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

Annex 2: Land productivity

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Executive Summary

This good practice guidance document (GPG) describes methods to measure degradation in Land productivity for reporting on UN Sustainable Development Gola (SDG) 15.3.1: The proportion of degraded land over total land area. Land productivity is the biological productive capacity of the land, the source of all the food, fibre and fuel that sustains humans. This can be measured at local to global scales using satellite remote sensing and indices of net primary productivity (NPP) of vegetation.

The method recommended for this assessment is modified the method proposed for the World Atlas of Desertification (Ivits and Cherlet 2016). Methods are presented in three Tier level options, with the complexity and rigour of analysis increasing in each higher Tier level.

The recommended primary dataset is Normalised Difference Vegetation Index (NDVI) in the Moderate Resolution Imaging Spectrometer (MODIS) MOD13Q1 data product. An alternative in Tier 1 is to use MODIS MOD17A3 modelled NPP product which shows estimates of NPP per year and which simplifies part of the processing stream. However, some loss of accuracy and local relevance is likely to occur when using the MOD17 data. Tier 2 includes the use of potentially higher resolution and more nationally relevant datasets, and involves the use of third party software to calculate annual NPP metrics from time series image data during the growing season each year. Calibration of the annual NPP measurements to account for variations in moisture availability is required for all datasets. Tier 3 is achieved by calibrating and validating annual NPP estimates against other data sources including field samples.

Degradation is calculated at the pixel scale based on three metrics calculated from the annual NPP estimates:

1. the trajectory slope of growing season NPP over time
2. Performance, which measures local productivity relative to other similar vegetation types in similar bioclimatic regions throughout the study area, and
3. State, which compares the current productivity level in a given area to historical observations of productivity in that same area.

These three metrics enable degradation to be identified in areas where productivity may be increasing over time but remains degraded in terms of productivity levels, for example. Areas of degradation have either a significantly negative trajectory slope in annual NPP, or in areas where the trajectory slope is not significantly negative a combination of low productivity. A 'support class' analysis is used to identify which degradation metric or combination of metrics indicates degradation in each pixel.

Datasets, and processing and analysis methods suitable for assessing land productivity degradation are developing rapidly. General guidance on dataset and productivity index selection, options for climatic calibration and reporting recommendations are provided.

Contents

1 Definition 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 (United Nations Statistical Commission 2016).

Land productivity can be measured across large areas from satellite 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/yr. Satellite remote sensing is the most effective way to measure NPP in fine detail at National scales. 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. There are many 'vegetation indexes' that can be calculated from image data which have been shown to be effective surrogates for fAPAR and highly correlated with NPP. These indexes highlight spectral wavelengths associated with aspects of plant cover, biomass and/or growth vigour. Each index is better suited to some landscapes and vegetation over types more than others.

For the purposes of reporting on SDG Indicator 15.3.1 it is not necessary to quantify the magnitude of change in NPP in units of biomass, only to know whether land productivity is increasing or decreasing, and whether the level of productivity is below 'normal'.

Productivity index is the algorithm used to measure land productivity levels from image data. One of the most commonly used surrogates of NPP is the Normalised Difference Vegetation Index (NDVI; Tucker 1979). The NDVI is a normalised ratio of near infra-red (NIR) wavelengths centred around 800 nm wavelength (eq 1), which are typically strongly reflected by live green vegetation, and red wavelengths centred around 650 nm wavelength which are within the photosynthetically active range of the spectrum and are typically strongly absorbed by live green vegetation. The general formula is:

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

NDVI values are unitless and range from -1 to +1. Many studies have demonstrated a strong correlation between NDVI, plant cover, biomass and growth vigour. NDVI is recommended for this assessment unless an alternative productivity index is demonstrated to be more suitable.

The NDVI is the most widely used and best known spectral indicator of land productivity. Limitations of the NDVI are its sensitivity to variations in soil background conditions, and its tendency to saturate at high cover and biomass levels. This can reduce accuracy where plant cover or biomass is very high (tropical rainforest) or very low (arid savannah). The NDVI is recommended for use unless the use of an alternative is justified. Some of the alternatives to NDVI are described in Section 5.3.

Land degradation is the reduction or loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns.

Regardless of the processing method used, degradation should always be interpreted from the available data in the context of local and in-situ knowledge about conditions in each region.

2 Introduction

The 47th session of the United Nations Statistical Commission agreed to a draft global indicator framework as a starting point to review progress towards SDG targets. The UN Convention to Combat Desertification (UNCCD) has taken responsibility for developing a framework for monitoring this target 15.3 and has convened an Inter-Agency and Expert Group (IAEG) that has proposed a sole indicator for indicator 15.3.1, the *"Proportion of land that is degraded over total land area."* They also proposed three sub-indicators that can be monitored by countries and used in concert to quantify the proportion of degraded land. These sub-indicators are:

1. Land cover
2. Land productivity
3. Carbon stocks (above and below ground)

Each of these sub-indicators responds to different elements of degradation: Land Cover addresses the state and changes in the structure and composition of the landscape from natural events and human activities. Carbon Stocks addresses issues of carbon sequestration, plant biomass and factors potentially affecting soil fertility. The Land Productivity indicator measures human impacts on the state, dynamics and performance of plant growth.

Measuring changes in land productivity at national to global scales is a highly active area of research and one where datasets and analysis methods and tools are developing rapidly. Consequently, there is an increasingly wide range of options that can be used to address each of the required processing steps. While Nations should strive to report changes in land productivity at the highest level of detail and rigour, Nations differ in their skills and resources to facilitate analyses, their access and availability of data sets and their land cover characteristics, making some methods more suitable than others.

2.1 Existing productivity degradation assessment methods

One of the earliest proposed methods for mapping map 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).

Other aspects of productivity have also been considered in similar analyses. Wessels et al. (2008) used a local NPP 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.

2.1.1 World Atlas of Desertification

The recently proposed method for assessing land productivity degradation for the World Atlas of Desertification (Ivits and Cherlet 2016) was developed by the European Commission's Joint Research Centre (JRC) to measure land degradation at global scales (referred to hereafter as the WAD method). The WAD method uses two NDVI data sources (Figure 1): the Global Inventory Monitoring and Modeling System (GIMMS) 3G NDVI dataset (http://ecocast.arc.nasa.gov/data/pub/gimms/3g.v0/) (Pinzon and Tucker 2014) and the Satellite pour l'Observation de la Terre (SPOT) VGT NDVI dataset (http://www.vgt.vito.be/). These have relatively coarse pixel sizes of 8 km and 1.15 km respectively, but they have a high capture frequency and long archives of historical data that are useful for identifying productivity trajectory at broad scales.

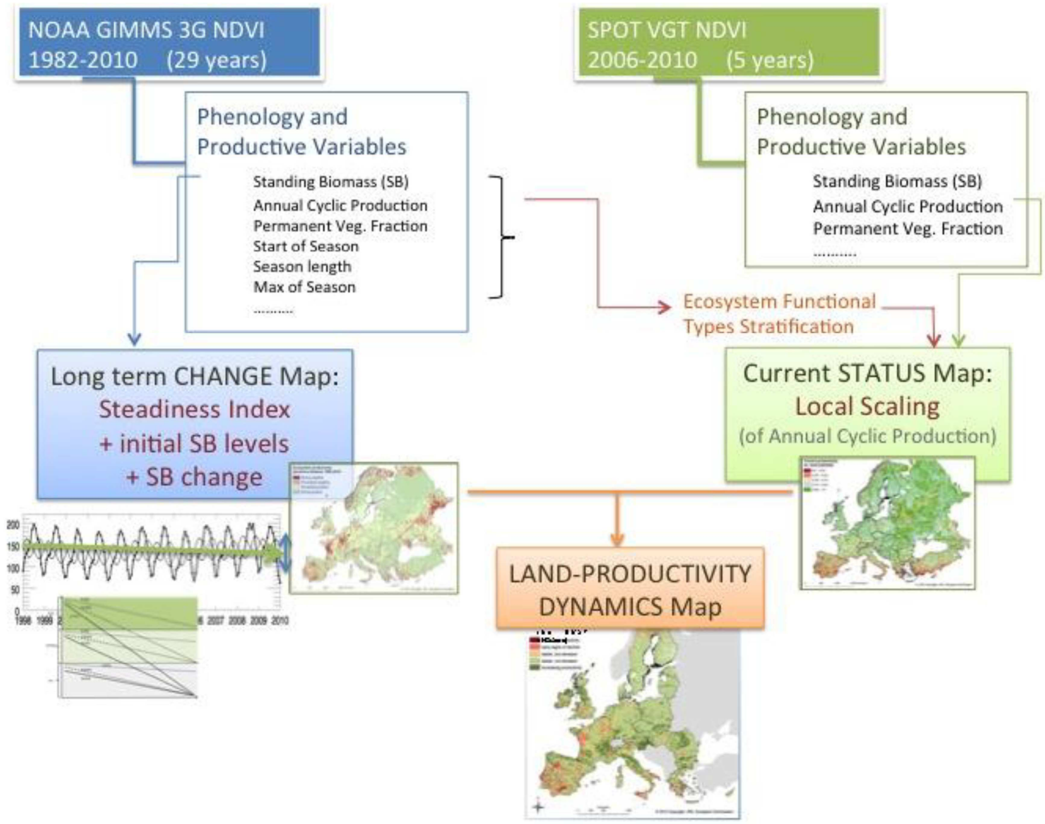

Figure 1. Scheme for calculating land cover productivity dynamics for the World Atlas of Desertification (Ivits and Cherlet 2016).

Productivity is assessed in terms of trajectory, performance and state. These three parameters can be used to identify degradation in areas of increasing productivity trend (trajectory) but low productivity compared to other regions of similar land cover type with similar climatic conditions (performance), or compared to the historical range of productivity levels for that location over time (state).

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 Nation-specific conditions. While the WAD method prescribes particular datasets and methods, some of these are best suited to certain land cover conditions and scales of analysis. 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 are a range of alternative ways to define the spatial units within which land productivity can be reported, some of which are discussed in more detail in the Indicator level GPG for this SDG. The methods presented in this guide are therefore largely based on the WAD method, but also recommends certain analyses which are not included in the WAD method.

Many options are available for conducting certain aspects of this analysis, including productivity datasets of different resolution, coverage and frequency, a range of methods for highlighting degradation in 'noisy' time series datasets. Options for the use of other datasets and methods that may be suitable in other regions are identified in the relevant sections below, and described in more detail in later sections of this report.

3 Method of Computation

3.1 Methodological Tiers

This good practice guidance document (GPG) provides guidance on how countries can measure changes in land productivity to assess degradation. This process is founded on the WAD method and is comprised of six main processing steps (Table 1).

Table 1. Processing steps, recommendations and options for assessing land productivity degradation

Processing step	Recommendations	Options	Report Section
Select image dataset	MODIS MOD17A3 modelled annual NPP	MODIS MOD13Q1 NDVI (all Tiers) or vegetation index from higher resolution National datasets (Tiers 2 & 3)	3.2
Calculate growing season metrics	From time series using TIMESAT (all Tiers, not required if using MOD17A3 modelled NPP)	From dry or cloud-free season, or coincident with time of sampling each year (Tiers 2 & 3).	3.3
Calibrate for moisture availability	Water use efficiency using MOD16 evapotranspiration (all Tiers)	Many alternatives (see Section 5.4)	3.4
Calculate productivity metrics	Trajectory slope, state and performance	All Tiers	3.5
Calculate degradation metrics	Significance tests for productivity metrics	All tiers	3.6
Validate productivity estimates	Required for Tier 3 only	Collect Earth, flux tower or destructive sample collection	3.7

Consistent with the IPCC guidelines and good practice guidance there are three tier levels of processing, with the level of accuracy, detail and processing complexity increasing at each tier level. Tier 1 uses global datasets or a model of annual net primary productivity (NPP) and is intended for use where data availability or processing capacity is limited. Tiers 2 & 3 use the NDVI or an alternative vegetation index calculated from a global or national-scale datasets. This improves the representativeness of national NPP estimates over the Tier 1 method but involves additional datasets and processing. Tier 3 includes validation of NPP estimates against additional sources of information, including field samples, to further improve the accuracy of degradation assessment.

3.2 Select an image dataset

A large number of satellite image datasets are available at no or very low cost that are well suited for assessing land productivity at global to National scales (Table 2). The key criteria for 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 grain and it should have the spectral bands required to calculate the required productivity indices. Some of the considerations and trade-offs in selecting an image dataset are described in more detail in Section 5.

Table 2. Low or no-cost satellite sensors and data streams utilized for land surface phenology studies (modified from - https://phenology.cr.usgs.gov/ndvi_avhrr.php). The MODIS MOD13Q1 NDVI product is recommended unless an alternative index is justified

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	1982-2015	8 km	Twice monthly
AVHRR/ MODIS	-	Daily	VIP30 (EVI2)	1981-2014	5.6 km	Monthly
Vegetation	SPOT	1-2 days	VITO	1999-present	1.15 km	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
TM	Landsat 4-5	16 days	USGS/EROS	1982-2011	30 m	Distributed by scene
ETM+	Landsat 7	16 days	USGS/EROS	1999-present	30 m	Distributed by scene
OLI*	Landsat 8	16 days	USGS/EROS	Feb 2013-present	30 m	Distributed by scene
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.

We recommend using the NDVI dataset available in the MODIS MOD13Q1 vegetation index product. This is pre-calibrated from surface reflectance data and includes Normalised Difference Vegetation Index (NDVI) at 250 m pixel resolution. These datasets are provided as composited 16-day product since the year 2000 (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod13q1).

An alternative at Tier 1 is to use a modelled global NPP product which can simplify the process of calculating annual NPP metrics. We recommend version 55 (or higher) of the MODIS MOD17A3 annual NPP estimates produced by the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod17a3). Pixel values in this dataset represent kilograms of carbon per square metre, averaged at 1km pixel resolution over each calendar year since 2000 (Running et al. 2004). The advantage of this dataset is that it simplifies the process of calculating annual NPP. However, there are a range of disadvantages associated with the use of a model rather than an index from a time-series dataset, which are discussed in Section 5.3.1.

Note that while Landsat 8 Operational Land Imager (OLI) and Sentinel 2 Multi Spectral Imager (MSI) are relative high resolution and well suited to productivity assessment at National scales, their relatively recent launch means that the archive of historical images is short and unlikely to be suitable for calculating baseline conditions. Productivity indices can be calibrated between these sources and those with longer archives, however, as described in Section 5.2.

3.2.1 Select a productivity index

We recommend using the MODIS MOD13Q1 NDVI unless the use of an alternative index or data source is justified. The NDVI has a long history of use, its limitations are well understood and it is well suited to assessing vegetation dynamics under most cover and biomass conditions. Reasons to use an index other than NDVI may include:

1. Limited data access or processing capability makes it necessary to use the MODIS MOD17A3 modelled annual NPP data
2. NDVI is less well suited to National land cover conditions than an alternative productivity index, such as in regions of very high or very low biomass or foliar cover
3. Higher resolution climate, land cover, productivity and/or field validation data are available
4. The existence of new or alternative datasets and analysis methods that are considered superior to those proposed in this document

A range of alternative productivity indices and models for assessing productivity have been developed that may be better suited to vegetation conditions in some regions or nations. Several of these are reviewed in more detail in Section 5.3. The choice to use an index other than NDVI should be justified in the report.

3.3 Calculate growing season metrics

Observations of land productivity integrated over the growing season have been highly correlated with end of growing season biomass (Fensholt et al. 2013) as well as mid-season (peak) biomass in rangeland areas (Moran et al. 2014). One of the advantages of using time series data is the ability to extract productivity observations from a specific period such as the growing season.

The freely available TIMESAT software (http://web.nateko.lu.se/timesat/timesat.asp) includes features for smoothing and calculating many parameters from satellite time series data (Eklundh and Jönsson 2015). The most important metric is the including the integral (sum) of NDVI values during the growing season (*iNDVI*) equivalent to region h in Figure 2.

The growing season is most easily identified in temperate regions where there is a pronounced seasonal change in productivity levels throughout the year. The growing season may vary each year, and can be defined in a number of ways: the date on which NDVI 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.

Such a pronounced cyclical variation in productivity may not occur in tropical regions or areas with very low vegetation cover however. In these cases the assessment season each year can be defined based on the expected period of highest biomass each year, the period of lowest cloud cover, or an arbitrary period chosen to coincide with field data collection (for Tier 3 methods in particular). Ideally, the assessment period should occur at approximately the same time each year, and/or represent growing conditions that are as similar between assessments periods as possible.

TIMESAT also includes features to smooth noise in the time series, such as from missing observations or cloud cover (red line in Figure 2). Smoothing the data in this way is important to maximise the comparability of NPP measurements between years, which may include more or fewer observations than others. Gaps in the data record should be filled using a cubic convolution filter calculated through the missing value's eight nearest neighbours. Ivits and Cherlet (2016) used an iterative 4th order polynomial Savitzky-Golay filter with a 50-day window, while Brioch et al., (2014) used a Savitzky-Golay filter with a 15 time-step window.

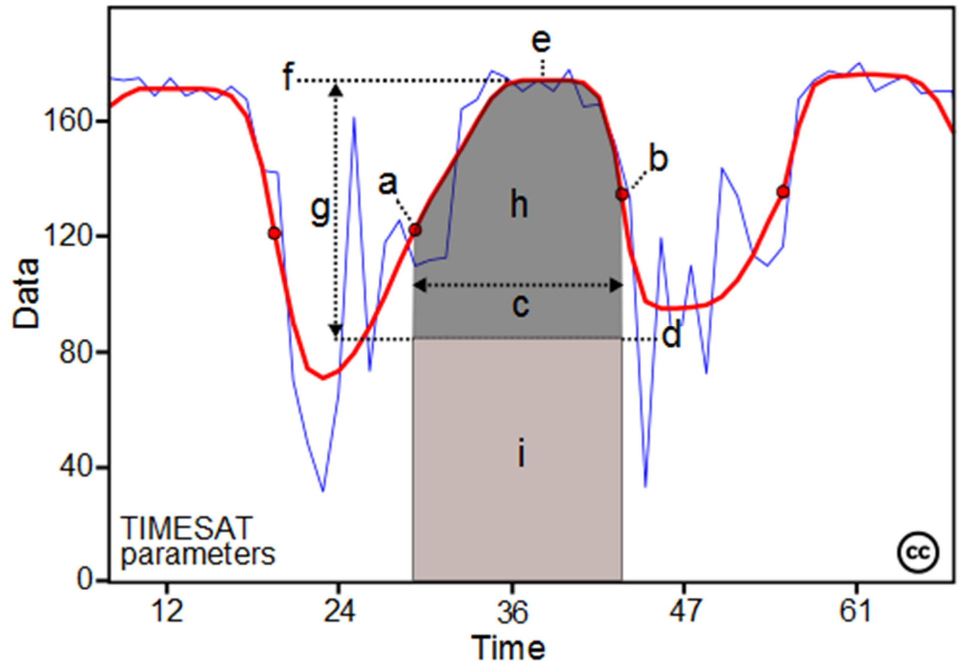

Figure 2. Some of the seasonality parameters generated in TIMESAT: (a) beginning of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) maximum value, (g) amplitude, (h) small integrated value, (h+i) large integrated value (source http://web.nateko.lu.se/timesat/timesat.asp?cat=0).

The smoothing function should be iteratively adjusted to minimise the smoothing impact on existing good observations, while also sufficiently smoothing extreme 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 tree vegetation.

This step is not necessary if the MODIS MOD17A3 modelled NPP dataset is being used. The processing steps described below are required for all datasets. For convenience in the following sections, NDVI is used to refer to any index or metrics of NPP calculated from an image dataset.

3.4 Calibrate for moisture availability

Moisture availability has been shown to be highly correlated with changes in NPP, especially in semi-arid areas where water is the limiting growth factor (Fensholt and Rasmussen 2011; Wen et al. 2012; Wessels et al. 2007). Separating degradation effects from other sources of variation in productivity observations is one of the main technical challenges, and one of the most contentious areas of research associated with this analysis. Several methods to calibrate time series images to minimise the influence of climatic or seasonal factors have been proposed, each of which may be suitable only in certain vegetation types, climatic regions or and 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 5.4.

We recommend calibrating $iNDVI$ measurements against evapotranspiration (ET), which is defined as precipitation minus the water lost to surface runoff, recharge to groundwater and changes to soil water storage (Ponce-Campos et al. 2013). A range of global ET datasets are available including the MODIS MOD16 dataset (http://www.ntsg.umt.edu/project/mod16) which reports ET at 8-day, monthly and annual intervals.

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 $iNDVI$ to iET indicates the water use efficiency (WUE) of vegetation (Ponce-Campos et al. 2013). The method for calculating WUE corrected $iNDVI$ ($iNDVI_w$) per year is:

$$iNDVI_w = \frac{iNDVI}{iET} \qquad (2)$$

where $iNDVI$ is the NDVI integrated over the growing season or relevant period each year, and *iET* is ET integrated over the same period.

3.5 Calculate productivity metrics

3.5.1 Trajectory slope

Trajectory slope indicates the trend of productivity over time. Productivity trajectory is calculated by fitting a robust, non-parametric linear regression method such as the Thiel-Sen median (Ivits and Cherlet 2016), which can be implemented using the 'mblm' package in R (https://cran.r-project.org/web/packages/mblm/mblm.pdf) or an alternative across the annual $iNDVI_w$ values for each year.

The Mann-Kendall 'z' score can calculated using the 'trend' package in R (https://cran.r-project.org/web/packages/trend/trend.pdf) and used to determine trend significance (Onyutha et al. 2016). Positive z scores indicate a trend of increasing productivity and negative scores indicate decreasing productivity. The significance of trajectory slopes at the P=0.05 level, calculated across more than 8 data points, should be reported in terms of three classes:

- Z score ≥ 1.96 = "Improving"
- Z score ≤ -1.96 = "Degrading"
- Z score > -1.96 AND < 1.96 = "Not Significant"

This assessment should be accompanied by a scatter plot Figure showing the annual NPP measurements per year, with a trend line fitted and slope indicated. This will aid in the interpretation of trends and their significance in relation to the variability of annual NPP in the time series. An example is shown in Figure 3

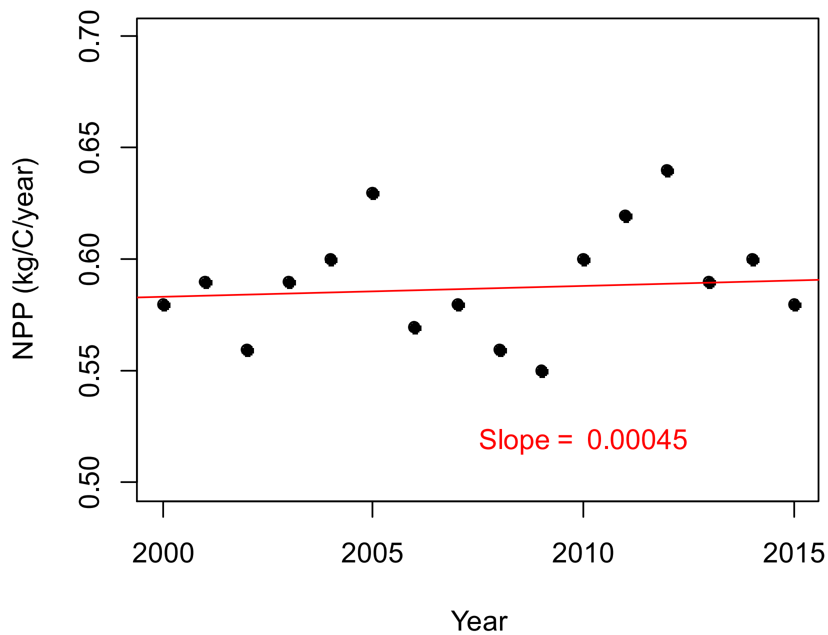

Figure 3. Example of NPP Figure to be included in the trajectory slope reports

3.5.2 State and state change

Productivity state represents the level of productivity in a given spatial unit (vector region or pixel for example) compared to observed productivity levels for that spatial unit over time. Productivity state can be interpreted as an indicator of relative standing biomass (Ivits and Cherlet 2016).

Classify $iNDVI_w$ values during the baseline period into 10 decile classes using the unsupervised ISODATA classification. These become the baseline $iNDVI_w$ classes. Productivity state change is assessed by comparing $iNDVI_w$ in the assessment year to the baseline $iNDVI_w$ classes. Productivity state change can be reported in terms of three classes relative to the baseline productivity state:

1. High – observed productivity in baseline $iNDVI_w$ classes 9 or 10
2. Moderate – observed productivity in baseline $iNDVI_w$ classes 6,7 or 8
3. Low – observed productivity in baseline $iNDVI_w$ classes 1,2,3,4 or 5

3.5.3 Performance

Productivity performance compares local productivity to productivity in the same bioclimatic regions across the study area in the assessment year. Bioclimatic region types describe areas with similar productivity potential due to similarities in moisture availability, soil and vegetation characteristics (see Ivits et al. (2013) and Wessels et al. (2008) for examples of stratifying the landscape for this productivity performance assessment. Bioclimatic regions may be classified from the land cover classes used to assess the land cover and land cover change sub-indicator, in combination with climate and moisture availability data such as Koppen Zones (http://people.eng.unimelb.edu.au/mpeel/koppen.html) or the MODIS MOD16 dataset (http://www.ntsg.umt.edu/project/mod16) used for WUE correction. Alternatively, the Food and Agriculture Organisation (FAO) of the United Nations produces Agricultural Suitability and Potential Yields spatial data through their Global Agro-Ecological Zones (GAEZ) programme (http://www.fao.org/nr/gaez/about-data-portal/agricultural-suitability-and-potential-yields/en/).

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 described the timing and productivity patterns during the growing season, and include the start and end dates of the growth 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 stratify the landscape. The resulting land units are highly correlated with the GlobCover land cover classes (http://due.esrin.esa.int/page_globcover.php), though Ivits et al. (2013) argue that defining bioclimatic regions based on growing season parameters is more relevant to analysis of productivity dynamics.

In order to identify bioclimatic regions using the WAD method, a larger number of parameters will need to be calculated from the growing season each year. More details on the WAD method approach for identifying bioclimatic regions is presented in Ivits and Cherlet (2016) and Ivits et al. (2013).

Within each bioclimatic region, calculate the 90th percentile of productivity index values. This level will be used to indicate the maximum productivity level (NPP_{max}) that can be achieved within each cover class. Productivity performance is then calculated as:

$$NPP_{max} = \frac{Observed\ iNDVI_w}{90\%\ iNDVI_w} \tag{3}$$

NPP_{max} Values close to 1 represent pixels in which productivity is close to the highest level for that land unit in that year. Performance values less than 0.5 indicate regions where productivity levels are low compared to other vegetation in the same bioclimatic region.

3.6 Calculate degradation metrics

Productivity metrics calculated from the baseline period can be used to identify areas of pre-existing degradation, and they also provide the context for comparing current conditions to identify new degradation.

The baseline period for assessment of SDG 15.3.1 is between the years 2000 to 2015. Consideration should be given to whether conditions during the baseline period are representative of 'normal' productivity conditions. In Australia for example, the millennium drought extended from the late 1990s to 2010 across southern part of the continent, and included some of the most severe rainfall and temperature anomalies on record. This should be taken into consideration when comparing contemporary observations with the baseline conditions. This GPG recommends calculating productivity trajectory slope, performance and state, and the baseline measurements is calculated and used differently in relation to each of these parameters.

3.6.1 Trajectory slope

- Existing degradation based on trajectory slope will be identified by a significant negative trajectory slope of a robust regression line fitted across annual $iNDVI_w$ measurements over the entire baseline period (2000-2015) as assessed using the Mann-Kendall Z score (z= ≤ -1.96)
- Emerging degradation will be identified by a significant negative s trajectory slope over the recent 10 years of data including the last 5 years of the baseline period and the recent 5 years of newly measured data using the Mann-Kendall Z score (z= ≤ -1.96)

3.6.2 Performance

- Existing degradation based on productivity performance will be identified by a mean productivity performance in the baseline period of less than 50% of the potential maximum (90th percentile of $iNDVI_w$ values each year)
- Emerging degradation will be identified based on productivity in the lowest 50% of the potential productivity range in that bioclimatic zone

3.6.3 State and state change

- Existing degradation based on productivity state will be identified using a 3 step process:
    1. Calculate 'early epoch' average productivity decile classes from 2000-2010 (11 years)
    2. Calculate 'late epoch' average productivity from 2011-2015 (5 years)
    3. Pixels in which the productivity level has dropped by two or more decile classes between the early and late epochs will be identified as degraded for this metric
- Emerging productivity will be identified by:
    1. Calculate average productivity across all baseline years (200-2015)
    2. Calculate average productivity state between 2016-2020 (repeated in 2021-2025, 2026-2030)
    3. Pixels in which productivity state has decreased by two or more decile classes between the recent and baseline state classes will be identified as degraded for this metric

3.7 Validate productivity estimates

Validation of productivity estimates against additional sources of data provides the highest possible accuracy of productivity assessment and degradation identification when implemented in a statistically rigorous way. Validation of remotely sensed predictions of NPP enables the uncertainty of predictions to be assessed, and provides an opportunity to calibrate NPP predictions to improve predictive accuracy or for the use of alternative vegetation indices.

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 NPP values likely to be encountered, cover conditions and the spatial extent over which predictions are being made. Consequently, a detailed description of all facets of validation is beyond the scope of this document.

There are a range of validation options available ranging from comparison with other correlated datasets to calibration against destructively sampled biomass data. Conversion to units of kg C/ha/year by linear regression against the MOD17A3 datasets may assist in reporting the magnitude of productivity dynamics, but by itself is not a reliable calibration method due to the uncertainties described above.

This section reviews some options, datasets and analytical methods for a range of validation methods that may be suitable for reporting on Indicator 15.3.1.

3.7.1 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 (http://www.openforis.org/tools/collect-earth.html). Collect Earth was developed to monitor forest 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.

3.7.2 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 (https://fluxnet.ornl.gov/) maintains a global network of flux towers (Figure 4) many of which are aligned with national flux monitoring programs.

Some examples of National flux tower programs include:

- Australia: TERN (http://www.tern.org.au/NASA-partners-with-TERN-to-map-global-carbon-bgp3623.html), OzFlux (http://www.ozflux.org.au/)
- Korea: KLTER (http://www.klter.org/emain.htm)
- USA: NEON (http://www.neonscience.org/science-design/collection-methods/flux-tower-measurements

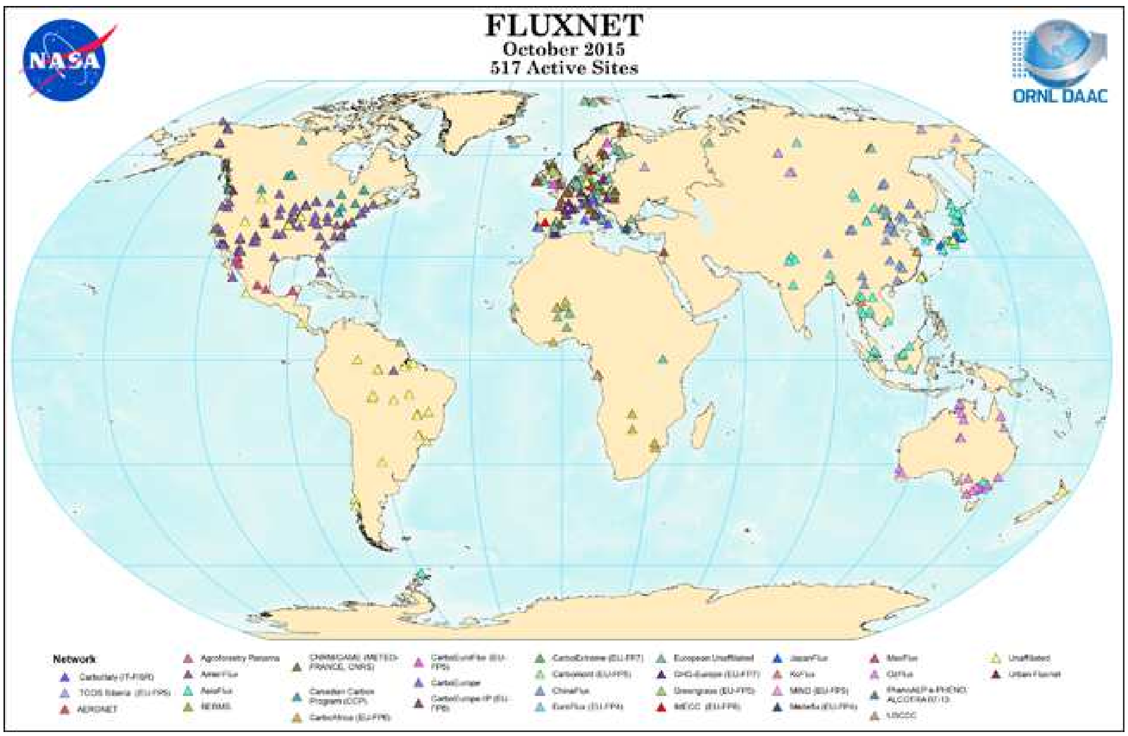

Figure 4. Fluxnet carbon flux tower locations as at October 2015 (source: https://fluxnet.ornl.gov/maps-graphics)

3.7.3 Destructive biomass sample collection

Validation of NPP estimates against destructive samples collected in the field, at the time of peak biomass, and coincident with image capture, provides the most rigorous assessment of NPP predictions.

One of the most comprehensive guides to field validation of remotely sensed datasets is the AusCover Good Practice Guidelines report (http://qld.auscover.org.au/public/html/AusCoverGoodPracticeGuidelines_2015_2.pdf). 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 data for NPP assessment 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.

3.8 Combining metrics to determine overall degradation state

Pixels showing degradation are those with:

1. Existing degradation identified from the baseline period
2. A significant negative trajectory slope in any combination of degradation metrics
    a. OR
3. A slope that is not significantly negative with
    a. Degradation indicated in the productivity state change analysis

    AND

    b. Degradation indicated in the productivity performance analysis

Degradation should be reported at the National scale as the area of degradation/total land area. Degradation probability should be calculated at the pixel scale and aggregated to the National scale for reporting. The metric to report is the proportion of degraded land divided by total land area.

3.9 Assessing degradation 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. A look up table can be used to classify the support for determinations of degradation based on the trajectory, state and performance metrics.

In order to interpret the likelihood of results indicating false positive or false negative degradation, a lookup table is used to identify 'support class' combinations of metrics in each pixel (**Error! Reference source not found.**). These classes can be used to review the combinations of metrics indicating degradation in each pixel, which can be used to support decisions around whether pixels are identified as degraded or otherwise.

Table 3. Lookup table indicating support class combinations of productivity metrics for determining a pixel as degraded. Pixels in support classes 1 to 5 show degradation. Y is degradation identified in that metric. N is not degraded in that metric.

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 trajectory slope because it is calculated over the entire time series and uses standardised statistical significance tests. While together the performance and state metrics provide reasonable spatial (performance) and temporal (state) support for a determination of degradation, their assessment based on comparison of fewer years of data increases the potential for false positive or negative results, and it is not recommended to determine overall degradation status based on either a significant state or performance analyses alone.

4 Rationale and Interpretation

The aim of this document is to propose a set of methods for assessing land productivity degradation that can be used by all countries ranging from those with very few datasets and little remote sensing capability, to those with substantial and sophisticated productivity research programs. Guidance on the methods and interpretation of results are presented in Method of Computation Section above.

For the purposes of this report it is not necessary to calculate the magnitude of change in productivity, but only to know the extent and direction of productivity change. For reporting of the extent and direction of change the unitless NDVI is suitable because of its simplicity, transferability between sensors, and because its characteristics of response to differences in plant growth vigour and biomass are well documented. The simplicity of its calculation, requiring only two spectral bands (red and NIR) means that it is able to be calculated from most Earth observation sensor data, and its robustness to a range of land cover conditions makes it highly suited as an indicator of changes in land productivity in many regions of the globe.

Plant productivity fluctuates over time in association with seasonal and phenological cycles, and variations in climatic conditions including moisture availability. Land degradation is a human process, which necessitates the calibration of the observations to minimise the influence of variables other than degradation on the time series measurements. One of the challenges to the simplicity of the Tier 1 methods is the lack of productivity indicators that are frequently updated and calibrated to minimise the influence of variations in moisture availability. The water availability calibration is therefore recommended at all Tier levels. Failure to calibrate for variations in moisture availability will reduce the sensitivity of the data to human induced degradation.

With currently available datasets this sub-indicator can be calculated annually. One of the objectives of this method, however, is to highlight sustained changes in productivity that are not associated with natural (climatic and hydrological) or managed (agricultural) changes in resource availability. Methods to assess the trajectory slope, productivity state and productivity performance in this document aim to indicate longer-term dynamics by incorporating longer time-series in the baseline calculations and the assessment of the metrics themselves. In addition, the reporting frequency for Indicator 15.3.1. is every five years, which enables trends to be assessed over five productivity observations, reducing the influence of individual observations on the assessment of degradation.

5 Sources and data collection

5.1 Dataset selection guiding principles

Data options and sources for each stage of this analysis have been described in the text above. We recommend using the NDVI available in the MODIS Vegetation Indices product MOD13Q1 from the

Terra satellite and MYD13Q1 from the Aqua satellite. This product includes NDVI at 250m pixel spacing over the entire globe, composited from surface reflectance calibrated daily observation over a period of 16 days to minimise cloud cover artefacts. These data are available from February 2000 to the present. Alternative data sources and/or vegetation indices may be preferred in certain land cover conditions or for other reasons, and the choice of alternatives should be justified in the report. Guiding principles for dataset selection in this analysis are shown in Table 4.

Table 4. Guiding principles for image dataset selection

Attribute	Recommendation
Temporal resolution	Time series datasets are required to assess land productivity 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 change is measured in future. Image datasets with long archives of frequently collected and consistent imagery provide the best opportunity to do this. More frequent observations provide more information on productivity changes over time, but the ideal frequency of observation is a balance between data size and the rate of change of productivity.
Spatial resolution	Coverage of the entire Nation is required for comprehensive National scale analysis. Some datasets show the landscape in more detail (smaller pixel sizes) than others. Large pixels reduce the size of datasets for a given extent of coverage but represent average reflectance over a large area, which may not be suitable in landscapes with very complex and contrasting productivity conditions. Smaller pixels can better represent variability in fine-grained landscapes but there are disadvantages also: higher resolution datasets are larger for a given extent of coverage, smaller pixels may not encapsulate sufficient spatial variability to represent a useful average productivity, and higher resolution datasets require increased accuracy in locating field sampling locations. 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, and 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.
Cost	Many image datasets are freely available and highly useful for assessing land productivity at national scales. Freely available datasets are available in a range of spatial, spectral and temporal resolutions. Very high resolution images including pixels less than about 10m x 10m in size are also available for purchase. High resolution datasets do not typically have an archive of repeat coverage historical images.
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.

There are also trade-offs to be considered when using high resolution imagery for productivity assessments. The advantages of higher resolution imagery include:

- The ability to 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
- Better representation of the range of productivity levels within the spatial features used for reporting degradation
- Improved ability to identify spatial anomalies, existing degraded locations or reference sites for model validation

The disadvantages include:

- Larger data volumes for a given land area

- A smaller area of integration of land cover characteristics per pixel, which can complicate the analysis of productivity at the vegetation community level
- The requirement for improved accuracy to locate field validation sites in the imagery. Accurate location within a raster image dataset requires that the sum of the spatial errors in image registration and positional location devices (GPS) should be less than 1 pixel

5.2 Interpolating productivity measurements between sensors

Given the short historical archive of some of the datasets identified in Table 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 model between productivity measurements may be suitable where sufficient overlap exists between the datasets. It is also be possible to calculate regression models between wavelength bands in the source imagery, such as the red bands in MODIS (band 1) with the red band in Sentinel 2 MSI (band 4) in order to recalculate the productivity index from the source data if 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, two alternative datasets could be transformed to match the MOD13 values. It may also be useful to interpolate the time series datasets 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).

5.3 Options for alternative land productivity indicators

The WAD method measures phenological parameters and productivity levels using the Normalised Difference Vegetation Index (NDVI; Tucker 1979). Many studies have demonstrated a strong correlation between NDVI and plant cover, biomass and growth vigour. NDVI response is well understood for a range of land cover conditions and it can be calculated from a large number of satellite image datasets including those with the longest archive of Earth observation imagery. In addition, by comparing spectral bands within each image, the NDVI overcomes many image calibration issues associated topography, atmospheric and illumination conditions, which makes it very consistent across large areas.

A large number of alternative land productivity indices and datasets have been developed which may be more suited to certain land cover conditions than others. Some of these alternatives are described below. 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 in the assessment of productivity state (due to the influence of these artefacts on the relative brightness of bands in each image) and comparisons of productivity between images.

5.3.1 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 1km 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 available at this time. Use of this dataset simplifies the process of quantifying NPP in 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 time series data the preferred option.

This model converts indices of fAPAR to estimated NPP using modelled parameters describing vegetation conversion efficiency (Ɛ) and climatic conditions (Running et al. 2004). The MOD17 NPP models include a range of indicator 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 a part of the growing season only, rather than over the full year (Fensholt et al. 2013; Ma et al. 2015). Further, the calendar year may split growing seasons in some regions, particularly including the summer growing season in the southern hemisphere temperate regions.

5.3.2 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 to three (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 were 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 $\mathbf{C}_1$, $\mathbf{C}_2$ are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the EVI algorithm are, **L**=1, $\mathbf{C}_1$=6, $\mathbf{C}_2$=7.5, and **G** (gain factor)=2.5 (Huete et al. 2002). The EVI is also provided on the MODIS MOD13Q1 dataset.

While the EVI may have some advantages under certain conditions (Huete et al. 2006), the inclusion of the blue band prevents it being calculated from several global datasets including the 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):

$$EVI2 = 2.5\frac{NIR - red}{NIR + 2.4red + 1} \tag{5}$$

EVI2 is available as an annual 5.6km resolution product via NASA's Making Earth Science Data Records for Use in Research Environments (MEaSUREs) program (https://lpdaac.usgs.gov/dataset_discovery/measures). 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 rather than an indicator of LAI, NDVI is preferred over the EVI because it is more directly related to fAPAR and has fewer factors which simplifies calculation and makes NDVI calculable from a larger range of satellite image datasets.

5.3.3 Fractional cover

An alternative to spectral indices, are fractional cover products 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 landcover 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.

5.4 Options for calibrating climate impacts in time series productivity data

Variations in measurements of plant productivity over time are caused by many factors including phenological and climatic variations in addition to the effects of human activities that cause degradation. In order to interpret degradation in inherently noisy time series it is necessary to account for these other factors. However, determining the best methods to distinguish degradation from natural influences in productivity time series measurements is a contentious and challenging issue: the factors influencing long-term productivity levels vary from place to place and over time, and some land cover types are more susceptible to influence from these factors than others.

While rainfall has been shown to have the strongest influence on productivity time series, NPP outcomes to a give rainfall level are also influenced by many factors. Rainfall 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 the climate calibration processes described below 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 (http://www.fao.org/geonetwork/srv/en/main.search?any=glada). These may be suitable in cases 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).

5.4.1 Rainfall use efficiency

Rainfall use efficiency (RUE) is the ratio of NPP to precipitation (Le Houerou 1984), and is reported annually. Accounting for RUE can improve the comparability of NPP between years and 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 (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 evaporates consumes most rainfall (Fensholt et al. 2013) or where the vegetation cover is so low that it's growth response is insufficient to register a significant change in the chosen productivity index.

5.4.2 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 with against annual NPP estimate 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 5.

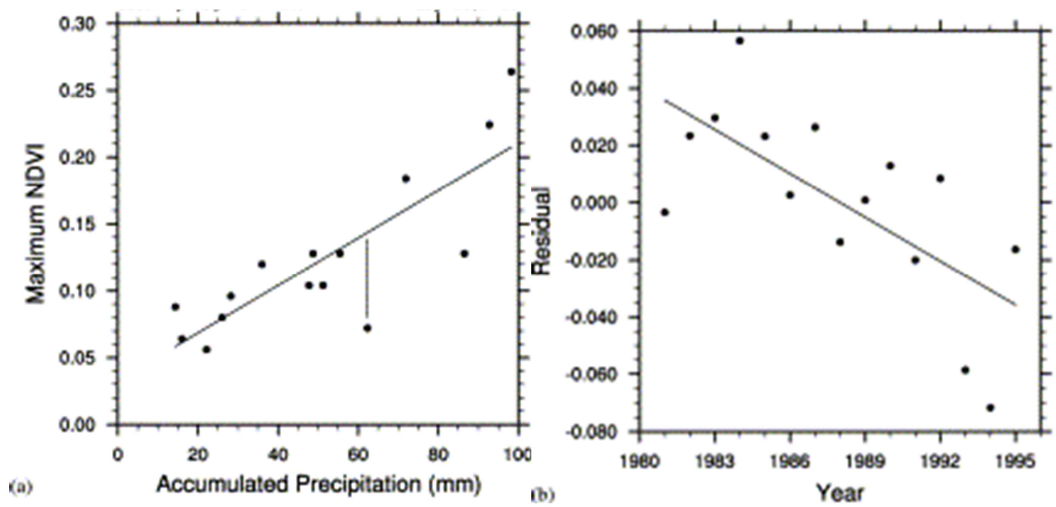

Figure 5. Linear regressions between (a) accumulated precipitation and the maximum NDVI – the residual is illustrated by the line, and (b) the temporal trend of associated residuals (source Evans and Geerken 2004).

Subsequent analysis of the sensitivity of RESTREND to land degradation using simulated data (Wessels et al. 2012) indicated that it is difficult to detect degradation using RUE or RESTREND where there is a positive trend in precipitation. RESTREND is best suited to detecting extreme and rapid degradation resulting in differences in ∑NDVI of around 20-40% between predicted and observed NDVI. Further, 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)..

5.4.3 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 within 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 RUE-corrected NDVI within the range of NDVI values observed across the full time series within each climatic zone. *rRUE* is implemented in a freely available R package (r2dRue - https://r-forge.r-project.org/R/?group_id=752).

The *rRUE* method simplifies the application of RUE methods across large areas which may have varying climatic conditions, but 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 NDVI 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 very active.

5.4.4 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, Helman et al., (2014) 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 normalisation and rescaling of NDVI 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 intensity. In practice, ideal control sites do not occur, and the sensitivity of this method is usually limited by differences in vegetation and land cover characteristics between the reference and test sites, or by slight differences in the timing and magnitude of rainfall.

5.4.5 Time series decomposition

5.4.5.1 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 (Cleveland et al. 1990) -available in R (http://stat.ethz.ch/R-manual/R-devel/library/stats/html/stl.html)- 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. They found STL useful for identifying the commencement and cessation of the growing season, and for indicating the overall trend of NDVI decline over their study period. Jacquin et al., (2010) interpreted their results in the context of local rainfall information, rather than by transforming the data to minimise climatic influences per se.

5.4.5.2 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 ab 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, breaks tend to be indicated in grasslands rather than forests because of the more pronounced and rapid growth responses
- Remains sensitive to changes in the time series provided: e.g. reanalysing a time series with the addition of recent data can identify an entirely different sequence of breaks.

5.4.6 Water use efficiency (WUE)

One of the assumptions in many RUE-based applications is that 100% 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 annual NPP to evapotranspiration (ET), defined as precipitation minus the water lost to surface runoff, recharge to groundwater and changes to soil water storage. These authors demonstrate a near linear relationship between NPP 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.

Ponce-Campos et al., (2013) 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. Other evapotranspiration data sources exist, though none appear to be available after 2014. These options include:

1. Global 8-day evapotranspiration data from MODIS, based on the Penman-Monteith equation (http://www.ntsg.umt.edu/project/mod16)
2. The GLEAM datasets (http://www.gleam.eu/) which are based on microwave remote sensing and calculate evapotranspiration using the Priestly and Taylor model

- Global annual and monthly potential evapotranspiration (http://www.cgiar-csi.org/data/global-aridity-and-pet-database), which is modelled using the WorldClim database (http://worldclim.org/) at approximately 1km spatial resolution

WUE correction appears to be the most hydrologically comprehensive and widely applicable of the rainfall calibration methods presented in this guide. The main limitation on the accuracy of WUE calibration is likely to be the availability and accuracy of the evapotranspiration data. Consideration of the methodological limitations and characteristics of each ET dataset should be made when using any of these data sets.

6 Comments and limitations

Land productivity is one of three sub-indicators used to assess degradation for SDG Indicator 15.3.1, along with **land cover and land cover change**, and **carbon stocks (above and below ground)**. Each of these sub-indicators responds to different elements of degradation, however they may also be considered complementary in some ways. Changes in land productivity or soil carbon levels may occur over time within a given land cover type, for instance. Changes in land cover type, however, will usually result in changed land productivity levels and dynamics, which in turn influences the carbon stocks in a given region. For this reason, when assessing degradation status on the basis of these three sub-indicators, it is convenient to aggregate fine scale results (such as from the pixel scale assessments in this method) to spatial features identified in the land cover and land cover change sub-indicator.

The methods described in this guide are based on the WAD method, which is best suited to assessing land productivity dynamics in water limited, temperate regions. This method also uses a range of non-parametric or qualitative analyses. This has advantages in terms of enabling nations to make decisions based on other sources of information to interpret the accuracy of degradation assessments using these methods. Potential disadvantages of qualitative analyses include that it can increase subjectivity, which can make results more difficult to compare between regions. Each Nation will differ in its land cover characteristics, access to datasets, analytical capability and development objectives, however, and a particular transition or change that may be mapped as degradation in one Nation may be a desirable outcome in another.

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 fail or new ones emerge. Currently, the MODIS sensors on board the Terra and Aqua satellites provide well calibrated, frequent and moderately high resolution NDVI data for the globe. While Terra and Aqua are well past their six-year design life (https://aqua.nasa.gov/) current predictions are that the MODIS sensors on both Terra and Aqua should be able to provide data into the 2020s.

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