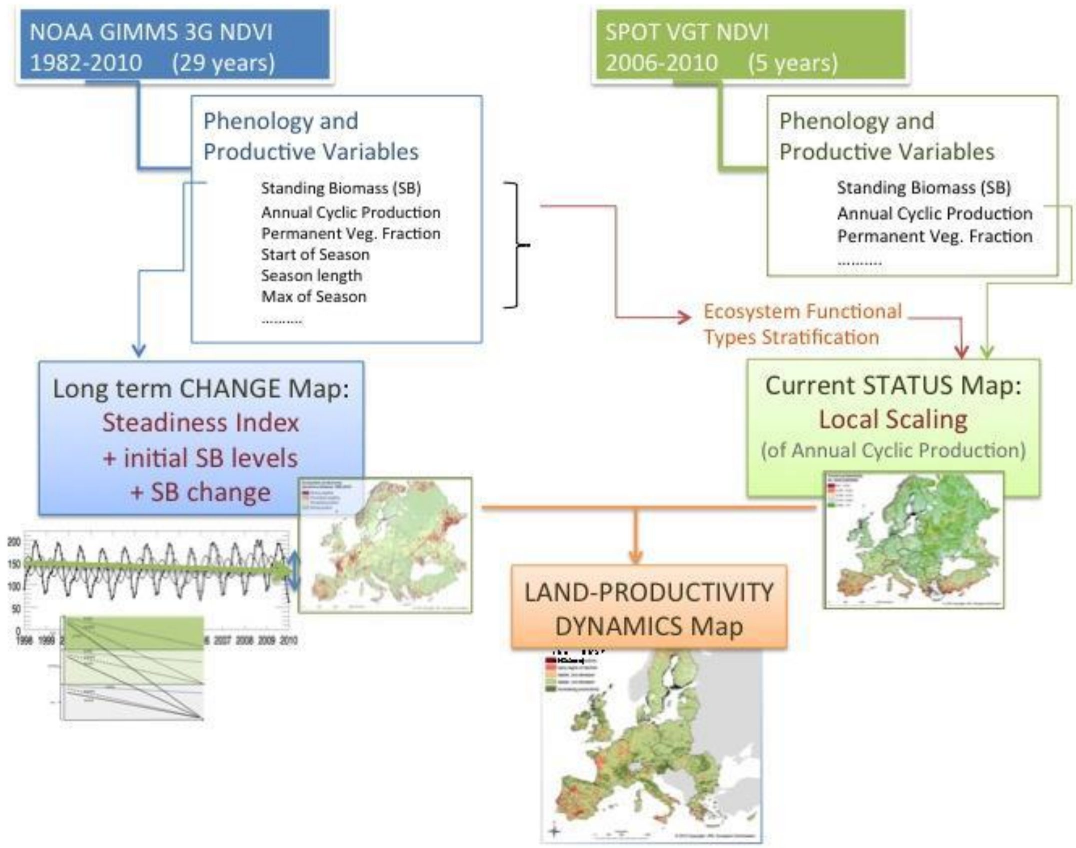
| | | | |
|---|---|---|---|
| | | | vegetation cover.<br>Calculate over a cloud-free period where necessary, and/or from imagery coincident with field sampling (Tiers 2 & 3). |
| **3.3.5** | Calculate time series metrics | Trend, Performance and State | All Tiers |
| **3.3.6** | Calculate degradation metrics | Calculate from the baseline period (2000-2015) | All Tiers<br>Degradation is determined by countries on the basis of NPP metrics and other information |
| **3.3.7** | Validation | Tier 3 only | Collect Earth, flux tower or destructive samples |

The initial baseline value ($t_0$) for land productivity, from which future changes are compared, is calculated from a baseline period from 2000-2015. Subsets of this period may be used to assess the baseline degradation status for certain metrics, such as the productivity State assessment. Change in these metrics over the reporting period is assessed by comparing new data to the initial values calculated from the baseline period.

This chapter describes three levels of methods, consistent with the International Panel on Climate Change (IPCC) Tier levels, in order to accommodate some of these differences. Countries will also vary in their range and distribution of productivity conditions, and certain analyses may be more suited to certain countries than others. Some of the processing options described are intended to increase the applicability of these methods to a wider range of countries.

**World Atlas of Desertification**: The recently proposed method for assessing land productivity trends for the World Atlas of Desertification (WAD) was developed by the European Commission's Joint Research Centre (JRC) to measure land degradation at global scales (Ivits and Cherlet 2016). The WAD method interprets NDVI in terms of three main metrics: Trend, State and Performance (see Figure 3.1). These three metrics can help identify potential degradation in areas where productivity may be increasing over time (Trend) but remains low relative to the historical range of productivity levels for that location over time (State) or compared to other regions of similar NPP potential (Performance).

**Figure 3.1: Scheme for calculating land cover productivity dynamics for the World Atlas of Desertification (Ivits and Cherlet 2016)**




Compared to other published methods, the WAD method includes more non-parametric and qualitative analyses, which provides opportunities for countries to interpret the calculated degradation extents in the context of local knowledge and conditions. While the WAD method prescribes particular datasets and methods, some of these are likely to be suited to some countries and scales of analysis more than others. For example, the WAD method includes a calculation of many phenological parameters that enable the landscape to be stratified into Ecosystem Functional Units (*sensu* Ivits et al. 2013), which is one basis upon which relative productivity performance can be measured across the landscape. In practice, there is a range of alternative ways to define the spatial units within which land productivity can be reported, including land cover classes as proposed in this GPG.

While the methods presented in this chapter are largely based on the WAD method, many options are available for conducting certain aspects of this analysis, including productivity datasets of different resolution, coverage and frequency, and a range of methods for identifying degradation in 'noisy' time series datasets. Some of the key options and considerations when making choices on the datasets and methods to use are presented throughout this chapter.

### 3.3.2 Selecting an Image Dataset

The range of available image data sources suitable for assessing land productivity is increasing as new Earth observation 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 ten years or more), 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 (see Table 3.2). An additional consideration in dataset selection is the spatial reference of the image data. Ideally, all datasets used for reporting should be spatially registered to the same datum and projection, which will simplify the process of overlaying map products and aggregating from the national to larger scales. The WGS84 datum[36] might be used as a default in the absence of a defined alternative national preference.

Many satellite image datasets are available at no or very low cost, and are particularly well-suited for assessing land productivity from global to national scales (see Table 3.3). 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 at this time. Productivity indices can be calibrated between these newer datasets and those with longer archives to provide more consistent measurements over time from multiple sensors.

**Table 3.2: Guiding principles for image dataset selection**

| Attribute | Recommendation |
|---|---|
| **Temporal resolution** | Time series datasets are required to assess land productivity and its change over time. This is essential for measuring the range of productivity variability, the trajectory of land productivity, and also the baseline conditions from which subsequent change is measured. Image datasets with long archives of frequently collected and consistent imagery provide the best opportunity to do this. More frequent observations provide more accurate information on productivity and its change over time, and a minimum frequency of observation is required to depict the most significant phases of the growth cycle such as the onset of the increased growth, the vegetation maximum, and the rates of productivity change at the commencement and cessation of the growing period. A balance between data size and the rate of change of productivity may also be important. |
| **Coverage and spatial resolution** | Large pixels reduce the size of datasets for a given extent of coverage but represent average conditions over a larger pixel area, which may not be suitable in landscapes with very complex or contrasting productivity conditions. Smaller pixels (higher spatial resolution) can more finely stratify the imagery to show the distribution of features of interest, which can improve the accuracy and representativeness of area measurements, especially in spatially-complex landscapes. However, smaller pixels provide a smaller area of integration of land cover characteristics, which can complicate the interpretation of features that become apparent at larger scales such as vegetation communities. Significantly higher image registration and GPS accuracy is also 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. |
| **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 the dataset. It is essential that datasets contain all the spectral wavelengths required to calculate the preferred productivity index. |

[36] http://earth-info.nga.mil/GandG/publications/NGA_STND_0036_1_0_0_WGS84/NGA.STND.0036_1.0.0_WGS84.pdf

| | |
|---|---|
| **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 fine grained or high contrast landscapes, are also available for purchase. High resolution datasets do not typically have an archive of repeat coverage historical images which is essential to assess change over time. |
| **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. |

**Table 3.3: Low or no-cost satellite sensors and data streams utilized for land surface phenology studies (modified from[37]).**

| Sensor | Satellite | Frequency | 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-present | 1.15 km | 10-day |
| **PROBA-V** | PROBA-V | 1-2 days | Copernicus Global Land Service http://land.copernicus.eu/global/products/ndvi | 2014-present | 333m and 1km | 10-day |
| **MODIS** | Terra | 1-2 days | MOD17 NPP | 2000 - present | 1 km | Annual |
| **MODIS** | Terra/ Aqua | 1-2 days | MOD13 vegetation index | 2000-present | 250 m, 500 m, 1 km | 8-day, 16-day |
| **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 |

[37] https://phenology.cr.usgs.gov/ndvi_avhrr.php

| | | | | | | |
|---|---|---|---|---|---|---|
| **OLI*** | Landsat 8 | 16 days | USGS/EROS | Feb 2013-present | 30 m | Distributed by scene |
| **MSI*** | Sentinel 2 | 5 days (from March 2017) | https://sentinel.esa.int/web/sentinel/home | Jun 2015-present | 10 m (VIS & NIR) | 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.

### 3.3.3 Selecting a Productivity Index

A productivity index is the algorithm used as a proxy to measure land productivity levels from image data. Productivity indices typically include spectral wavelengths correlated with aspects of plant cover, biomass and/or growth vigour. NPP is not directly measured by Earth observation sensors but is estimated from known correlations between the fraction of absorbed photosynthetically active radiation (fAPAR) and plant growth vigour and biomass.

The most widely used and best known index of plant productivity is the Normalized Difference Vegetation Index (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 (eq 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 live green vegetation.

The general formula is:

$$NDVI = \frac{NIR - red}{NIR + red} \qquad (1)$$

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 Earth observation satellite image datasets, including those with the longest archive of imagery such as the Landsat and Advanced Very High Resolution Radiometer (AVHRR) series. By comparing spectral bands within each image, the NDVI minimizes artefacts from a range of features that typically introduce errors into Earth observation imagery, including topographic shading effects, atmospheric and illumination conditions, which improve the consistency of NDVI data across large areas.

The main limitations of the NDVI are that it can be sensitive to variations in soil background conditions, and that it has a tendency to saturate at high cover and biomass levels. This potentially can reduce the accuracy of biomass and cover models in tropical rainforest or arid savannah regions.

A large number of 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 (see Section 3.5.2).

Note that an increase in NPP or productivity index values does not necessarily indicate improving conditions or lower levels of land degradation. Increases in NPP and/or a productivity index calculated from image data should only be considered degradation when interpreted in the context of land cover change and other local data and information.

### 3.3.4 Calculating Growing Season Metrics

Data can be extracted from time series image datasets, such as those shown in Table 3.3, that are highly correlated with ANPP. Due to the natural cycles of growth and senescence in most vegetation communities, ANPP is best represented by a subset of observations captured during the period of highest plant growth, i.e., the growing season.

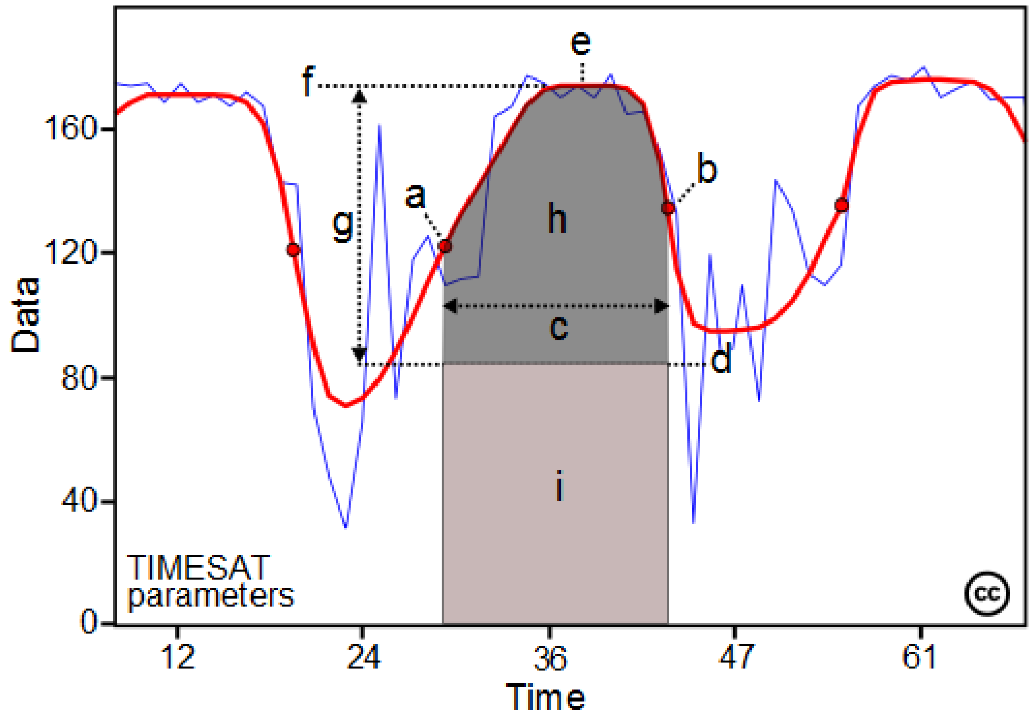
The growing season is most easily identified from time series satellite observations in temperate regions where there is a pronounced seasonal change in productivity levels throughout the year. Such pronounced cyclical variation in productivity may not occur in tropical regions or areas with low vegetation 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 when using Tier 3 methods. 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[38] (Eklundh and Jönsson 2015) includes features for automatically identifying the growing season and calculating a range of annual metrics from time series data. Similar features are available in the SPIRITS software[39] which is more suited to medium and coarse resolution imagery. The outcome of processing the productivity time-series imagery with TIMESAT will be one data point for each year of data, per parameter.

Figure 2.2 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 ANPP 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 2.2) 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).

[38] http://web.nateko.lu.se/timesat/timesat.asp
[39] http://spirits.jrc.ec.europa.eu/

**Figure 2.2: 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).**




To calculate the small integral it is necessary to define the growing season in terms of productivity index values. The growing season may vary in its duration, timing and magnitude each year, and can be identified in several ways in TIMESAT: proportional parameters such as the date on which the index reaches 30% of the maximum NDVI either side of the NDVI peak (Fensholt et al. 2013), or the minimum NDVI plus 10% of the pre-season minimum for season start, and the minimum NDVI plus 10% of the post-season minimum for season end (Ma et al. 2015) have been used.

Recent studies have demonstrated improved correlations with field samples of ANPP 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. In the absence of field data, the method that provides the greatest extent of valid growing season data is often the most suitable.

TIMESAT also includes features to smooth noise in the time series, such as from missing observations or cloud cover (red line in Figure 2.2). Smoothing the data in this way can improve the comparability of ANPP measurements between years, which may include more or fewer observations in different years. Gaps in the data record should be filled using a cubic convolution filter calculated through the missing value's eight nearest neighbours. For example, Ivits and Cherlet (2016) used an iterative 4$^{th}$ order polynomial Savitzky-Golay filter with a 50-day window, while Brioch et al., (2014) used a 15 time-step window.

The smoothing function should be iteratively adjusted to minimize the smoothing impact on observations that are known to be accurate, while also sufficiently smoothing outlier values responding to factors other than productivity changes. Considerations in setting smoothing parameters should also include differences in the rate and magnitude of rainfall response between vegetation communities, such as herbaceous and arboreal.

#### 3.3.4.1 Calibrating for Moisture Availability

Some additional processing of the time series datasets may be valuable under certain circumstances. In many regions, variations in ANPP 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; 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.

Separating the effects of variations in 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. 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 may help to identify the human factors contributing to productivity degradation. Several methods to calibrate time series images to minimize the influence of climatic or seasonal factors have been proposed, each of which may be suitable only in certain vegetation types, climatic regions or for detecting only certain types or magnitudes of degradation. Some of the most commonly used or best developed climate calibration methods, including their application, strengths and weaknesses are described in Section 3.5.3.

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) which compares NPP measurements against evapotranspiration (ET), defined as precipitation minus the water lost to surface runoff, recharge to groundwater and changes to soil water storage (Ponce-Campos et al. 2013). While calibrating for moisture availability is an optional part of this analysis, a comparison of both the WUE corrected and non-WUE corrected NPP datasets may help to interpret the relative influence of climate versus other factors as drivers of land degradation.

### 3.3.5 Calculating Time Series Metrics

#### 3.3.5.1 Trend

Productivity Trend describes the trajectory of change in productivity over time. 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.[40] The Mann-Kendall 'Z' score[41] calculated using the 'trend' package in R can be used to determine trend

[40] https://cran.r-project.org/web/packages/mblm/mblm.pdf
[41] https://cran.r-project.org/web/packages/trend/trend.pdf

significance (Onyutha et al. 2016). Positive Z scores indicate a trend of increasing productivity and negative scores indicate decreasing productivity.

Productivity trend assessments in the baseline period should be calculated using all 16 annual productivity measurements in the baseline period between the years 2000-2015. The significance of trajectory slopes at the $P \leq 0.05$ level should be reported in terms of three classes:

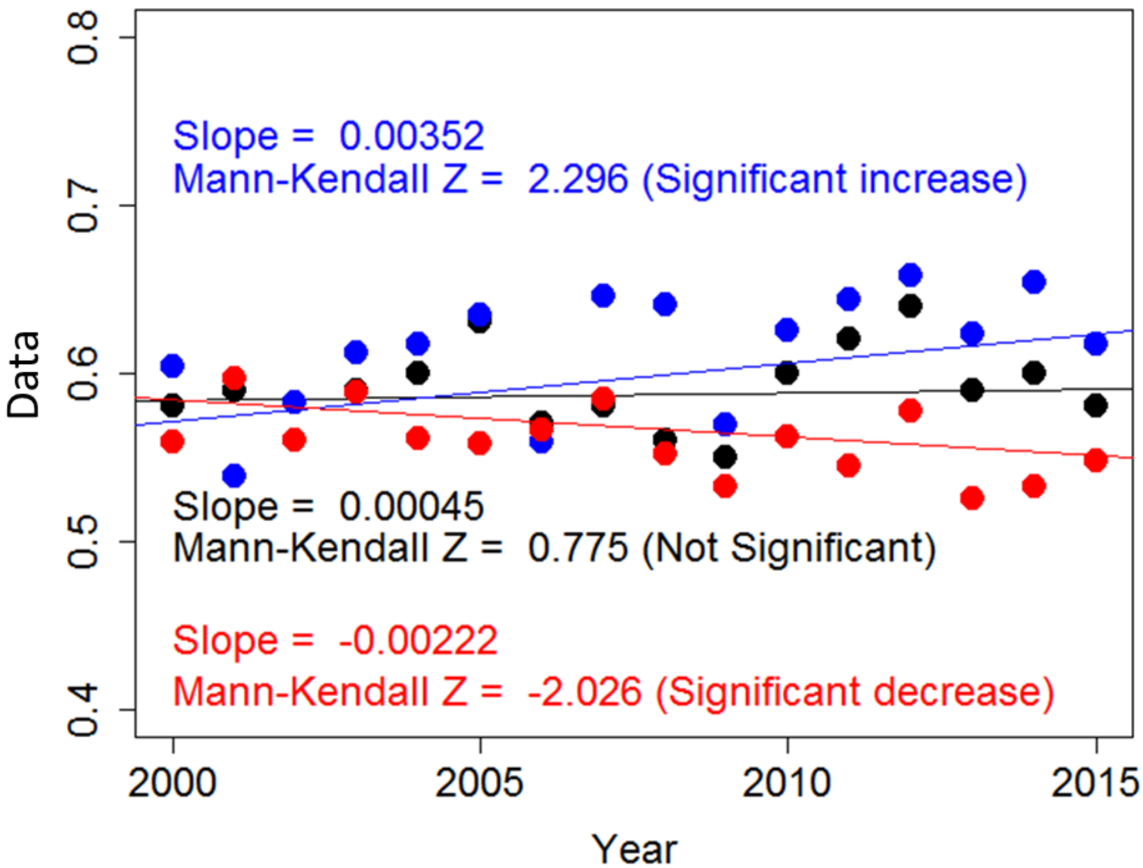
- Z score < -1.96 = Potential degradation, as indicated by a significant decreasing trend,
- Z score > 1.96 = Potential improvement, as indicated by a significant increasing trend, or
- Z score > -1.96 AND < 1.96 = No significant change

Significant change in productivity trend between the baseline and reporting periods may be difficult to detect if the new assessment is made following the addition of a single new annual NPP measurement to the 16 baseline measurements. The influence of individual data points (an additional year of data) on the trend slope will also probably reduce as the number of data points increases over time. For this reason, the significance of the trend slope for the reporting periods should be calculated over the 8 most recent years of data, which is a sufficient number of data points for the Thiel-Sen method (Ivits and Cherlet 2016). For example, reporting in 2018 should calculate trend over the years 2010 to 2017. Monitoring the trend over this shorter period for each reporting cycle makes the assessment more relevant to contemporary conditions and should be more responsive to the impacts of remediation activities.

Productivity trends in the reporting periods should be reported as potential degradation, potential improvement or no significant change based on the direction and significance of the trend observed over the 8 years of data analysed in the reporting period. 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 (2000 to 2015) and reporting periods should be included in the report. We do not recommend scrutinising changes in the slope of the trend as an indicator of change in productivity degradation levels except in the terms described above.

This assessment should be accompanied by a scatter plot figure showing the annual productivity measurements, with a linear trend line fitted and slope indicated. Figure 3.3 shows an example of a suitable trend plot. 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. The trend plot provided in the report should include only one trend line per region.

**Figure 3.3: Example of productivity trend Figure to be included in the reports. The blue points show a significant increase and the red points show a significant decrease over the same period. The trend plot provided in the report should include only one trend line per region.**




#### 3.3.5.2 State

Productivity State represents the level of relative productivity in a spatial unit (pixel or feature) compared to the historical observations of productivity for that spatial unit over time (Ivits and Cherlet 2016). Changes in productivity state are assessed by classifying annual productivity estimations into 10 classes, then identifying where contemporary observations of productivity fit in that class structure (see Figure 3.4). Areas in which the productivity has reduced by two or more classes between the baseline and reporting periods indicate potential degradation.

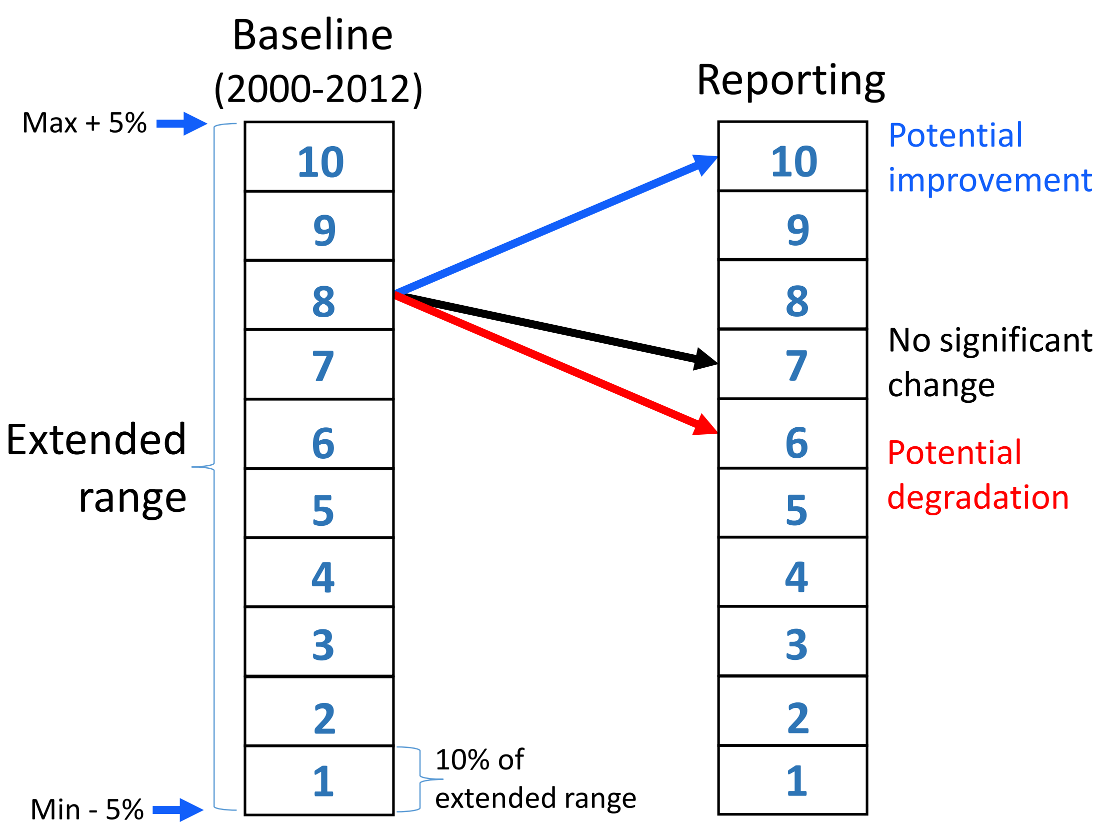
Defining class boundaries should be based on the range of productivity values between the years 2000-2012. This period may not include the very highest or lowest productivity levels observed in any given region, so an 'extended range' should be calculated based on the observed range of productivity values. The extended range would span 110% of the observed range, from the lowest observed value minus 5% of the observed range to the maximum observed value plus 5%. This extended range prevents very high or low productivity observations from occurring on the outer class boundaries. The extended range should be classified into 10 classes each spanning 10% of the extended range. These become the

baseline state classes that should be used to compare productivity change for subsequent monitoring periods.

Productivity state changes in the baseline period should be calculated by comparing the mean of the productivity measurements from 2013, 2014 and 2015, to baseline state classes. Change assessments in the reporting periods should compare productivity measurements, averaged over the reporting years, to the baseline state classes. For reporting in 2018, productivity estimates should be averaged over 2016, 2017 and 2018 (if available).

Since very small changes in productivity could theoretically result in a change from one state class to another, areas that remain within their original baseline state class, or change by only one class between the baseline and reporting periods, should be reported as no significant change. A decrease of two or more classes indicates potential degradation, and an increase of two or more classes indicates potential improvement.

**Figure 3.4: Illustration of the Productivity State assessment.**

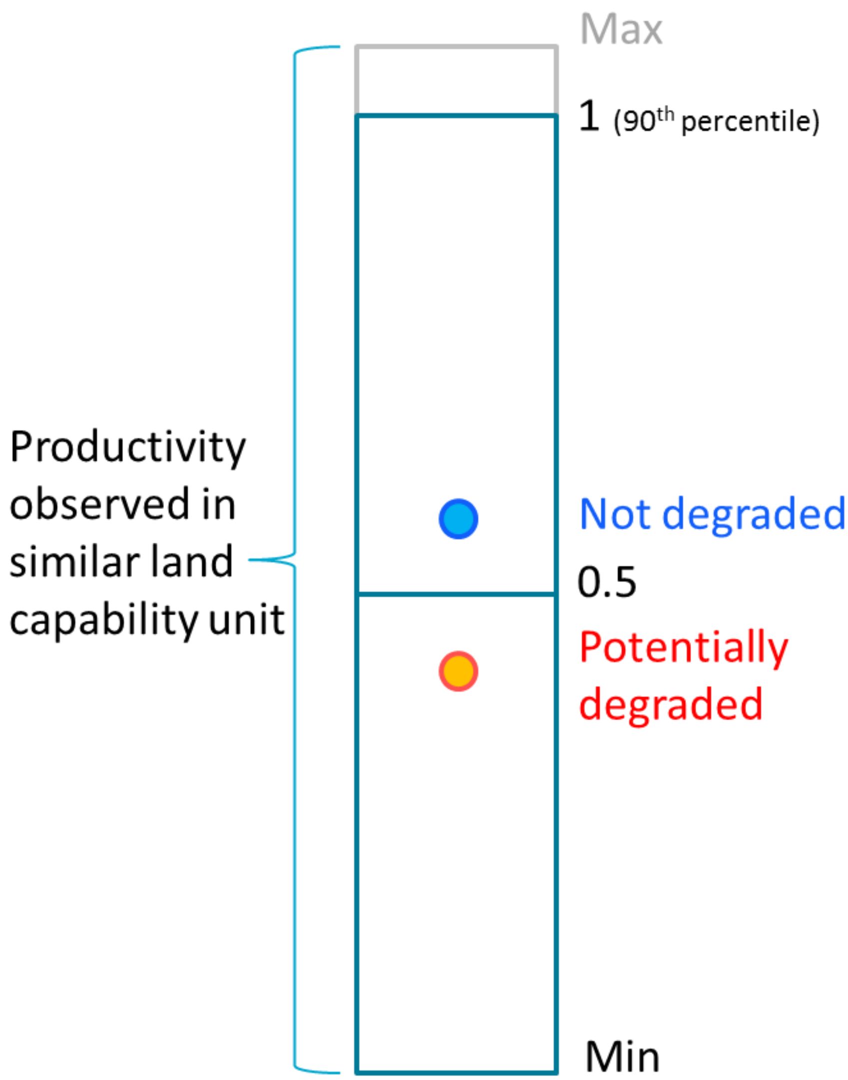



#### 3.3.5.3 Performance

Productivity Performance compares local productivity levels to the range of productivity levels measured from similar land units across the study area in the assessment year (Figure 3.5). Productivity

performance assessment indicates how a region is performing relative to other regions with similar productivity potential.

**Figure 3.5: Illustration of the Productivity Performance. Performance compares productivity within a land capability unit. Pixels or regions where productivity is in the lower half for that land capability unit may indicate potential degradation.**




To calculate productivity performance it is necessary to stratify the study region into areas with similar productivity potential based on factors such as species composition, moisture availability and soil conditions. The WAD method recommends stratifying the landscape into 'functional units' based on a large number of uncorrelated phenological and productivity metrics calculated from the productivity time series (Ivits and Cherlet 2016; Ivits et al. 2013). Parameters calculated from the time series describe the timing and productivity patterns during the growing season, and include the start and end dates of the growing season, the date of maximum productivity, the productivity level at season commencement and maximum productivity level amongst others. A principal component analysis of these variables,

followed by an unsupervised classification, is then used to identify functional units. The distribution of land capability units produced using this method is highly correlated with the GlobCover land cover classes, which may be suitable as an alternative basis for stratification.[42]

Land units may also be classified into 'land capability units' (Wessels et al. 2008) based on factors such as the land cover classes used to assess the land cover and land cover change sub-indicator in combination with terrain, soil, climate and moisture availability. Useful data sources for this purpose may include Köppen Zones,[43] the MODIS MOD16 evapotranspiration dataset[44] used for WUE correction, and the Agricultural Suitability and Potential Yields spatial data available through the FAO's Global Agro-Ecological Zones (GAEZ) programme.[45]

Productivity Performance for a given pixel is calculated in comparison with the 90th percentile of productivity index value within the relevant land unit, which is a reasonable estimate of the maximum productivity level ($NPP_{max}$) that can be achieved within each land unit. Productivity performance in each land unit is calculated as:

$$Performance = \frac{Observed\ NPP}{NPP_{max}} \tag{3}$$

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 values less than 0.5 indicate regions where productivity levels are low, and may indicate degradation.

Changes in 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. Productivity performance in the reporting periods should be calculated from the mean annual productivity assessments over the years between the previous (or baseline) assessment up to the current year. For reporting in 2018, performance would be calculated from an average of the 2016 and 2017 productivity measurements.

### 3.3.6 Calculating Degradation Metrics

The baseline period for assessment of land productivity is from 2000-2015. The baseline period serves two functions:

1. To determine the initial ($t_0$) degradation state, and
2. As a comparison to assess change in degradation for each reporting period

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

[42] http://due.esrin.esa.int/page_globcover.php
[43] http://people.eng.unimelb.edu.au/mpeel/koppen.html
[44] http://www.ntsg.umt.edu/project/mod16
[45] http://www.fao.org/nr/gaez/about-data-portal/agricultural-suitability-and-potential-yields/en/

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 increasing productivity and potentially underestimate the true extent of land degradation. Calibrating the productivity measurements to adjust for moisture availability (described in Section 3.5.3) can be used to indicate the potential influence of climatic conditions on the baseline period in this case.

### 3.3.7 Validating Productivity Estimates

Productivity estimates retrieved from vegetation indices, such as the NDVI, can be well-correlated with changes in ANPP, and are often a reliable source of information regarding relative changes in productivity levels in space and time, and across a wide range of land cover types. However, the accuracy of remotely sensed productivity estimates can be influenced by a range of factors, including the signal to noise ratio of the image data, model forms and parameters, the sensitivity of the productivity index to changes in productivity, image registration and field sampling location errors, errors associated with field sampling methods, and the number and timing of cloud-free observations during the growing season.

Validation of productivity estimates against additional sources of data enables the accuracy of productivity predictions to be assessed when implemented in a statistically rigorous way. Validation against field samples or another calibrated dataset also enables relative productivity units to be converted into biomass units such as kg/ha/year. While this is not essential, it can be useful to improve the estimation of productivity changes across a wider range of land cover types, and may also be useful for identifying land degradation hotspots and planning remediation activities.

Validating remotely-sensed predictions is a substantial field of research, and the required data varies with the spatial grain of the imagery being used, the range of ANPP values likely to be encountered, land cover conditions and the spatial extent over which predictions are being made. A detailed description of all facets of validation is beyond the scope of this GPG. However, some additional detail on the range of options is presented in Section 3.5.4.

In the absence of validation against quantitative ANPP field data, reporting on the land productivity sub-indicator should include information describing the known potential errors in the tools, methods and datasets used where possible, including estimations of the magnitude of those errors. Validated prediction accuracy should be reported in terms of the proportion of variance explained by regression ($R^2$) and model significance (P values), and/or root mean squared errors (RMSE) of prediction.

### 3.3.8 Combining Metrics to Determine Degradation Class

Pixels showing degradation are those with:

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

The extent of degradation in the reporting period should be added to the area of degradation mapped during the baseline or previous assessment period that remains degraded.

## 3.4 Rationale and Interpretation

### 3.4.1 Spatial Aggregation

For reporting consistency between the sub-indicators, it will be necessary to aggregate from pixel to polygon scales. Guidance for spatial aggregation in Chapters 1 and 2 recommends aggregating pixels up to the scale of spatial features shown in the land cover and land cover change sub-indicator. Changes in land productivity or soil organic carbon levels may occur over time within a given land cover type. Changes in land cover type, however, will usually result in changed land productivity levels and dynamics, which may in turn influence carbon stocks in a given region. The spatial features identified in the land cover and land cover change analysis can encompass a range of productivity and SOC levels, and are therefore a logical basis for spatial aggregation.

Chapters 1 and 2 recommend classifying a polygon as degraded if more than 10% of pixels in that polygon are classified as degraded. That threshold may not be appropriate in some countries in that it may result in a large number of false positive or false negative assessments. Adjustments to this threshold should consider consistency with the other sub-indicators, in addition to the extent of degraded land identified as an outcome of the spatial aggregation process.

### 3.4.2 Assessing Support Class

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. In order to interpret the likelihood of results indicating false positives or false negatives, a lookup table is used to identify 'support class' combinations of metrics in each pixel (see Table 3.4). These classes can be used to review the combinations of metrics indicating degradation in each pixel and identify potential sources of uncertainty in the productivity assessment. Note that this support class analysis is only for the Land Productivity sub-indicator and is entirely separate from the "One Out, All Out" principle used to estimate SDG indicator 15.3.1.

**Table 3.4: Lookup table indicating support class 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.**

| Class | Trajectory | 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 |

The most dependable indicator of degradation is a significant negative Trend because it is calculated over the entire time series (i.e., the baseline period) and uses a statistical significance test. This is included in support classes 1 to 4. The convergence of evidence from the combination of both the State and Performance metrics provide reasonable temporal and spatial support for a determination of degradation (support class 5). However, the absence of a statistical significance test for these metrics may increase the potential for false positive or false negative assessments. Therefore, it is not recommended to identify degradation based on either a significant State or Performance analysis alone. Support classes 6 to 8 are combinations of land productivity metrics that do not indicate declining land productivity. National reports could include a map of support class distribution and a discussion or assessment of potential sources of error.

## 3.5 Data Sources and Collection

This chapter presents guidance for using satellite image data to measure trends in land productivity as reflected in NPP. Many options are available in terms of datasets, thresholds and processing methods, and some of these may be more suitable in certain countries than in others. In particular, certain datasets and processes may be required only for certain Tier methods. This section discusses in detail of some of the options described in the methodology section above.

### 3.5.1 Interpolating between Sensors

Given the short historical archive of some of the datasets identified in Table 3.2, 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.

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, such as the red band in MODIS (band 1) and the red band in Sentinel 2 MSI (band 4), where the recalculation of the productivity index from the source data is required.

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. More detail on the application and validation of the linear regression calibration method can be found in Reeves et al. (2015).

### 3.5.2 Options for Alternative Land Productivity Indicators

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 over time. 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.

#### 3.5.2.1 MODIS MOD17A3 Global NPP Model

The MODIS MOD17A3 data product (hereafter referred to as MODIS NPP) estimates the annual change in kilograms of carbon per square metre, averaged at 1 km pixel resolution, integrated over each calendar year since 2000 (Running et al. 2004; Running and Zhao 2015). This is the only globally available, annually updated NPP dataset that is currently available. The use of this dataset simplifies the process of quantifying productivity into biomass units that can be measured in the field, and this dataset has been used to convert NDVI units to biomass 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 productivity 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.

#### 3.5.2.2 Enhanced Vegetation Index

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 Enhanced Vegetation Index (equation 4) (EVI; Huete et al. 2002; Huete 1988):

$$EVI = G\frac{NIR - red}{NIR + C1 \times red - C2 \times blue + L} \tag{4}$$

Where **L** is the canopy background adjustment that addresses nonlinear differential NIR and red radiant transfer through a canopy, and **C**$_1$, **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 Advanced Very High Resolution Radiometer (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 5) using only the red and NIR bands has been proposed (Jiang et al. 2008):

$$EVI2 = 2.5\frac{NIR - red}{NIR + 2.4red + 1} \qquad (5)$$

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.[46] 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.

#### 3.5.2.3 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; 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.

Potential sources of bias in these products include that cover types are defined by spectral models that may not be representative of cover conditions in all regions, and that the cover estimates are based on field measurements of the proportion the cover types which may be subject to measurement error.

### 3.5.3 Options for Calibrating Climate Impacts

Variations in plant productivity over time are caused by many factors including phenological and climatic variations in addition to human activities. 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: the factors influencing long-term productivity levels vary from place

[46] https://lpdaac.usgs.gov/dataset_discovery/measures

to place and over time, and productivity levels in certain regions are more susceptible to influence from some factors than others.

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 (GLADA) website.[47] 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).

#### 3.5.3.1 Rainfall Use Efficiency

Rainfall use efficiency (RUE) is the ratio of annual ANPP to precipitation (Le Houerou 1984). Accounting for RUE can improve the comparability of ANPP 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.

#### 3.5.3.2 Residual Trends (RESTREND)

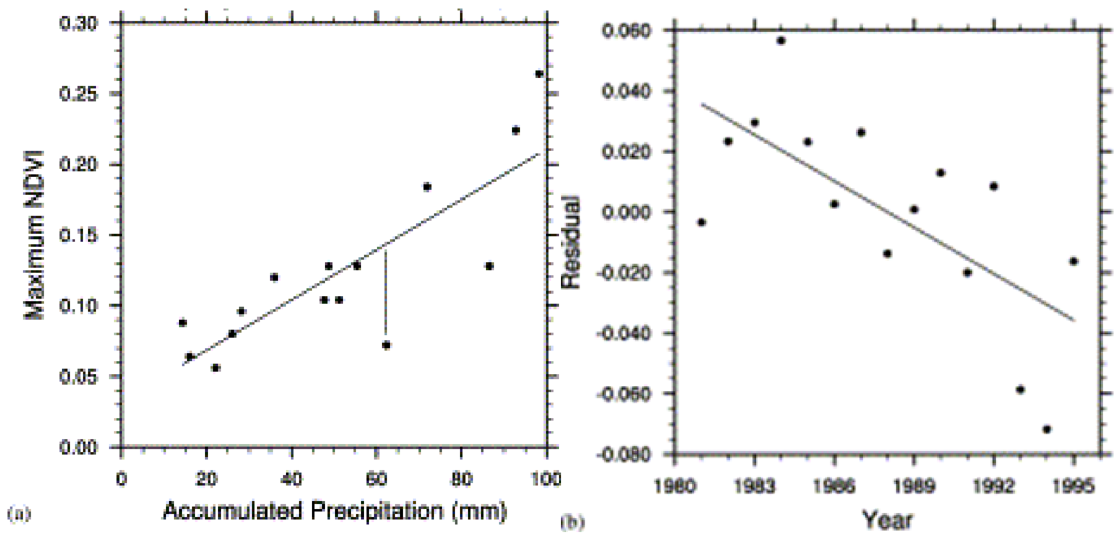
RESTREND (Evans and Geerken 2004; Wessels et al. 2007) is a development of the RUE method that uses linear regression models to predict an NDVI for a given rainfall amount. RESTREND calculates a linear model between the natural log of annual rainfall and ANPP estimates based on the observation that vegetation productivity typically reaches a plateau in years with very high rainfall beyond which it does not increase (Hein et al., 2011 and 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 3.6.

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

[47] http://www.fao.org/geonetwork/srv/en/main.search?any=glada

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 3.6: 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 (Evans and Geerken 2004).**




### 3.5.3.3 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 6).

$$rRUE_{me} = \frac{RUE_{OBS\_me} - RUE_{EXP\_me\_P05}}{RUE_{EXP\_me\_P05} - RUE_{EXP\_me\_P95}} \quad (6)$$

*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).[48]

The *rRUE* method simplifies the application of RUE methods across large areas which may have varying climatic conditions, yet it 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 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.

[48] https://r-forge.r-project.org/R/?group_id=752

#### 3.5.3.4 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.

#### 3.5.3.5 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[49] (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, and
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 'raw' 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 commencement and cessation 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 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.

[49] http://stat.ethz.ch/R-manual/R-devel/library/stats/html/stl.html

#### 3.5.3.6 Water Use Efficiency (WUE)

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.

Ponce-Campos et al., (2013) describe the calculation of Ecosystem Water Use Efficiency ($WUE_e$) which is the ratio of ANPP to evapotranspiration (ET), defined as precipitation minus the water lost to surface runoff, recharge to groundwater and changes to soil water storage. They demonstrate a near linear relationship between ANPP and ET across grassland and forest biomes in the United States, Puerto Rico and Australia, which simplifies the calibration process over the non-linear relationship that typically occurs between NPP and rainfall.

They 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. Alternatively, a range of global ET datasets are available including:

1. Global 8-day evapotranspiration data from MODIS, based on the Penman-Monteith equation[50]
2. The GLEAM datasets[51] which are based on microwave remote sensing and calculate evapotranspiration using the Priestly and Taylor model
3. Global annual and monthly potential evapotranspiration,[52] which is modelled using the WorldClim database[53] at approximately 1km spatial resolution

ET observations should be integrated from the time series data over the same period as the productivity observations each year (iET). Calibration is performed by calculating the ratio of NPP to iET, which indicates the water use efficiency (WUE) of vegetation (Ponce-Campos et al. 2013). The method for calculating WUE corrected NPP ($NPP_w$) per year is:

$$iNPP_w = \frac{iNPP}{iET} \tag{7}$$

WUE correction appears to be the most hydrologically comprehensive and widely applicable of the rainfall calibration methods described here. The main limitation on the accuracy of WUE calibration is likely to be the availability and accuracy of the evapotranspiration data. The limitations and suitability of ET datasets should always be carefully considered.

### 3.5.4 Options for Validating NPP Measurements

#### 3.5.4.1 Collect Earth

Collect Earth is a free and open source software package that facilitates the interrogation of high resolution image data using the Google Earth interface.[54] Collect Earth was developed to monitor forest

[50] http://www.ntsg.umt.edu/project/mod16
[51] http://www.gleam.eu/
[52] http://www.cgiar-csi.org/data/global-aridity-and-pet-database
[53] http://worldclim.org/
[54] http://www.openforis.org/tools/collect-earth.html

cover and land cover change for the purposes of greenhouse gas emissions reporting. Collect Earth can be used to validate conditions at selected sampling sites using Google Earth, BingMaps and Google Earth Engine interfaces. This can be especially useful to investigate areas of particular anomaly, and to identify the underlying causes of degradation. Limitations of Collect Earth for validating productivity estimates include that the interpretation of land surface conditions may be dependent on the expertise of the assessor, access to imagery such as the NDVI may be limited, and Google is blocked in certain regions of the globe.

#### 3.5.4.2 Flux Tower Data

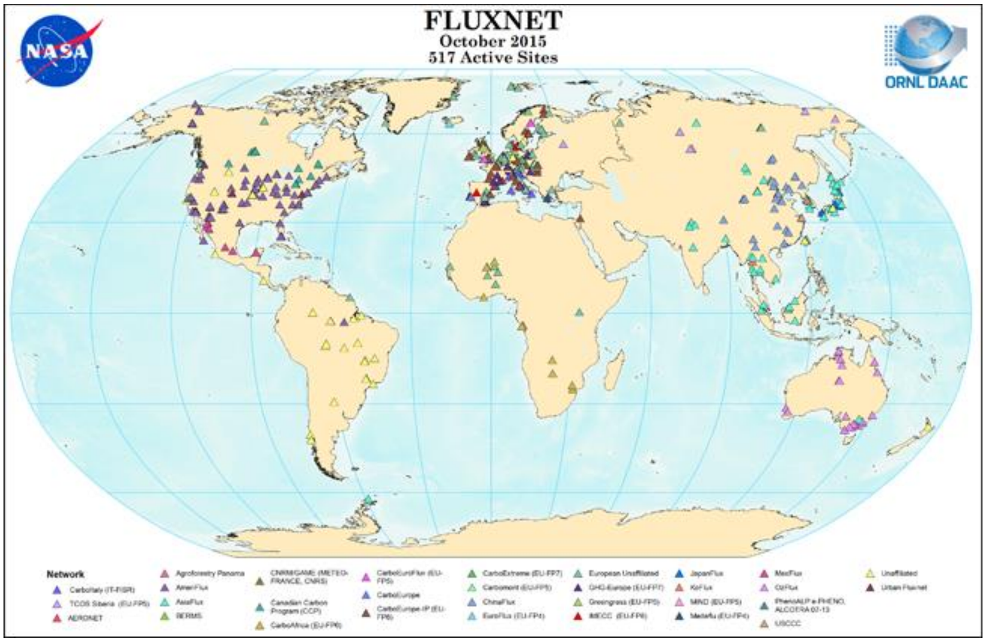
Flux towers measure the exchange of carbon dioxide between plant canopies and the atmosphere and are a direct correlate with NPP at local scales (Running et al. 1999). Fluxnet[55] maintains a global network of flux towers (see Figure 3.7) many of which are aligned with national flux monitoring programs. Some examples of National flux tower programs include:

- Australia: TERN[56] and OzFlux[57]
- Korea: KLTER[58]
- USA: NEON[59]

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 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.

[55] https://fluxnet.ornl.gov/
[56] http://www.tern.org.au/NASA-partners-with-TERN-to-map-global-carbon-bgp3623.html
[57] http://www.ozflux.org.au/
[58] http://www.klter.org/emain.htm
[59] http://www.neonscience.org/science-design/collection-methods/flux-tower-measurements

**Figure 3.7: Fluxnet carbon flux tower locations as of October 2015**[60]




### 3.5.4.3 Destructive biomass sample collection

Validation of productivity estimates against destructive samples collected in the field, at the time of peak biomass and coincident with image capture provides the most rigorous validation of productivity estimates. It also enables the relative productivity estimates from indices such as the NDVI to be converted to biomass units such as kg/ha/year, which may improve the representation of productivity estimates in space and time, and assist in identifying land degradation hotspots and planning remediation activities.

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. One of the most comprehensive guides to field validation of remotely sensed datasets is the AusCover Good Practice Guidelines report.[61] This includes methods for assessing biomass in a range of land cover types including forests and woodlands, crops, pastures and grasslands (Schaefer 2015).

For accurate NPP validation it is important to coordinate the collection of field data with the date of peak biomass. Some institutions have protocols to collect destructive biomass samples at the same time each year. For example, Moran et al. (2014) integrated productivity observations from the commencement of the growing season to the first week in August, which is the annual period of field sample collection designed to coincide with the period of peak biomass in their study region.

[60] https://fluxnet.ornl.gov/maps-graphics
[61] http://qld.auscover.org.au/public/html/AusCoverGoodPracticeGuidelines_2015_2.pdf

## 3.6 Comments and Limitations

Chapter 3 outlined the key considerations for implementing national scale monitoring of the land productivity sub-indicator used to estimate SDG indicator 15.3.1. It draws on recognized principles and existing knowledge of good practice with respect to assessing trends, state and performance in the sub-indicator. While not prescriptive or final, it presents a range of options that are relevant to the datasets and processing methods that are available at this time, and should be reviewed in the context of new developments. Variations in the distribution and dynamics of land productivity between countries will make some methods more suitable than others. In addition, new datasets and processing methods are constantly emerging

Changes in land productivity or soil organic carbon levels may occur over time within a given land cover type. Changes in land cover type, however, will usually result in changed land productivity levels and dynamics, which in turn influence the carbon stocks in a given region. For this reason, when assessing the degradation status on the basis of these three sub-indicators, it is best to aggregate fine scale results, such as from the pixel scale assessments, to spatial features identified in the land cover and land cover change sub-indicator.

For the most part, the methodology described here is based on the WAD method, which is best suited to assessing land productivity dynamics in water-limited, temperate regions. Moisture availability correction methods may be used to increase the range of land cover types and regions over which these methods can be applied. The WAD method also uses a range of non-parametric or qualitative analyses which has advantages in terms of providing the opportunity for countries to include other sources of information to interpret the accuracy of degradation assessments. The potential disadvantages of qualitative analyses include increased subjectivity which can limit comparability between regions. Each country will differ in its land cover characteristics, access to datasets, analytical capability and development objectives, thus a particular transition or change that may be assessed as degradation in one country may be considered desirable and productive in another.

Finally, the continued availability of data from any particular source cannot be guaranteed, and 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, which should improve the quality and comparability of data between countries and at larger regional and global scales.

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# 4. Sub-Indicator on Carbon Stocks, Above and Below Ground

## 4.1 Executive Summary

Chapter 4 of this Good Practice Guidance (GPG) describes the methodology and data sources available for establishing baselines and evaluating change in the sub-indicator on carbon stocks, above and below ground. It is one of the three sub-indicators being used to derive Sustainable Development Goal (SDG) indicator 15.3.1 ("Proportion of degraded land over total land area"). As outlined in the United Nations Convention to Combat Desertification (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.

Carbon stocks reflect the integration of multiple processes affecting plant growth as well as the gains and losses from terrestrial organic matter pools. They are elementary to a wide range of ecosystem services, and their levels and dynamics are reflective of land use and management practices. This chapter provides guidance on approaches that countries can use to determine **baseline SOC levels** and estimate **change in SOC stocks**. Consistent with the Intergovernmental Panel on Climate Change (IPCC 2006) guidelines, 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). Some guidance on approaches for estimating change in carbon stocks in other pools, such as above ground biomass, is also provided.

Where country-specific data and capacities are unavailable, the Tier 1 method for estimating change in SOC stocks is informed by the IPCC equations contained in 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. This Tier 1 method uses information on land cover change along with climate/land cover default change factors (available for land cover change, inputs and management) to estimate changes in carbon stock for mineral soils and default annual emission factors to estimate the losses of carbon following drainage and/or fire for organic soils. The original IPCC Tier 1 methodology constructs reference carbon stocks (baseline carbon stocks) based on broad global estimates of default soil carbon stocks under natural vegetation, stratified by climate/soil type. For change factors however, the Tier 1 method is strongly reliant on the sub-indicator of land cover change to estimate changes in SOC stocks (see Chapter 2).

Where possible, the Tier 2 method should be employed to complement default values with national datasets (both for SOC baselines and for change factors) even if they are only able to better specify certain components of the Tier 1 method. While SOC stock change is estimated based on land cover 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.

The Tier 3 method incorporates more advanced methods, such as country-specific digital soil mapping, 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.

In reality, most countries will use a blend of methods from Tier 1 -3, depending on their national requirements and availability of expertise and resources. Regardless of the method, the computation of the sub-indicator involves the following steps:

1. Estimation of an average SOC stock (0-30 cm) and ideally some estimate of uncertainty for each identified spatial feature for the baseline period.
2. Comparison of SOC stock in the monitoring period with the average baseline SOC stock for the same spatial feature.
3. Assessment of whether there has been an increase, decrease or no change in SOC stock for each identified spatial feature, and assignment of whether the area is considered degraded or not degraded.
4. Identification and justification of potential “false positives” and explainable anomalies.

## 4.2 Definitions and Concepts

**Carbon stock** is the quantity of carbon in a pool or a reservoir which has the capacity to accumulate or release carbon. Ecosystem carbon pools are composed of biomass (above and below ground), dead wood and litter, and soil organic matter (IPCC 2003).

**Total carbon stock** is the quantity of carbon in all of the components of ecosystem carbon pools.

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

**Below ground biomass** is 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.

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

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

**Soil organic matter** includes organic carbon in mineral and organic soils (including peat) to a specified depth chosen by the country and applied consistently through the time series. Live fine roots (of less than 2 mm diameter) are included with soil organic matter where they cannot be distinguished from it empirically.

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

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

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

Where $SOC_m$ is the mass of organic carbon in the soil (%), $\rho$ 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).[62]

**Baseline ($SOC_{t0}$)** carbon stocks are required to enable an assessment of the initial status of the sub-indicator in absolute terms. This means that it is good practice to determine the baseline for SOC stocks for the year 2015. This is referred to as $t_0$ and future reporting is referred to as $t_1,\ldots,t_n$. The baseline could be quantified over an extended period prior to $t_0$ (e.g., a suitable epoch between 2000 and 2015) as the spatial variability of SOC is ~1 order of magnitude higher than the temporal variability of SOC when land use has been unchanged for 20+ years. Lands undergoing dramatic land use change (e.g., forest to crop land) are an exception.

**Monitoring Period ($t_n$)** is the time period over which the sub-indicator is measured and quantified for the monitoring period using the same methods employed for the baseline period. As regards slow changing variables, such as SOC stocks, reporting every four years may not be practical or offer reliable change detection for many countries.

**Change in SOC stocks**, is defined as the change in SOC stocks between the monitoring period ($t_n$) and the baseline ($t_0$), in the units of tons of carbon per hectare (t C $ha^{-1}$) and include the variance of the change if derived from repeat measurements.

## 4.3 Methodology

The methodological approach to this sub-indicator ranges from a broad Tier 1 to a highly detailed and complex Tier 3. While the preferred method of assessing change in SOC stocks is the direct observation of SOC dynamics through repeated sampling at regular time intervals, SOC dynamics can also be derived from application of relationships between environmental and management factors and SOC stocks, such as those derived from experimental field-trials, chronosequence studies, and monitoring networks. Once established, these relationships can then be applied to estimate SOC dynamics from changes in environmental and management factors. This applies to both Tier 1 and Tier 2 methods, while a Tier 3 method usually requires SOC stocks to be either directly measured *in-situ* for each reporting period, or

[62] Quantifying SOC stock at fixed depths as the product of soil bulk density, organic carbon concentration, proportion of coarse fragments and depth provides a simple approach for reporting change in SOC stock. However, in the context of land use/management change, this method can systematically overestimate SOC stocks where bulk densities have 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).

more often measurement are combined with process-based ecosystem models to estimate SOC changes.

In this section, guidance is provided for determining the baseline SOC stock and estimating change in SOC stocks as well as options for the quantitative and qualitative assessment of the sub-indicator. The following steps are required for all three methods:

1. Estimation of an average SOC stock (0-30 cm) and variance (depending on Tier method) for each identified spatial feature for the baseline period.
2. Comparison of SOC stock in the monitoring period with the average baseline SOC stock for the same spatial feature.
3. Assessment of whether there has been an increase, decrease or no change in SOC stock for each identified spatial feature, and assignment of whether the area is considered degraded or not degraded.
4. Identification and justification of potential "false positives" and explainable anomalies.

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

### 4.3.1 Choice of Method

The tiered approach to the method of computation (IPCC 2006) considers a range of datasets and processing options are presented 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). Ideally, this 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.

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

The Tier 1 method for reference SOC estimates and change factors is recommended when national data and/or processing capacity is limited. Progressing from Tier 1 to Tier 3 methods represents a reduction in the uncertainty of SOC estimates, though at a cost of an increase in the complexity of measurement processes and analyses. Frequently, national assessments combine methods from lower Tiers with higher Tiers for pools which are less significant or too costly to measure. Thus in reality a combination of Tiers is usually employed.

The Tier 1 method for SOC change factors 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 (UNFCCC). Of most relevance to the carbon stocks sub-indicator is the 2003 Good Practice Guidance for Land Use, Land-use Change and Forestry (IPCC 2003), the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006) which consolidates and updates previous guidance, and the 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands (IPCC 2014), which fills gaps and extends the 2006 Guidelines and updates emission/removal factors including on wetlands and drained soils. The IPCC will produce a Methodology Report by 2019 as a supplement (not full revision) to be used in conjunction with the 2006 IPCC Guidelines.[63] Although there may be some refinement in change factors and likely some additional factors, these changes would be in-line with countries striving to implement Tier 2 and 3 methods.

**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 (e.g., toxicities). Within these constraints, the actual amount of organic carbon contained in a soil will be determined by the balance between carbon inputs and losses, which are strongly influenced by land management and soil type. Agricultural practices that alter rates of carbon input (e.g., plant residues, compost, mulch) or loss (e.g., removal of crops, cultivation) change the stock of soil organic carbon.

The IPCC defaults for SOC stocks and change factors use 'strata' based on factors such as land use and land management. While 'land use' refers essentially to the six IPCC categories (i.e. Forest Land, Cropland, Grassland, Wetlands, Settlements, Other Land), land management refers to stratification of the main land uses. For mineral soils, land management is a required level of stratification for consistency with IPCC factors for SOC stock change, while the defaults for reference stock, i.e. under native vegetation, are based on default climate regions and seven broad soil classes.[64] For organic soils, IPCC default coefficients stratify the areas by climatic region.

Here the term 'homogeneous land cover unit' is used instead of the IPCC term 'stratum' to avoid confusion with land cover terminology. All land in a homogeneous land cover unit 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 'spatial feature' is the spatial unit (e.g., watershed, polygon) is reported on and is likely to be a mix of land cover classes, while a homogeneous land cover unit is a uniform land cover class within a spatial feature.

[63] http://www.ipcc-nggip.iges.or.jp/public/mtdocs/pdfiles/1608_Minsk_Scoping_Meeting_Report.pdf
[64] Default IPCC soil classes are defined in Volume 4 of the IPCC 2006 Guidelines, Annex 3A.5; IPCC default soil classes derived from the Harmonized World Soil Data Base are available at http://isric.org/explore/portals

### 4.3.2 Estimating the Baseline

The estimation of SOC in the baseline period ($SOC_{t_0}$) for a given 'spatial feature' is based on a national-level assessment of carbon stocks during the baseline period (2000-2015) or the most appropriate epochs from the period. Global land cover data sets are now available annually, such as the European Space Agency's Climate Change Initiative Land Cover (CCI-LC) dataset (see Chapter 2). An historical averaging approach to minimize the effects of seasonal and inter-annual climate variability is the simplest option for estimating the baseline. The absolute numerical value of the metric for each spatial feature is quantified by averaging across an extended (10–15 year) period prior to the year 2000 ($t_0$), 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).

Thus, 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 monitoring period for a given spatial unit, and makes no assumptions about the initial status of SOC stocks for that particular spatial unit. However, as outlined in Chapter 1, an initial baseline ($t_0$) is required to derive the indicator "*Proportion of land that is degraded over the total land area"*. 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.

As discussed earlier, 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. Therefore, 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, etc.) could be used. As a starting point, the IPCC (2006) reference SOC stocks under native vegetation based on 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. The determination of initial baseline status would then be guided by comparing the actual value with the benchmark or potential value within some agreed bounds, where baseline values less than the relevant benchmark and within agreed bounds would be considered degraded. However, there are a number of issues with this option.

For example, the IPCC defaults for SOC reference stocks for native vegetation have 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 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 3 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 a given spatial unit. While this approach may be valid for land productivity where changes occur over short timeframes, SOC stocks are likely to change over longer 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 than 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 (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). Some examples of the types of data for SOC stock that could be used to inform a baseline are provided in Table 4.1.

**Table 4.1: 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
[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; or
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 Earth observation to derive the baseline stocks (or reference stocks as per IPCC 2006) is described in the calculations below. However, it is likely that these estimates will be subject to large uncertainty.

Alternatively, a national approach where countries either: i) use the same linear equations as the global default method in conjunction with country-specific factors to improve the accuracy of the relative change factors, reference SOC stocks, climate regions, soil types, and/or land management classification systems, or ii) use high-resolution global, such as SoilGrids250m (Hengl et al. 2017), or national maps, such as the 90 m grid SOC stock baseline used in Australia (Viscarra Rossel et al. 2014) to improve the accuracy of the reference SOC stocks. This is likely to reduce uncertainty in the estimates, 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. A spatio-temporal data model assimilation approach that uses easily accessible Earth observation data for the updating, but is underpinned by on-ground monitoring could be used.

### 4.3.3 Estimating SOC Stock Changes

It is good practice to apply the same approaches for baseline assessment and monitoring within the same Tier method. Where a default approach is used, the same equations used for estimating baseline SOC stocks should also be used in the monitoring year. Where a national monitoring approach is used, standardized spatial and temporal sampling for the estimation of both baseline SOC stocks and SOC stocks in the monitoring year should be used (de Gruitjer et al. 2006; Brus et al. 2014). This will enable consistent comparisons and improve the assessment of whether SOC stocks are increasing, decreasing or stable. The application of the same methods for the monitoring period (rather than the baseline period) will lead to estimates of SOC stock at the end of the monitoring period ($SOC_{t_n}$).

#### 4.3.3.1 Default Methods

Where country-specific data/capability are currently lacking, a default ('Tier 1') approach can be used, noting that a national approach is preferable (see below). IPCC Tier 1 methods generally assume that the changes occur over 20 years and that land ceases to be in a conversion category 20 years after the conversion occurred (see Table 4.2). The influence of land use and management on SOC is very different in mineral versus organic soil types (for discussion, see Section 2.3.3, IPCC 2006). Therefore, separate guidance is provided for estimating carbon stock change in mineral soils and organic soils based on the IPCC good practice guidance and guidelines. Here we follow the definition of organic soils as provided in the IPCC 2006 Guidelines, which follows that in the World Reference Base for Soil Resources (FAO 1998). 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); however carbon stocks in organic soils can be estimated in a Tier 3 method (IPCC 2006).

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

$$\Delta SOC = \Delta SOC_{mineral} - L_{organic} \qquad (2)$$

Where:

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

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

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

Note that most spatial features will not include organic soils.

**Table 4.2: Conceptual framework for quantifying changes in soil organic carbon (SOC) stocks.**

| 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. | Apply IPCC Tier 1 methods to assess SOC stock change (0-30 cm) after default 20-year period;[1] methods differ for mineral and organic soils. |
| **Tier 2** | Apply IPCC Tier 2 method, i.e., update of SOC reference stocks and associated stock change factors with country-specific values. SOC reference stocks can be determined from global or national high-resolution, digital soil maps or from measurements (e.g., national soil surveys). | Apply IPCC Tier 2 method using stock change factors with country-specific values; |
| **Tier 3** | Two general approaches:<br>a) Where available and robust, apply methods that relate SOC stock to environmental and management factors, using statistical learning methods, such as used in state-of-the-art digital soil mapping studies, using best available baseline data for SOC stock and environmental covariates (e.g. land cover) for the defined reference period. Where possible, refine established global relationship using national data, including using measured soil data for the period 2000-2015;<br><br>b) Derived from ecosystem (process-based) modelling. | a) Apply methods derived from baseline data to changed environmental and management conditions observed during the reporting year, i.e. use relationships derived from global or national digital soil mapping products, including measured soil data for the reporting period;<br><br>b) Derived from ecosystem modelling, calibrated 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.

**Mineral Soils**: Tier 1 methods for estimating SOC stock changes on mineral soils can be utilized for this sub-indicator. The approach considers globally-established reference stocks for SOC (0-30 cm), default management factors, and rules to derive SOC stocks for defined changes in land use (e.g., Forestland to Cropland) and land management, with consideration of broadly defined 'climate-soil' classes (IPCC 2006). SOC stock change is derived from applying these rules while assuming a default time interval of 20 years (proxy for next SOC stock equilibrium) and simplified linear rate of change. The reference SOC stocks, i.e., under native vegetation, are based on land areas that are stratified by climate regions and default soil classes. The stock change factors are very broadly defined and include:

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

- an input factor (*FI*) representing different levels of carbon input to soil.

All land in a homogeneous land cover unit should have common biophysical conditions (i.e., climate and soil type) and management history over the time period to be considered together for analytical purposes. It will also be necessary to ensure that these units can be aggregated to default land cover classes. Many spatial features will have more than one homogeneous land cover class (particularly for soil type and management system). In such cases, spatially-weighted averaging is required. Change in organic carbon stocks in mineral soils is estimated using Equation 2.25 (Chapter 2, Volume 4 of the 2006 IPCC Guidelines) and reproduced here:

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

and

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

Where:

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

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

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

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

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

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

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

*s* represents the IPCC soil classes that are present in a spatial feature;

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

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

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

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

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

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

**Organic Soils**: 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 (Chapter 2 of the IPCC 2013 Wetlands Supplement) is produced here:

$$L_{organic} = L_{drainage} + L_{fire} \quad (4)$$

Where:

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

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

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

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

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

Where:

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

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

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

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

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

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

Where:

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

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

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

$f$ 1, 2 …*F* fire types

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

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

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

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

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

The amount of fuel that can be burnt is given by the area burnt annually and the mass of fuel available in that area. Default values are provided in Tables 2.6 and 2.7 of the IPCC 2013 Wetlands Supplement. 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).

#### 4.3.3.2 National Methods

Where possible, it is good practice for countries to use a national approach to reduce uncertainty, even if they are only able to better specify certain components of the default approach (see Table 4.2). A model-based approach is one where maps (global or country-specific) are used to derive the estimates of SOC stocks. The advantage of this approach is that it results in spatially-explicit maps that can be used for sub-national accounting for different activities. The disadvantage is that it is based on a model of the spatial variation and if this model does not describe the variation adequately or is largely uncertain, then the estimates (i.e., the map) will also be largely uncertain. The alternative is a design-based approach. In some cases, this approach may be more useful for monitoring because, if adequately designed, unbiased estimates of SOC stocks can be made over the total land area. Design-based methods can use less data (e.g., where compositing of samples is used), but the uncertainties of the estimates of the mean can be large.

Two alternative approaches are suggested for Tier 2 methods. 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.

Reference soil carbon stocks can be determined from high-resolution digital soil maps or from measurements, for example, as part of national soil surveys. This will provide more representative values for an individual country and the ability to better estimate probability distribution functions that can be used in a formal uncertainty analysis (IPCC, 2003). Reference stocks should be consistent across

the land uses. Accepted standards for sampling and analysis of SOC and bulk density should be used and documented. Stock change factors can be estimated from long-term experiments or other field measurements (e.g., chronosequence studies) for a particular country or region. The depth of measurement and time frame over which the management difference has been expressed should be provided (IPCC 2006).

For **organic soils**, 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 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. Such relationships can now be derived routinely from digital soil mapping (Minasny et al. 2013; Arrouays et al. 2014; Hengl et al. 2017).

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 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. A further refinement is to replace globally or regionally established relationships with relationships calibrated using national data.

The above soil mapping approaches make predictions at point locations. By implication, spatial aggregation is possible to any desired spatial reporting unit and for administrative or physical units. More advanced national methods which better capture annual variability in fluxes (Tier 3) may also be used. Such methods may include using calibrated and validated models, and/or developing a measurement-based inventory with a monitoring network to capture SOC stock changes. Tier 3 approaches involve the development of an advanced estimation system that will typically better capture annual variability in fluxes, unlike Tier 1 and 2 approaches that mostly assume a constant annual change in 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 are capable of capturing longer-term legacy effects of land use and management.

Two general approaches using the Tier 3 method are recommended. The first uses the digital soil mapping approach described above for Tier 2 along with measured soil data for the period 2000-2015.

The sampling approach requires the collection of a sufficiently large set of soil data for each reporting period to derive SOC maps and SOC stock estimates at an accuracy level that allows statistically-significant detection of relevant SOC stock changes. It also requires that for the baseline assessment, all data used are within the time period 2000-2015. SOC maps are now being derived using state-of-the-art digital soil mapping techniques (Viscarra Rossel et al. 2014; Ließ et al. 2016; Sreenivas et al. 2016; Hengl et al. 2017). Since maps are required for this approach, a model-based approach is recommended instead of a design-based approach (Brus and de Gruijter 1997; de Gruijter et al. 2006; Webster 2007; Heuvelink et al. 2012; Viscarra Rossel et al. 2016a). The second approach combines measurements with process-based ecosystem models to estimate changes in SOC stocks. For example, a country-scale Tier 3 assessment of SOC has been developed for Japan by linking the RothC model and spatial datasets, including soil maps, land use, climate, and agricultural activity (Shirato 2017).

#### 4.3.3.3 Estimating Change in SOC Stocks

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

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

Where:

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

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

$SOC_{t_n}$ = soil organic carbon stock for final monitoring period for spatial feature (t C ha$^{-1}$).

#### 4.3.3.4 Estimating Uncertainty

It is good practice to report uncertainties in estimates and to minimise uncertainty as far as practical, even if these uncertainties are not used in a formal sense (i.e., in statistical tests). For Tier 1, uncertainty is based on the propagation of the uncertainty in the IPCC factors. Here 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. We then discuss approaches for assessing uncertainty in Tier 2 and 3 methods.

**Default Methods**: The IPCC Guidelines recommend the use of a 95% confidence interval, which is the interval that has a 95% probability of containing the unknown true value. Therefore it is good practice to report the 95% confidence interval with estimates of baseline SOC stocks and SOC stocks at the end of

the monitoring period. This 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.[65]

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, IPCC 2006) for the uncertainty of the product, expressed in percentage terms is:

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

Where:

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

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

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

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

Where:

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

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

**Higher Tier Methods**: Where map products are used, it is good practice for these to be accompanied by uncertainty quantifications. Heuvelink (2014) outlines statistical approaches (using probability distributions) for model-based quantification of uncertainty for map products, including:

- *Direct quantification through geostatistical modelling*: where a geostatistical model of the soil property of interest is defined and conditioned to available information, such as point profile observations and environmental covariates, by kriging. This provides an interpolated map and its associated uncertainty.
- *Geostatistical modelling of error in existing maps*: where the associated uncertainty of an existing, deterministic soil property map, is quantified by developing a geostatistical model of the differences between the map and independent observations.

[65] 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).

- *Expert judgement*: where expert judgements of uncertainty are used. These are likely to be subjective and cannot produce a full probabilistic model of uncertainty, but in some circumstances may be the best available option.

Alternatively, statistical validation can be used to derive a 'model-free' assessment. Validation provides summary measures of uncertainty (e.g., mean error, root mean squared error), and is best conducted using probability sampling of independent observations of the soil property of interest (Heuvelink 2014). For Tier 2 and 3 approaches, as a minimum, cross-validation of explicit modelling of uncertainties should be done. Monte Carlo simulation can also be used to provide estimates of uncertainty (Viscarra Rossel et al. 2014) and to evaluate how the uncertainty of the soil map propagates through the subsequent analysis (Heuvelink 1998).

#### 4.3.3.5 Assessing Change in SOC Stocks

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 monitoring period for each land cover class/unit by combining uncertainties as described above. If the 95% confidence interval of the difference does not cover zero, then the change is significant, with the direction of change determined from Eqn. 6.

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

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

- **Degraded**: Spatial features with more than 10% average net reduction in SOC stocks between baseline and current observations.

- **Not degraded**: Spatial features with less than 10% average net reduction, no change or an average net increase in SOC stocks between baseline and current observations.

An arbitrary >10% change threshold is suggested, however, further refinement and justification of this threshold value is needed. This is likely to be a country decision based on available information, practicalities, etc.

The examples provided in Box 4.1 and Box 4.2 give some indication of the magnitude of change that might be estimated using the default method. Two contrasting scenarios under the default approach give both a 10% increase based on changed management (reduced tillage) of 80% of the area of a spatial feature that was annual cropland (no degradation), and a 25% decrease based on conversion of 70% of the area of a spatial feature from native forest to annual cropland (degradation).

Others have suggested that interim procedures are required so that assessments of change can be 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); and/or
- 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).

#### 4.3.3.6 National and Sub-National Contexts

In the absence of, or as a complement to, national data, it is good practice to contextualize global and regional data sets with information at the national and, where possible, sub-national level. For example, in some cases, carbon stocks may be increasing for land use transitions that are actually considered land degradation, such as woody encroachment in grassland. Another example relates to identifying potential "hotspots" of degradation. An average computed for a country may hide hotspots of intense degradation that may be very significant (e.g., they may be the most fertile soils in the country).

Assessment of "false positives" or degradation "hotspots" requires knowledge and interpretation at the local level. The most common approach involves the use of site-based data or a combination of quantitative and qualitative data. It is good practice to incorporate the capacity to generate an "explainable anomalies" or "false positive" map and a "hotspots" map when deriving the sub-indicator, maintaining original data with anomalies identified and explained. Further discussion is provided in Section 4.4.

#### 4.3.3.7 Summary of Computational Steps

1. Where a default approach is used:
    a. Reference soil carbon stocks will be determined and documented for all major soil types, stratified by climate regions.
    b. Stock change factors and emission factors will be determined and documented for all land uses/management systems, and where needed, any additional sub-types.
2. An assessment of SOC stocks within each homogeneous land cover unit of the defined disaggregation scheme will be made for the baseline.
3. An average SOC stock will be generated for each identified spatial feature for the baseline period. The 95% confidence interval around the average will also be reported.
4. During the reporting period, the monitored SOC will be compared with the average baseline SOC for the same spatial feature by calculation of the relative percentage change (Eqn. 8).
5. The most appropriate method to assess whether change results in a significant decrease in SOC (degraded) or an increase or no change in SOC (not degraded) will be applied. Where estimated overall uncertainties are relatively low, a statistical approach is the most robust way to estimate whether change is significant. As an alternative, assessment of both the direction of change and magnitude of the relative percentage change in SOC stocks, relative to some defined threshold, is suggested.
6. Increases in SOC stocks may not always be representative of a positive change. Potential false positives and explainable anomalies should be defined, justified and maintained in the original dataset.

#### 4.3.3.8 Examples using Default Calculations

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

The following example (modified from IPCC 2003) shows calculations for aggregating areas of SOC stock change within a spatial feature over a 5-year reporting period. The spatial feature 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 in Table 2.3, IPCC 2006, native reference carbon stock ($SOC_{REF}$) for the region is 88 t C ha$^{-1}$.

At the beginning of the calculation period, the distribution of cropland systems 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, Vol. 4 in the IPCC 2006 Guidelines. Using Eqn 3a & b[1], initial soil carbon stocks ($SOC_0$) for the area were:

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

With parameters:

| | Low C input | Medium C input |
|---|---|---|

| | Full till | Full till |
|---|---|---|
| Area | 4000 | 6000 |
| Reference carbon stock ($SOC_{REF;}$ t C $ha^{-1}$) | 88 | 88 |
| 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 |

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

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

With parameters:

| | Low C input<br>Full till | Medium C input<br>Reduced till | Medium C input<br>No till |
|---|---|---|---|
| Area (A) | 2000 | 7000 | 1000 |
| Reference carbon stock ($SOC_{REF;}$ t C $ha^{-1}$) | 88 | 88 | 88 |
| Land use stock change factor ($F_{LU}$) | 0.69 | 0.69 | 0.69 |
| Management regime stock change factor ($F_{MG}$) | 1.0 | 1.08 | 1.15 |
| 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: (671,968 – 587,770) t C / 20 yr = 84,198 t C/ 20 yr = 4,210 t C $yr^{-1}$ increase.

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

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

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

$F_{LU}$: long-term cultivated 0.69±12%;

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

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

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:

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

And for $t_n$ is:

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

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

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

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

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

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

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

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

In the (current) measurement year:

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

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

Degradation is assessed separately for each homogeneous land cover unit (in this case soil type) within the spatial feature, with the ordering of parameters within the equation as per Example 1:

**<u>LAC soils</u>**

$t_0$ 3,000 ha × 24 t C $ha^{-1}$ = 72,000 t C

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

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

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

$F_{LU}$: long-term cultivated 0.69±12%;

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

$F_I$: low input 0.92±14%.

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:

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

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

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

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

Area LAC soils degraded = 2,000 ha

**HAC soils**

$t_0$ 7,000 ha × 38 t C $ha^{-1}$ = 266,000 t C

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

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

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

$F_{LU}$: long-term cultivated 0.69±12%;

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

$F_I$: low input 0.92±14%.

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

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

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

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

Area LAC degraded = 5,000 ha

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

## 4.4 Rationale and Interpretation

Soil organic carbon (SOC) is a fundamental part of the terrestrial ecosystem and its accumulation 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) as well as ecosystem functioning. Consequently, one of the greatest priorities for action concluded by the Intergovernmental Technical Panel on Soils (ITPS) in their Technical Summary[66] 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*".

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

Although carbon stocks in non-forested ecosystems are typically largest in the soil pool where woody perennial vegetation is present, the largest pool tends to be in the biomass except where growing on organic soils (GFOI 2016). Further, in forested systems, changes in SOC stocks may not always capture degradation. For example, conversion of native forest to pasture may not result in a change in SOC stock (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.

Computation of the carbon stocks sub-indicator requires that the area of land in each spatial unit at times $t_0$ and $t_n$ is identical, and that exactly the same pools of carbon (including reference depths for SOC) are included in all time steps. Land use categories and carbon stocks may change with improved knowledge, however, and may therefore to be retrospectively corrected.

### 4.4.1 Uncertainty

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

**Choice of Method**: The main consideration in the selection of the default or nationally-specific method by a country is the current and likely future availability of data. Data sources are described in Section 4.5. The choice of method will have implications for the level of uncertainty in the estimate of changes in the SOC metric. The default method draws on area data (i.e., activity data) generated from the assessment of land cover change in combination with reference and emission factors obtained from the IPCC default tables corresponding to broad continental land cover types and management regimes. As such, derived estimates provide limited resolution of how carbon stocks vary sub-nationally and have large uncertainty.

The inclusion of national data (and/or use of higher order methods) is a more rigorous approach to generating estimates of changes in SOC stocks, however, this requires higher levels of effort and resources. Reducing uncertainty in estimates requires improving stratifications and/or increasing the number of soil samples to use for the estimation. The capacity to do this will require improvements in analytical capabilities and analysis (see Section 4.5.2). Requirements include ground measurements, such as national inventories repeated through time, and intensive monitoring sites. Data from national inventories can provide information for default estimation methods, and for developing modelling approaches. Detailed information (at fine scale) generated at intensive monitoring sites can help address the difficulty of estimating stocks and stock changes by supporting development of model parameters, including emissions and removals factors. Derived estimates using such higher order methods provide information sub-national scale and have lower uncertainty.

**Estimating Change**: Both land cover areas and carbon densities have uncertainties which need to be combined when estimating changes in carbon stocks. Similarly, uncertainties for estimates of non-$CO_2$ greenhouse gas emissions are calculated by combining component emission/removal factors and activity data uncertainties. Each of the IPCC default values 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).

**False Positives**: In general, areas with long-term declining carbon stocks may be considered degraded while areas with increasing carbon stocks may be considered improving. However, estimated changes in carbon stocks also require contextualization with information at national and sub-national levels. For example, in some cases, carbon stocks may be increasing for land use transitions that are actually considered land degradation, such as woody encroachment (i.e., land cover change from grassland to shrubland). Assessment of this type of exception (i.e., "false positive") requires knowledge and interpretation at the local level. Identification of false positives could be assessed by using site-based data, and/or qualitative information and stakeholder perspectives from surveys, workshops, in-depth interviews, and the establishment of expert panels. Once the false positive areas have been identified, these transitions would need to be designated as a "negative change". The relevant land area associated with this change would need to be included with other areas of negative change in the calculation of the overall indicator.

To give these considerations a practical implication, the concept of minimum detectable change/difference could be introduced. Combined with a power analysis, it can be estimated how many samples are necessary to significantly detect a change and/or how many years need to pass until a change is detectable given a certain number of samples and expected rate change (Maillard et al. 2016).

## 4.5 Data Sources and Collection

The type and availability of data will vary by country. This section reviews existing or forthcoming datasets in the context of their spatial and temporal resolution, accuracy and validation, consistency, and historic and current temporal availability. These data are sourced from freely-available global datasets, IPCC Good Practice Guidance (2003), IPCC guidelines (2006) and other documents (e.g., Wetlands Supplement 2013) and nationally-contributed datasets. There is also a discussion on monitoring methods for estimating SOC stock change.

### 4.5.1 Global Datasets

Where country-specific data are not available, it is good practice to apply the best available defaults for SOC stocks to national land cover maps obtained by Earth observation data (see Chapter 1). The minimum would be the six land cover classes used by the IPCC (i.e., Forest land, Grassland, Cropland, Wetlands, Settlements, Other land) and relevant stratifications based on soil type and land management

combined with default values for relative stock change factors associated with land use, management and inputs (also from IPCC default tables). In some cases, it may be difficult to report 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. There is already a precedent for this by countries reporting on degradation for REDD+ using national data.

Global default methods for estimating changes in SOC stocks are strongly reliant on land cover change data, which include:

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

At the broadest level, the IPCC provides a systematic approach for estimating carbon stock changes in soils (IPCC 2003; 2006; 2013). IPCC defaults exist for the minimum six land cover 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 IPCC default values for reference SOC stocks and stock change factors reflect the most recent review of changes in soil organic carbon with conversion of native soils. Some limitations of using the IPCC defaults include the lack of relative change factors for some climates, as well as a paucity of change factors for specific management scenarios. The available defaults are summarised for mineral (see Eqn. 3) and organic soils (see Eqns. 4-6) in Table 4.3 and 4.4, respectively. They are also provided in the IPCC Emission Factor Data Base which is regularly updated.[67]

**Table 4.3: Source of defaults in IPCC guidance documents for factors associated with change in SOC stocks in mineral soils.**

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

[67] http://www.ipcc-nggip.iges.or.jp/EFDB/main.php

**Table 4.4: 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 | Tables 2.7 |

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

Neutrality target setting, 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, and others have compiled and harmonized national soil information in several global datasets. These have different spatial resolutions and are at different stages of development, but have potential for estimating reference SOC stocks. Existing freely-available sources include:

- **Harmonized World Soil Database (HWSD)**[68] - This is the current de facto standard soil grid for the world despite its acknowledged shortcomings (GSP 2014). Version 1.2 is the latest update. Spatial resolution is 30 arc seconds (about 1 km). ISRIC has updated the HWSD (Batjes, 2016) resulting in a database (**WISE30sec**)[69] with more depth intervals and more parameters quantified, and an estimate of uncertainty (SD). There is no assessment of accuracy.
- **SoilGrids250m**[70] (Hengl et al. 2017) - An operational global 3D soil information system at 250 m spatial resolution. Products of SOC percentage, bulk density, gravel fraction and depth to bedrock can be used to calculate a predicted SOC stock for 0-30 cm (and to a greater depth). Accuracy was assessed using 10-fold, repeated cross-validation. Relative to SoilGrids1km, the amount of explained variation for SOC was improved from about 23% to about 69%. It should be noted that, as for the IPCC defaults, the predictions derived from soil maps at a specified location will have very wide confidence intervals. In general, the use of datasets with the highest spatial resolution is recommended.

Currently under development are the:

- **GlobalSoilMap**[71] (Arrouays et al. 2014a,b) – This is a digital soil map project that aims to provide a fine-resolution (100 m) global grid of soil functional properties, including SOC stock, with estimates of their associated uncertainties. A gridded date-map will be made to indicate the date (in years) that the soil property value most closely reflects. To date, several countries have produced grids of soil properties, including SOC and bulk density. However, progress on this has been very slow.
- **Global Soil Organic Carbon map** - Under the Global Soil Partnership (GSP), FAO member countries and all GSP partners have been invited to support and contribute to the development of the Global Soil Organic Carbon map (GSOC map) that will be released by the end of 2017.[72] Initial guidelines for sharing national data/information to compile the GSOC map have recently been released,[73] as has a Soil Organic Carbon Mapping Cookbook.[74]

[68] http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/
[69] http://www.isric.org/projects/world-inventory-soil-emission-potentials-wise
[70] http://www.isric.org/content/faq-soilgrids
[71] http://www.globalsoilmap.net/
[72] http://www.fao.org/global-soil-partnership/resources/highlights/detail/en/c/435193/
[73] http://www.fao.org/3/a-bp164e.pdf
[74] http://www.fao.org/3/a-bs901e.pdf

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

- There is a paucity of data on bulk density and gravel content. Misuse of these data in calculation of SOC stocks can lead to systematic overestimation (Poeplau et al. 2017);
- Measurements for SOC (%), bulk density, gravel content and soil depth have been collected with different measurement methods;
- Soil data were collected over a large period of time (approximately the past 60 years for SOC, with the bulk centred on ~1995) and predictions were not made for a specific year (but assumed so in the absence of other, more suitable global data);
- Soil data were collected for various purposes, so there may be sampling bias (e.g., an over-representation of agricultural areas is common);
- The collection of legacy data (WoSIS[75]) is nowhere near exhaustive, with much existing legacy data yet to be shared by data providers (Arrouays et al. 2017).

Many of these issues identified for SoilGrids250m are also relevant to the other global maps that exist or are under development. Further, many map soil organic carbon content and bulk density but not soil carbon stocks which requires multiplying the maps and averaging the depths to derive the 0- 30 cm SOC stocks. Not all of the currently available global map products are likely to provide a better alternative to the IPCC defaults. However, SoilGrids250m is likely to be a better alternative for deriving reference SOC stocks, although as might be expected, it may provide estimates that are biased. Where available, regional and country-specific sampling campaigns for mapping produced to GlobalSoilMap specifications, are likely to provide an improvement over global estimates (see below).

The global spatial products described above for estimating SOC reference stocks are currently not dynamic. However, even if planned improvements in the accuracy of predictions are made, the global grid (even time-stamped releases over several decades) would not necessarily be the most effective way of detecting SOC stock change. Other strategies are more sensitive, such as a well-designed monitoring network such as Land Use/Cover Area Frame Statistical Survey (LUCAS)(see below), 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.

### 4.5.2 National Datasets

National land cover products are based on earth observation data at finer resolutions than for global products. Landsat satellites provide a time series of remotely sensed digital images spanning 40 years and are being used widely in monitoring activities (available datasets are summarized in Chapter 2). Broadly, national datasets for land cover change can include:

[75] https://www.earth-syst-sci-data.net/9/1/2017/essd-9-1-2017.html

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

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

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

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

**Baseline SOC Stocks**: Examples of existing regional (continent) and country baseline maps for SOC stocks are provided in Table 4.5. Recent information on surveyed SOC stock estimates from 20 regions in the world is also provided in Minasny et al. (2017).

**Table 4.5: Examples of continents/countries that have estimated spatially-explicit baselines of SOC stocks for the 0–30 cm layer.**

| Country/continent | Reference |
|---|---|
| **Australia** | Viscarra Rossel et al. (2014) |
| **Chile** | Pandarian et al. (2016) |
| **Denmark** | Adhikari et al. (2014) |
| **Europe** | de Brogniez et al. (2015) |
| **France** | Mulder et al. (2016) |
| **Mexico** | Vargas 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) |
| **Turkey** | Madenoglu et al. (2017) |
| **USA** | Odgers et al. (2012) |

As concluded by the Intergovernmental Technical Panel on Soils (ITPS) in their Technical Summary[76] of the Status of the World's Soil Resources (Action 4, page ix), 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 trend in the condition of soil, and an initial emphasis should be on improving observation systems, including for soil organic carbon.

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

- **Recommendation 1**: An enduring and authoritative system for monitoring and forecasting the condition of the Earth's soil resources should be established under the auspices of the Global Soil Partnership to meet international and regional needs.

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

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

The subsequent Pillar 4 Implementation Plan[77] provides the guidance to build the global soil information system based on soil data sets provided by national and other institutional soil information institutions according to product specifications, and recognizes governance as an important element of the plan.

**Country-specific defaults**: 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 they should use these in accordance with Tier 2 methods for preparing National Greenhouse Gas Inventories in IPCC (2006). Ground-based data can be used to estimate SOC values and to derive stock change factors for mineral soils, as well as to estimate emissions and removals factors for organic soils. For nationally-derived default data on SOC stocks, it is good practice to:

1. Use standardised measurement units, i.e., tonnes SOC per ha for 0–30 cm depth.
2. Where available and robust, use national spatial datasets for SOC reference stocks (e.g., see Table 4.4.
3. Where available, use their own information on the effect of management within land cover classes (i.e., change factors for land use change, management within land uses and/or inputs on SOC stocks).

For the latter, existing agricultural field trials provide one immediately available resource for the study of management impacts on soil carbon sequestration. These data sets have both informed soil carbon modelling (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). A recent review (Sanderman and Baldock 2010) highlighted some of the difficulties in using field trial data in a predictive capacity to account for changes in SOC stocks, and presented a critical evaluation of current IPCC Guidelines (IPCC 2006) for accounting for emissions or removals resulting from SOC stock changes. They found that results from most agricultural field trials indicate a relative increase in soil carbon stocks with the

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

adoption of various improved management practices. However, the few available studies with time series data suggest that this relative gain is often due to a reduction or cessation of soil carbon losses rather than an actual increase in stocks. Thus they argued that stock change data from agricultural field trials may have limited predictive power when the state of the soil carbon system is unknown and that current IPCC accounting methodologies developed from the trial results may not properly credit these management activities. This suggests 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.

**Ground-based data**: More advanced approaches would include integration of ground-based data from national monitoring systems with Earth observation and modelling. Because estimates from default values and maps have wide associated uncertainties, more sensitive methods are recommended to detect 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, and 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; and
- Research data that can be used to estimate emissions and removals.

Judicious soil monitoring networks (SMNs) 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; Minasny and McBratney 2006; Heuvelink 2007; Webster and Oliver 2007; Lark 2016).

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

- Spatial sampling strategies (site selection, sampling locations, number of samples, bulking, etc.)

- Temporal sampling strategies (timing, frequency)
- Measurement (consistency, accuracy, cost, etc.)
- Scaling of point measurements to areal estimates

Specific guidance on these aspects is context-specific, and is not provided here, but is covered in a number of references (McKenzie et al. 2002; de Gruijter et al. 2006; Chappell et al. 2013; Arrouays et al. 2014c; DotE 2014b). 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. 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[78] (>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 SMNs 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 SMNs and other field sampling programs should be stored in a 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). For example, see Box 4.3.

[78] Regional differences e.g. where "< 1mm" is used as the limit, mainly former Soviet Union and satellite countries.

**Box 4.3: Example of statistically-based sampling of soil using LUCAS**

The European project LUCAS (Land Use/Cover Area Frame Statistical Survey)[79] may provide some guidance for monitoring, although some modifications are recommended in the context of SOC stocks. In 2009, the European Commission extended the periodic LUCAS to sample and analyse the main properties of topsoil in 23 Member States of the European Union (EU).[80] This topsoil survey represents the first attempt to build a consistent spatial database of the soil cover across the EU based on standard sampling and analytical procedures, with the analysis of all soil samples being carried out in a single laboratory. Approximately 20,000 points were selected out of the main LUCAS grid for the collection of soil samples. A second round of sampling is being processed. The topsoil survey was designed to monitor a number of soil properties. In the context of monitoring SOC stocks, two modifications would be recommended. First, sampling to depths that meet IPCC standards (i.e., to 30 cm) rather than the 20 cm currently used in LUCAS, 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 have now been adapted for the planned 2018 sampling to collect samples for the assessment of new properties including bulk density and thickness of the organic horizon in peat soils.[81]

**Proximal sensing**: The development of new analytical methods based on sensing can help with the acquisition of data for SOC stocks, including estimating baselines (see Box 4.4). Sensors can provide rapid, accurate, non-destructive and inexpensive measurements of soil properties. For carbon accounting, they need to be accurate, sensitive to detecting small changes in SOC stocks, and enable timely feedback to account for the change. There are current reviews on the use of soil sensing for measuring SOC concentration which highlight the usefulness of visible-near infrared (vis–NIR) and mid-infrared (mid-IR) spectroscopy (Stenberg et al., 2010; Bellon-Maurel and McBratney, 2011; Viscarra Rossel et al., 2011; Reeves et al., 2012; Izaurralde et al., 2013). Although there are fewer articles that address the sensing of soil bulk density, there have been some recent advances that use gamma-ray attenuation to accurately measure soil bulk density (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., vis–NIR; gamma-ray attenuation, digital cameras) with robust statistical analytics and modelling are being developed to address the lack of such data for monitoring SOC stocks (Viscarra Rossel et al. 2017). Further, there is recent work demonstrating the use of soil sensors for SOC stock baselining (Viscarra Rossel et al. 2016a).

**Box 4.4: Example of deriving a baseline using current and historical point data and archived soil samples combined with spectroscopic sensors**

Viscarra Rossel et al (2014) derived a baseline for SOC stocks in Australia for the period 2000–2013. They utilised data from a national Soil Carbon Research Program that produced current data on SOC stocks for agricultural regions of Australia. However, with this dataset alone, it would have been impossible to map the whole of the country because there was no data for the large majority of areas in the north, northwest and centre of Australia.

[79] http://esdac.jrc.ec.europa.eu/projects/lucas
[80] http://esdac.jrc.ec.europa.eu/ESDB_Archive/eusoils_docs/other/EUR26102EN.pdf
[81] http://publications.jrc.ec.europa.eu/repository/bitstream/JRC105923/jrc105923_lucas2018_jrctechnicalreport.pdf

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 is now being used elsewhere in the United States of America and in China.

Viscarra Rossel and Bouma (2016) provide discussion on the use of proximal soil sensors and their role in the development of sustainable agricultural productions systems and innovative environmental and regional policies. They suggested that proximal soil sensing can be also used to effectively monitor SOC stock for accounting purposes and be central to the adoption of best agronomic practices that also reduce greenhouse gas emissions and allow significant carbon sequestration to reach the '4 per 1000' (Minasny et al. 2017) proposal made by the French authorities ahead of the 21st Conference of Parties to the United Nations Framework Convention on Climate Change.

## 4.6 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 briefly describes current methods that could be used to estimate total carbon stocks.

### 4.6.1 Default Methods

Where country-specific data and capacities are currently lacking, a default or Tier 1 methods 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). The equation for estimating the change in total carbon stocks (Eqn. 11) in a spatial feature is modified from Equation 2.3 in Chapter 2, Volume 4 of the 2006 IPCC Guidelines and excludes harvested wood products:

$$\Delta C = \Delta C_{AB} + \Delta C_{BB} + \Delta C_{DW} + \Delta C_{LI} + \Delta SOC \qquad (11)$$

Where:

$\Delta C$ = total carbon stocks in the spatial feature;

$\Delta C_{AB}$ = carbon stocks in aboveground biomass in the spatial feature;

$\Delta C_{BB}$ = carbon stocks in belowground biomass in the spatial feature;

$\Delta C_{DW}$ = carbon stocks in dead wood in the spatial feature;

$\Delta C_{LI}$ = carbon stocks in litter in the spatial feature;

$\Delta SOC$ = organic carbon stocks in soil in the spatial feature.

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

IPCC defaults exist for the minimum six land cover classes and are stratified further into combinations based on climate, ecology, disturbance or management. Spatial stratification based on these defaults would further improve the quality of the results at the national level. The available IPCC defaults are provided in the 2003 Good Practice Guide, 2006 Guidelines and 2013 Wetlands Supplement for above ground biomass stocks, root to shoot ratios (for estimating below ground biomass from above ground biomass) and debris stocks, and are summarised in Tables 4.6 and 4.7, respectively. They are also provided in the IPCC Emission Factor Data Base which is regularly updated.[82]

[82] http://www.ipcc-nggip.iges.or.jp/EFDB/main.php

**Table 4.6: 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 |
|---|---|---|---|
| **Carbon fraction of above ground forest biomass** | Default = 0.5 | Table 4.3 | |
| **Ratio of below ground biomass to above ground biomass** | Table 3A.1.8 | Table 4.4 | |
| **Above ground biomass stocks in natural and plantation forests** | Tables 3A.1.2 & 3A.1.3 | Tables 4.7-4.11 (excl. 11B) | |
| **Above ground biomass for various types of perennial croplands** | Table 3.3.2 | Table 5.3 | |
| **Biomass carbon stocks present on Land Converted to Cropland in the year following conversion** | Table 3.3.8 | Table 5.9 | |
| **Above ground biomass for various types of grasslands** | Table 3.4.2 | | |
| **Ratio of below-ground biomass to aboveground biomass for the major grassland & savanna ecosystems of the world** | Table 3.4.3 | Table 6.1 | |
| **Biomass stocks present on grassland, after conversion from other land use** | Tables 3.4.2 & 3.4.9 | Table 6.4 | |
| **Above ground biomass stocks in mangroves** | | | Table 4.3 |
| **Ratio of below ground biomass to above ground biomass in coastal wetlands** | | | Tables 4.5, 4.9 & 4.10 |

**Table 4.7: 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 |
|---|---|---|---|
| **Forest litter and dead wood carbon stocks** | Table 3.2.1 & 3.2.2 | Table 2.2 | |
| **Litter and dead wood stocks in mangroves** | | | Table 4.7 |

### 4.6.2 National Methods

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.

Under Tier 2 methods, country-specific data on ratios of below ground to above ground biomass can be used to estimate below ground stock changes. For land converted to a new land cover class, Tier 2 methods to calculate annual change in biomass stocks replace Equation 2.4 by Equation 2.15 (Vol. 4, IPCC 2006), where the changes in carbon stock are calculated as a sum of increase in carbon stock due to biomass growth, changes due to actual conversion (difference between biomass stocks before and after conversion), and decrease in carbon stocks due to losses. Tier 2 methods for estimating carbon stock changes in dead organic matter (DOM) pools calculate the changes in dead wood and litter carbon pools (Equation 2.17, Vol 4, IPCC 2006). Two methods can be used: either tracking inputs and outputs (the Gain-Loss Method, Equation 2.18) or estimating the difference in DOM pools at two points in time (Stock-Difference Method, Equation 2.19). These estimates require either detailed inventories that include repeated measurements of dead wood and litter pools, or models that simulate dead wood and litter dynamics. The same equation is used for dead wood and litter pools, but their values are calculated separately.

As for SOC stocks, in most cases it is envisaged that estimates of changes in carbon stocks above and below ground 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.

### 4.6.3 Biomass Products

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

Global and regional biomass map products:

- **New IPCC Tier-1 Global Biomass Map for the Year 2000**[83] **-** In conjunction with GLC2000 land cover data, thisglobal map shows biomass carbon stored in above and below ground living vegetation at 1 km resolution.
- **The National Biomass and Carbon Dataset (NBCD2000)**[84] - This provides basal area-weighted canopy height, above ground live dry biomass, and standing carbon stock for the year 2000 at 30 m resolution for the conterminous United States. It is based on a combination of data from the USDA Forest Service Forest Inventory and Analysis, the 2000 Shuttle RADAR Topography Mission (SRTM) and Landsat-7/ ETM+. This is a good example of how national forest inventory plot data can be combined with remote sensing data to produce maps of biomass.
- **National Level Carbon Stock Dataset (Tropics)**[85] **-** This provides maps of above ground live woody biomass at 500 m resolution for the tropics in 2007-2008. A combination of field measurements and space-borne LIDAR observations at 70 m spatial resolution from the Geoscience Laser Altimeter System (GLAS) instrument on board the Ice, Cloud and land Elevation Satellite (ICESat), and optical MODIS imagery at 500 m spatial resolution, were used.
- **JPL Carbon Maps**[86] **-** The Jet Propulsion Laboratory of NASA and the California Institute of Technology provide a biomass product similar to that of the WHRC National Level Carbon Stock Dataset. The maps provide forest above ground carbon and biomass for sub-Saharan Africa, the Americas south of latitude 30° N, and South-East Asia and Australia between the latitudes of 40° N and 30° S at 1 km resolution. Point-based estimates of biomass generated from a combination of field data and space-borne LIDAR data from ICESat/GLAS were extrapolated using optical data from MODIS and RADAR data from SRTM and QuickSCAT.
- **Integrated pan-tropical biomass map**[87] - This 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.

A global biomass map, currently being developed by the GlobBiomass project,[88] 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.

**National biomass products**: There is potential for integration of ground-based data with remote sensing to estimate biomass at the local level. Airborne LIDAR, calibrated using ground-based estimates of

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83 http://cdiac.ornl.gov/epubs/ndp/global_carbon/carbon_documentation.html
84 http://whrc.org/publications-data/datasets/national-biomass-and-carbon-dataset/
85 http://whrc.org/publications-data/datasets/pantropical-national-level-carbon-stock/
86 http://carbon.jpl.nasa.gov/
87 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
88 http://globbiomass.org/products/global-mapping/

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

Under the GlobBiomass project, sub-national mapping is underway, where biomass stock and change maps with better spatial resolution than the global reference map (50-150 m) and with a multi temporal approach comprising three epochs: 2000 or 2005, 2010 (reference year), and 2015 will be produced. The regional (sub-national) maps will aim for an overall accuracy of at least 80% in five different regional mapping sites: Mexico (tropical-woodland),[89] Poland (temperate zone),[90] Sweden (boreal zone),[91] Indonesia/Kalimantan (tropical zone),[92] and South Africa (savanna mosaic).[93]

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

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

Whilst the biomass products described above represent significant advancements in research and development, existing large-scale biomass maps derived from remote sensing data need extensive in-country testing to confirm that they are reliable for application in specific landscape types and at the spatial scale of interest (GFOI 2016). Therefore, in the absence of such extensive ground verification, these data sources would not yet be considered operational in the context of this good practice

[89] http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-mexico/
[90] http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-poland/
[91] http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-sweden/
[92] http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-indonesiakalimantan/
[93] http://globbiomass.org/products/regional-mapping/regional-biomass-mapping-south-africa/

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

## 4.7 Comments and Limitations

Chapter 4 of the GPG outlines the key principles to assist countries in implementing national scale monitoring of SOC stocks as a contribution to national reporting on SDG indicator 15.3.1. It draws on existing knowledge of good practice with respect to assessing the baseline and changes in SOC stocks.

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. 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).

Recognizing the limited availability of datasets on SOC stock at national and regional levels, the uncertainties associated with the suitability of existing data for monitoring SOC stock changes, and insufficient quantitative evidence linking SOC stock changes to the various land and soil degradation drivers and processes, the FAO/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.

As regards a four year reporting frequency proposed for the indicator, itis 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).

Using IPCC defaults requires soil types to be clustered when used for stratification. These are the seven default IPCC soil classes defined in IPCC 2006, Annex 3A.5.[94] For a national approach using country-specific defaults and the default equations (Tier 2), it may be difficult to get agreement on what soil classification system to use. Problems with the existing broad scale maps of soil types are being addressed, using state-of-the-arts digital soil mapping and other approaches. Critically, to assess changes over time, such approaches depend heavily on the availability of up-to-date field measurements (monitoring programmes). Furthermore, not only soil type can be considered, but other covariates, which improve the predictions of SOC stock distribution, such as slope or other variables derived from digital elevation models, climate variables, soil texture, etc.[95]

[94] http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_03_Ch3_Representation.pdf
[95] http://www.fao.org/soils-portal/soil-survey/soil-classification/world-reference-base/en/

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